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EXPERIMENTOLOGY

²

AN OPEN SCIENCE APPROACH TO EXPERIMENTAL PSYCHOLOGY METHODS

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³⁸ PREFACE

³⁹ As scientists and practitioners, we often want to create generalizable,
⁴⁰ causal theories of human behavior. As it turns out, experiments—in
⁴¹ which we use random assignment to measure a causal effect—are an
⁴² unreasonably effective tool to help with this task. But how should we
⁴³ go about doing good experiments?

⁴⁴ This book provides an introduction to the workflow of the experimen-
⁴⁵ tal researcher working in psychology or the behavioral sciences more
⁴⁶ broadly. The organization of the book is sequential, from the plan-
⁴⁷ ning stages of the research process through design, data gathering, anal-
⁴⁸ ysis, and reporting. We introduce these concepts via narrative examples
⁴⁹ from a range of sub-disciplines, including cognitive, developmental, and
⁵⁰ social psychology. Throughout, we also illustrate the pitfalls that led to
⁵¹ the “replication crisis” in psychology.

52 To help researchers avoid these pitfalls, we advocate for an open-science
53 based approach in which transparency is integral to the entire experi-
54 mental workflow. We provide readers with guidance for preregistra-
55 tion, project management, data sharing, and reproducible report writ-
56 ing.

57 *The story of this book*

58 Experimental Methods (Psych 251) is the foundational course for in-
59 coming graduate students in the Stanford psychology department. The
60 course goal is to orient students to the nuts and bolts of doing behav-
61 ioral experiments, including how to plan and design a solid experiment
62 and how to avoid common pitfalls regarding design, measurement, and
63 sampling.

64 Almost all student coursework both before and in graduate school deals
65 with the content of their research, including theories and results in their
66 areas of focus. In contrast, our course is sometimes the only one that
67 deals with the *process* of research, from big questions about why we do
68 experiments and what it means to make a causal inference, all the way
69 to the tiny details of project organization, like what to name your di-
70 rectories and how to make sure you don't lose your data in a computer
71 crash.

⁷² This observation leads to our book's title. "Experimentology" is the
⁷³ set of practices, findings, and approaches that enable the construction of
⁷⁴ robust, precise, and generalizable experiments.

⁷⁵ The centerpiece of the Experimental Methods course is a replication
⁷⁶ project, reflecting a teaching model first described in Frank and Saxe
⁷⁷ (2012)¹ and later expanded on in Hawkins, Smith et al. (2018).² Each
⁷⁸ student chooses a published experiment in the literature and collects
⁷⁹ new data on a pre-registered version of the same experimental paradigm,
⁸⁰ comparing their result to the original publication. Over the course of
⁸¹ the quarter, we walk through how to set up a replication experiment,
⁸² how to pre-register confirmatory analyses, and how to write a repro-
⁸³ ducible report on the findings. The project teaches concepts like re-
⁸⁴ liability and validity, which allow students to analyze choices that the
⁸⁵ original experimenters made—often choices that could have been made
⁸⁶ differently in hindsight!

⁸⁷ At the end of the course, we reap the harvest of these projects. The
⁸⁸ project presentations are a wonderful demonstration of both how much
⁸⁹ the students can accomplish in a quarter and also how tricky it can be to
⁹⁰ reproduce (redo calculations in the original data) and replicate (recover
⁹¹ similar results in new data) the published literature. Often our repli-
⁹² cation success rate for the course hovers just above 50%, an outcome

¹ Frank, Michael C, and Rebecca Saxe. 2012. "Teaching Replication." Perspectives on Psychological Science 7: 595–99.

² Hawkins, Robert D, Eric N Smith, Carolyn Au, Juan Miguel Arias, Rhia Catapano, Eric Hermann, Martin Keil, et al. 2018. "Improving the Replicability of Psychological Science Through Pedagogy." Advances in Methods and Practices in Psychological Science 1 (1): 7–18.

⁹³ that can be disturbing or distressing for students who assume that the
⁹⁴ published literature reports the absolute truth.

⁹⁵ This book is an attempt to distill some of the lessons of the course (and
⁹⁶ students' course projects) into a textbook. We'll tell the story of the
⁹⁷ major shifts in psychology that have come about in the last ten years,
⁹⁸ including both the "replication crisis" and the positive methodological
⁹⁹ reforms that have resulted from it. Using this story as motivation, we
¹⁰⁰ will highlight the importance of transparency during all aspects of the
¹⁰¹ experimental process from planning to dissemination of materials, data,
¹⁰² and code.

¹⁰³ *What this book is and isn't about*

¹⁰⁴ This book is about psychology experiments. These will be typically be
¹⁰⁵ short studies conducted online or in a single visit to a lab, often—though
¹⁰⁶ certainly not always—with a convenience sample. When we say "exper-
¹⁰⁷ iments" here we mean **randomized experiments** where some aspect of
¹⁰⁸ the participants' experience is **manipulated** by the experimenter and
¹⁰⁹ then some outcome variable is **measured**.³

¹¹⁰ The central thesis of the book is that:

³ We use bold to indicate the introduction of new technical terms.

111 Experiments are intended to make maximally unbiased,
112 generalizable, and precise estimates of specific causal
113 effects.

114 We'll explore the implications of this thesis for a host of topics, includ-
115 ing causal inference, experimental design, measurement, sampling, pre-
116 registration, data analysis, and many others.

117 Because our focus is on experiments, we won't be talking much about
118 observational designs, survey methods, or qualitative research; these
119 are important tools and appropriate for a whole host of questions, but
120 they aren't our focus here. We also won't go into depth about the
121 many fascinating methodological and statistical issues brought up by
122 single-participant case studies, longitudinal research, field studies, or
123 other methodological variants. Many of the concerns we raise are still
124 important for these types of studies, but some of our advice won't trans-
125 fer to these less common designs.

126 Even for students who are working on non-experimental research, we
127 expect that a substantial part of the book content will still be useful,
128 including chapters on replication (chapter 3), ethics (chapter 4), statis-
129 tics (chapters 5, 6, 7), sampling (chapter 10), project management (chap-
130 ter 13), and reporting (chapters 14, 15, 16).

¹³¹ In our writing, we presuppose that readers have some background in
¹³² psychology, at least at an introductory level. In addition, although we
¹³³ introduce a number of statistical topics, readers might find these sections
¹³⁴ more accessible with an undergraduate statistics course under their belt.
¹³⁵ Finally, our examples are written in the R statistical programming lan-
¹³⁶ guage, and for chapters on statistics and visualization especially (chap-
¹³⁷ ters 5, 6, 7, 15, 16), some familiarity with R will be helpful for under-
¹³⁸ standing the code. None of these prerequisites are necessary to read
¹³⁹ the book, but we offer them so that readers can calibrate their expecta-
¹⁴⁰ tions.

¹⁴¹ *How to use this book*

¹⁴² The book is organized into five main parts, mirroring the timeline of
¹⁴³ an experiment: 1) Foundations, 2) Statistics, 3) Planning, 4) Execution,
¹⁴⁴ and 5) Reporting. We hope that this organization makes it well-suited
¹⁴⁵ for teaching or for use as a reference book.⁴

¹⁴⁶ The book is designed for a course for graduate students or advanced un-
¹⁴⁷ dergraduates, but the material is also suitable for self-study by anyone
¹⁴⁸ interested in experimental methods, whether in academic psychology
¹⁴⁹ or any other context—in our out of academia—in which behavioral ex-
¹⁵⁰ perimentation is relevant. We also hope that some readers will come to

⁴ If you are an instructor who is planning to adopt the book for a course, you might be interested in our resources for instructors, including sample course schedules, in appendix A.

¹⁵¹ particular chapters of the book because of an interest in specific topics
¹⁵² like measurement (chapter 8) or sampling (chapter 10) and will be able
¹⁵³ to use those chapters as standalone references. And finally, for those in-
¹⁵⁴ terested in the “replication crisis” and subsequent reforms, chapters 3,
¹⁵⁵ 11, and 13 will be especially interesting.

¹⁵⁶ Ultimately, we want to give you what you need to plan and execute
¹⁵⁷ your own study! Instead of enumerating different approaches, we try to
¹⁵⁸ provide a single coherent – and often quite opinionated – perspective,
¹⁵⁹ using marginal notes and references to give pointers to more advanced
¹⁶⁰ materials or alternative approaches. Throughout, we offer:

¹⁶¹ – **Case studies** that illustrate the central concepts of a chapter,
¹⁶² – **Accident reports** describing examples where poor research prac-
¹⁶³ tices led to issues in the literature, and
¹⁶⁴ – **Depth boxes** providing simulations, linkages to advanced tech-
¹⁶⁵ niques, or more nuanced discussion.

¹⁶⁶ While case studies are often integral to the chapters, the other boxes
¹⁶⁷ can typically be skipped without issue.

¹⁶⁸ *Themes*

¹⁶⁹ We highlight four major cross-cutting themes for the book: TRANSPARENCY, MEASUREMENT PRECISION, BIAS REDUCTION, and GENERALIZABILITY.⁵

⁵ Themes are noted using SMALL CAPS.

¹⁷² — TRANSPARENCY: For experiments to be reproducible, other researchers need to be able to determine exactly what you did. Thus, every stage of the research process should be guided by a primary concern for transparency. For example, preregistration creates transparency into the researcher’s evolving expectations and thought processes; releasing open materials and analysis scripts creates transparency into the details of the procedure.

¹⁷⁹ — MEASUREMENT PRECISION: We want researchers to start planning an experiment by thinking “what causal effect do I want to measure” and to make planning, sampling, design, and analytic choices that maximize the precision of this measurement. A downstream consequence of this mindset is that we move away from a focus on dichotomized inferences about statistical significance and towards analytic and meta-analytic models that focus on continuous effect sizes and confidence intervals.

¹⁸⁷ — BIAS REDUCTION: While precision refers to random error in a measurement, measurements also have systematic sources of error that

189 bias them away from the true quantity. In our samples, analyses,
190 experimental designs, and in the literature, we need to think care-
191 fully about sources of bias in the quantity being estimated.

- 192 – GENERALIZABILITY: Complex behaviors are rarely universal across
193 all settings and populations, and any given experiment can only
194 hope to cover a small slice of the possible conditions where a be-
195 havior of interest takes place. Psychologists must therefore con-
196 sider the generalizability of their findings at every stage of the
197 process, from stimulus selection and sampling procedures, to ana-
198 lytic methods and reporting.

199 Throughout the book, we will return to these four themes again and
200 again as we discuss how the decisions made by the experimenter at ev-
201 ery stage of design, data gathering, and analysis bear on the inferences
202 that can be made about the results. The introduction of each chapter
203 highlights connections to specific themes.

204 *The software toolkit for this book*

205 We introduce and advocate for an approach to reproducible study plan-
206 ning, analysis, and writing. This approach depends on an ecosystem of
207 open-source software tools, which we introduce in the book’s appen-
208 dices.⁶

⁶ These appendices are available online at <https://experimentology.io> but not in the print version of the book, since their content is best viewed in the web format.

- 209 – The R statistical programming language and the RStudio⁷ inte-
210 grated development environment,
211 – Version control using git and GitHub⁸, allowing collaboration on
212 text documents like code, prose, and data, storing and integrating
213 contributions over time (appendix B),
214 – The RMarkdown and Quarto tools for creating reproducible re-
215 ports that can be rendered to a variety of formats (appendix C),
216 – The tidyverse family of R packages, which extend the basic
217 functionality of R with simple tools for data wrangling, analysis,
218 and visualization (appendix D), and
219 – The ggplot2 plotting package, which makes it easy to create
220 flexible data visualizations for both confirmatory and exploratory
221 data analyses (appendix E).

⁷ [https://posit.co/download/rstudio-
desktop/](https://posit.co/download/rstudio-desktop/)

⁸ <https://github.com/>

222 Where appropriate, we provide **code boxes** that show the specific R
223 code used to create our examples.

224 *Onward!*

225 Thanks for joining us for Experimentology! Whether you are casu-
226 ally browsing, doing readings for a course, or using the book as a ref-
227 erence in your own experimental work, we hope you find it useful.

²²⁸ Throughout, we have tried to practice what we preach in terms of re-
²²⁹ producibility, and so the full source code for the book is available at
²³⁰ <https://github.com/langcog/experimentology>. We encourage you to
²³¹ browse, comment, and log issues or suggestions.⁹

⁹ The best way to give us specific feedback is to create an issue on our github page at <https://github.com/langcog/experimentology/issues>.

²³² *Acknowledgments*

²³³ Thanks first and foremost to the many generations of students and TAs
²³⁴ in Stanford Psych 251, who have collectively influenced the content of
²³⁵ this book through their questions and interests.

²³⁶ Thanks to the staff at the MIT Press, especially Philip Laughlin and Amy
²³⁷ Brand, for embracing a vision of a completely open web textbook that is
²³⁸ also reviewed and published through a traditional press. We appreciate
²³⁹ your support and flexibility.

²⁴⁰ We adapt the Contributor Roles (CRediT) Taxonomy¹⁰ to describe our
²⁴¹ contributions to this manuscript, and we recommend that you do so in
²⁴² your work as well.

¹⁰ Learn more at <https://credit.niso.org/>.

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|

322

FOUNDATIONS

1 EXPERIMENTS

323



LEARNING GOALS

- Define what an experiment is
- Contrast observational and experimental studies using causal graphs
- Understand the role of randomization in experiments
- Consider constraints on the generalizability of experiments

324

325 Welcome to *Experimentology*! This is a book all about the art of running
326 experiments in psychology. Throughout, we will be guided by a simple
327 idea:

328 The purpose of experiments is to estimate the magnitude
329 of causal effects.¹

330 Starting from our core idea, we'll provide advice about how to navi-
331 gate things like experimental design, measurement, sampling, and more.

¹ Perhaps you're already saying, "That's not what I thought experiments were for! I thought they were for testing hypotheses." Bear with us and we hope we'll convince you that our definition is a bit more general, and that testing a hypothesis is one thing you can do with a measurement.

332 Our decisions about each of these will determine how precise our es-
333 timate is, and whether it is subject to bias. But before we get to those
334 topics, let's start by thinking about *why* we might do an experiment, a
335 topic that will intersect with our key themes of BIAS REDUCTION and
336 GENERALIZABILITY.

337 1.1 *Observational studies don't reveal causality*

338 If you're reading this book, there's probably something about psychol-
339 ogy you want to understand. How is language learned? How is it that
340 we experience emotions like happiness and sadness? Why do humans
341 sometimes work together and other times destroy one another? When
342 psychologists study these centuries-old questions, they often transform
343 them into questions about **causality**.²

344 1.1.1 *Describing causal relationships*

345 Consider the age-old question: does money make people happy? This
346 question is—at its heart—a question about what interventions on the
347 world we can make. Can I get more money and make myself happier?
348 Can I *cause* happiness with money?

² Defining causality is one of the trickiest and oldest problems in philosophy, and we won't attempt to solve it here! But from a psychological perspective, we're fond of Lewis (1973)'s "counterfactual" analysis of causality. On this view, we can understand the claim that *money causes happiness* by considering a scenario where if people *hadn't* been given more money, they *wouldn't* have experienced an increase in happiness.

³⁴⁹ How could we test our hypothesized effect of money on happiness?
³⁵⁰ Intuitively, many people think of running an **observational study**. We
³⁵¹ might survey people about how much money they make and how happy
³⁵² they are. The result of this study would be a pair of measurements for
³⁵³ each participant: [money, happiness].

³⁵⁴ Now, imagine your observational study found that money and happi-
³⁵⁵ ness were related—statistically **correlated** with one another: people with
³⁵⁶ more money tended to be happier. Can we conclude that money causes
³⁵⁷ happiness? Not necessarily. The presence of a correlation does not
³⁵⁸ mean that there is a causal relationship!

³⁵⁹ Let's get a bit more precise about our causal hypothesis. To illustrate
³⁶⁰ causal relationships, we can use a tool called **directed acyclic graphs**
³⁶¹ (DAGs, Pearl 1998). Figure 1.1 shows an example of a DAG for money
³⁶² and happiness: the arrow represents our idea about the potential causal
³⁶³ link between two variables: money and happiness.³ The direction of
³⁶⁴ the arrow tells us which way we hypothesize that the causal relation-
³⁶⁵ ship goes.

³⁶⁶ The correlation between money and happiness we saw in our observa-
³⁶⁷ tional study is consistent with the causal model in figure 1.1; however,
³⁶⁸ it is also consistent with several alternative causal models, which we will
³⁶⁹ illustrate with DAGs below.

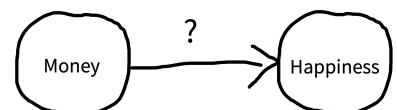


Figure 1.1
The hypothesized causal effect of money on happiness.

³ In this chapter, we're going to use the term “variables” without discussing why we study some variables and not others. In the next chapter, we'll introduce the term “construct,” which indicates a psychological entity that we want to theorize about.

³⁷⁰ 1.1.2 *The problems of directionality and confounding*

³⁷¹ figure 1.2 uses DAGs to illustrate several causal models that are consistent
³⁷² with the observed correlation between money and happiness. DAG
³⁷³ 1 represents our hypothesized relationship—money causes people to be
³⁷⁴ happy. But DAG 2 shows an effect in completely the opposite direction!
³⁷⁵ In this DAG, being happy causes people to make more money.

³⁷⁶ Even more puzzling, there could be a correlation, but no causal relationship
³⁷⁷ between money and happiness in either direction. Instead, a third
³⁷⁸ variable—often referred to as a **confound**—may be causing increases in
³⁷⁹ both money and happiness. For example, maybe having more friends
³⁸⁰ causes people to both be happier and make more money (DAG 3). In
³⁸¹ this scenario, happiness and money would be correlated even though
³⁸² one does not cause the other.

³⁸³ A confound (or several) may entirely explain the relationship between
³⁸⁴ two variables (as in DAG #3); but it can also just *partly* explain the re-
³⁸⁵ lationship. For example, it could be that money does increase happiness,
³⁸⁶ but the causal effect is rather small, and only accounts for a small
³⁸⁷ portion of the observed correlation between them, with the friendship
³⁸⁸ confound (and perhaps others) accounting for the remainder.

³⁸⁹ In this case, because of the confounds, we say that the observed corre-

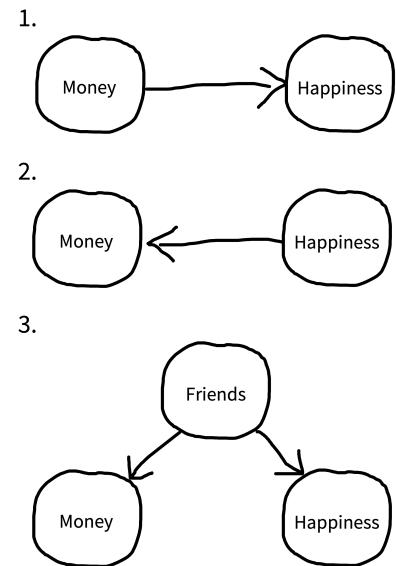


Figure 1.2
 Three reasons why money and happiness can be correlated.

390 lation between money and happiness is a **biased** estimate of the causal
391 effect of money on happiness. The amount of bias introduced by the
392 confounds can vary in different scenarios—it may only be small, or it
393 may be so strong that we conclude there’s a causal relationship between
394 two variables when there isn’t one at all.

395 The state of affairs summarized in figure 1.2 is why we say “correlation
396 doesn’t imply causation.” A correlation between two variables *is consistent*
397 *with* a causal relationship between them, but it’s also consistent with
398 other relationships as well.⁴

399 You can still learn about causal relationships from observational stud-
400 ies, but you have to take a more sophisticated approach. You can’t just
401 measure correlations and leap to causal conclusions. The “causal rev-
402 olution” in the social sciences has been fueled by the development of
403 statistical methods for reasoning about causal relationships from obser-
404 vational datasets.⁵ As interesting as these methods are, however, they
405 are only applicable in certain specific circumstances. In contrast, the
406 experimental method *always* works to reduce bias due to confounding
407 (though of course there are certain experiments that we can’t do for
408 ethical or practical reasons).

⁴ People sometimes ask whether *causation implies correlation* (the opposite direction). The short answer is “also no.” A causal relationship between two variables often means that they will be correlated in the data, but not always. For example, imagine you measured the speed of a car and the pressure on the gas pedal / accelerator. In general, pressure and speed will be correlated, consistent with the causal relationship between the two. But now imagine you only measured these two variables when someone was driving the car up a hill—now the speed would be constant, but the pressure might be increasing, reflecting the driver’s attempts to keep their speed up. So there would be no correlation between the two variables in that dataset, despite the continued causal relationship.

409 1.2 Experiments help us answer causal questions

410 Imagine that you (a) created an exact replica of our world, (b) gave
411 \$1,000 to everybody in the replica world, and then (c) found a few years
412 later that everyone in the replica world was happier than their matched
413 self in the original world. This experiment would provide strong evi-
414 dence that money makes people happier. Let's think through why.

415 Consider a particular person—if they are happier in the replica vs. orig-
416 inal world, what could explain that difference? Since we have repli-
417 cated the world exactly, but made only one change—money—then that
418 change is the only factor that could explain the difference in happiness.

419 We can say that we **held all variables constant** except for money, which
420 we **manipulated** experimentally, observing its effect on some **measure**—
421 happiness. This idea—holding all variables constant except for the spe-
422 cific experimental manipulation—is the basic logic that underpins the
423 experimental method (as articulated by Mill 1882).⁶ Let's think back to
424 our observational study of money and happiness. One big causal infer-
425 ence problem was the presence of “third variable” confounds like hav-
426 ing more friends. More friends could cause you to have more money
427 and also cause you to be happier. The idea of an experiment is to hold
428 everything else constant—including the number of friends that people
429 have—so we can measure the effect of money on happiness. By holding

⁵ In fact, DAGs are one of the key tools that social scientists use to reason about causal relationships. DAGs guide the creation of statistical models to estimate particular causal effects from observational data. We won't talk about these methods here, but if you're interested, check out the suggested readings at the end of this chapter.

⁶ Another way to reason about why we can infer causality here follows the counterfactual logic we described in an earlier footnote. If the definition of causality is counterfactual (“what would have happened if the cause had been different”), then this experiment fulfills that definition. In our impossible experiment, we can literally *see* the counterfactual: if the person had \$1,000 more, here's how much happier they would be!

430 number of friends constant, we would be severing the causal links be-
 431 tween friends and both money and happiness. This move is graphically
 432 conveyed in figure 1.3, where we “snip away” the friend confound.

433 1.2.1 We can’t hold people constant

434 This all sounds great in theory, you might be thinking, but we can’t
 435 actually create replica worlds where everything is held constant, so how
 436 do we run experiments in the real world? If we were talking about
 437 experiments on baking cakes, it’s easy to see how we could hold all of
 438 the ingredients constant and just vary one thing, like baking temperature.
 439 Doing so would allow us to conduct an experimental test of the effect of
 440 baking temperature. But how we can “hold something constant” when
 441 we’re talking about people? People aren’t cakes. No two people are
 442 alike and, as every parent with multiple children knows, even if you try
 443 to “hold the ingredients constant” they don’t come out the same!

444 If we take two people and give one money, we’re comparing two *differ-*
 445 *ent* people, not two instances of the same person with everything held
 446 constant. It wouldn’t work to *make* the first person have more or fewer
 447 friends so they match the second person—that’s not holding anything
 448 constant, instead it’s another (big, difficult, and potentially unethical)
 449 intervention that might itself cause lots of effects on happiness.

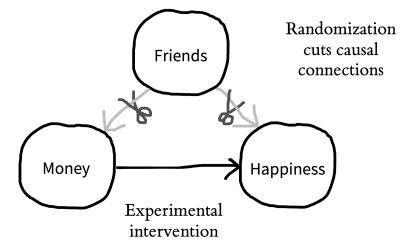


Figure 1.3

In principle, experiments allows us to “snip away” the friend confound by holding it constant (though in practice, it can be tough to figure out how to hold something constant when you are talking about people as your unit of study).

450 You may be wondering: why don't we just ask people how many friends
 451 they have and use this information to split them into equal groups? You
 452 could do that, but this kind of strategy only allows you to control for
 453 the confounds you know of. For example, you may split people equally
 454 based on their number of friends, but not their education attainment.
 455 If educational attainment also impacts both money and happiness, you
 456 still have a confound. You may then try to split people by both their
 457 number of friends and their education. But perhaps there's another con-
 458 found you've missed: sleep quality! Similarly, it also doesn't work to se-
 459 lect people who have the same number of friends—that only holds the
 460 friends variable constant and not everything *else* that's different between
 461 the two people. So what do we do instead?⁷

462 1.2.2 Randomization saves the day

463 The answer is **randomization**. If you randomly split a large roomful
 464 of people into two groups, the groups will, on average, have a similar
 465 number of friends. Similarly, if you randomly pick who in your experi-
 466 ment gets to receive money, you will find that the money and no-money
 467 groups, on average, have a similar number of friends. In other words,
 468 through randomization, the confounding role of friends is controlled.
 469 But the most important thing is that it's not *just* the role of friends that's

⁷ Many researchers who have seen re-
 gression models used in the social sci-
 ences assume that “controlling for lots of
 stuff” is a good way to improve causal
 inference. Not so! In fact, inappropri-
 ately controlling for a variable in the ab-
 sence of a clear causal justification can ac-
 tually make your effect estimate *more* bi-
 ased (Wysocki, Lawson, and Rheumtulla
 2022).

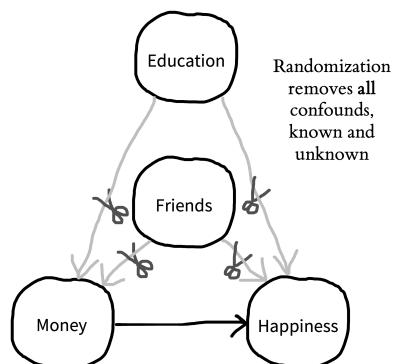


Figure 1.4
 If you randomly split a large group of people into groups, the groups will, on average, be equal in every way.

470 controlled; educational attainment, sleep quality, and all the other con-
471 founds are controlled as well. If you randomly split a large group of
472 people into groups, the groups will, on average, be equal in every way
473 (figure 1.4).

474 So, here's our simple experimental design: we randomly assign some
475 people to a money group and some people to a no-money control group!
476 (We sometimes call these groups **conditions**). Then we measure the
477 happiness of people in both groups. The basic logic of randomization
478 is that, if money causes happiness, we should see more happiness—on
479 average—in the money group.⁸

480 Randomization is a powerful tool, but there is a caveat: it doesn't work
481 every time. *On average*, randomization will ensure that your money and
482 no-money groups will be equal with respect to confounds like number
483 of friends, education attainment, and sleep quality. But just as you can
484 flip a coin and sometimes get heads 9 out of 10 times, sometimes you use
485 randomization and still get more highly-educated people in one condi-
486 tion than the other. When you randomize, you guarantee that, on aver-
487 age, all confounds are controlled. Hence, there is no systematic bias in
488 your estimate from these confounds. But there will still be some noise
489 from random variation.

490 In sum, randomization is a remarkably simple and effective way of hold-

⁸ You may already be protesting that this experiment could be done better. Maybe we could measure happiness before and after randomization, to increase precision. Maybe we need to give a small amount of money to participants in the control condition to make sure that participants in both conditions interact with an experimenter and hence that the conditions are as similar as possible. We agree! These are important parts of experimental design, and we'll touch on them in subsequent chapters.

491 ing everything constant besides a manipulated variable. In doing so,
492 randomization allows experimental psychologists to make unbiased es-
493 timates of causal relationships. Importantly, randomization works both
494 when you do have control of every aspect of the experiment—like when
495 you are baking a cake—and even when you don’t—like when you are
496 doing experiments with people.⁹

DEPTH

Unhappy randomization?

As we’ve been discussing, random assignment removes confounding by ensuring that—on average—groups are equivalent with respect to all of their characteristics. Equivalence for any *particular* random assignment is more likely the larger your sample is, however. Any individual experiment may be affected by **unhappy randomization**, when a particular confound is unbalanced between groups by chance.

Unhappy randomization is much more common in small experiments than larger ones. To see why, we use a technique called **simulation**. In simulations, we invent data randomly following a set of assumptions: we make up a group of participants and generate their characteristics and their condition assignments. By varying the assumptions we use, we can investigate how particular choices might change the structure of the data.

To look at unhappy randomization, we created many simulated versions of our money-happiness experiment, in which an experimental group re-

⁹ There’s an important caveat to this discussion: you don’t always have to randomize *people*. You can use an experimental design called a **within-participants** design, in which the same people are in multiple conditions. This type of design has a different set of unknown confounds, this time centering around *time*. So, to get around them, you have to randomize the order in which your manipulation is delivered. This randomization works very well for some kinds of manipulations, but not so well for others. We’ll talk more about these kinds of designs in chapter 9.

ceives money and the control group receives none, and then happiness is measured for both groups. We assume that each participant has a set number of friends, and that the more friends they have, the happier they are. So when we randomly assign them to experimental and control groups, we run the risk of unhappy randomization—sometimes one group will have substantially more friends than the other.

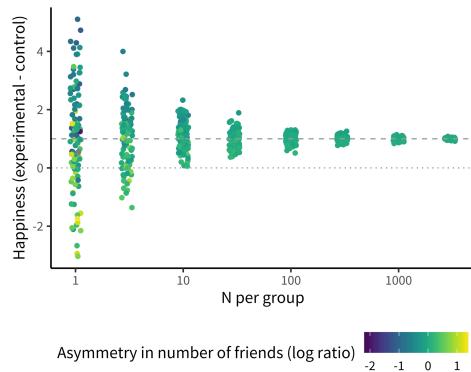


Figure 1.5
Simulated data from our money-happiness experiment. Each dot represents the measured happiness effect (vertical position) for an experiment with a set number of participants in each group (horizontal position). Dot color shows how uneven friendship is between the groups. The dashed line shows the true effect.

figure 1.5 shows the results of this simulation. Each dot is an experiment, representing one estimate of the happiness effect (how much happiness is gained for the amount of money given to the experimental group). For very small experiments (e.g., with 1 or 3 participants per group), dots are very far from the dashed line showing the true effect—meaning these estimates are extremely noisy! And the reason is unhappy randomization. The upper and lower points are those in which one group had far more friends than the other.

There are three things to notice about this simulation. First, the noise

overall goes down as the sample sizes get bigger: larger experiments yield estimates closer to the true effect. Second, the unhappy randomization decreases dramatically as well with larger samples. Although individuals still differ just as much in large experiments, the *group* average number of friends is virtually identical for each condition in the largest groups.

Finally, although the small experiments are individually very noisy, the *average effect* across all of the small experiments is still very close to the true effect. This last point illustrates what we mean when we say that randomized experiments remove confounds. Even though friendship is still an important factor determining happiness in our simulation, the average effect across experiments is correct and each individual estimate is unbiased.

499

500 1.3 Generalizability

501 When we are asking questions about psychology, it's important to think
502 about who we are trying to study. Do we want to know if money in-
503 creases happiness in *all people*? In people who live in materialistic so-
504 cieties? In people whose basic needs are not being met? We call the
505 group we are trying to study our **population of interest**, and the people
506 who actually participate in our experiment our **sample**. The process of
507 **sampling** is then what we do to recruit people into our experiment.

508 Sometimes researchers sample from one population, but make a claim
509 about another (usually broader) population. For example, they may run
510 their experiment with a particular sample of U.S. college students, but
511 then generalize to all people (their intended population of interest). The
512 mismatch of sample and population is not always a problem, but quite
513 often causal relationships are different for different populations.

514 Unfortunately, psychologists pervasively assume that research on U.S.
515 and European samples generalizes to the rest of the world, and it of-
516 ten does not. To highlight this issue, Henrich, Heine, and Norenzayan
517 (2010) coined the acronym WEIRD. This catchy name describes the
518 oddness of making generalizations about all of humanity from exper-
519 iments on a sample that is quite unusual because it is Western, Edu-
520 cated, Industrialized, Rich, and Democratic. Henrich and colleagues
521 argue that seemingly “fundamental” psychological functions like visual
522 perception, spatial cognition, and social reasoning all differ pervasively
523 across populations—hence, any generalization from an effect estimated
524 with a WEIRD sub-population may be unwarranted.

525 In the early 2000’s, researchers found that gratitude interventions—like
526 writing a brief essay about something nice that somebody did for you—
527 increased happiness in studies conducted in Western countries. Based on
528 these findings, some psychologists believed that gratitude interventions

529 could increase happiness in all people. But it seems they were wrong.
530 A few years later, Layous et al. (2013) ran a gratitude experiment in
531 two locations: the U.S. and South Korea. Surprisingly, the gratitude
532 intervention decreased happiness in the South Korean sample. The re-
533 searchers attributed this negative effect to feelings of indebtedness that
534 people in South Korea more prominently experienced when reflecting
535 on gratitude. In this example, we would say that the findings obtained
536 with the U.S. sample may not **generalize** to people in South Korea.

537 Issues of generalizability extend to all aspects of an experiment, not just
538 its sample. For example, even if our hypothetical cash intervention ex-
539 periment resulted in gains in happiness, we might not be warranted in
540 generalizing to different ways of providing money. Perhaps there was
541 something special about the amount of money we gave or the way we
542 provided it that led to the effect we observed. Without testing multi-
543 ple different intervention types, we can't make a broad claim. As we'll
544 see in chapter 7 and chapter 9, this issue has consequences for both our
545 statistical analyses and our experimental designs (Yarkoni 2020).

546 Questions of generalizability are pervasive, but the first step is to simply
547 acknowledge and reason about them. Perhaps all papers should have a
548 Constraints on Generality statement, where researchers discuss whether
549 they expect their findings to generalize across different samples, exper-

550 imental stimuli, procedures, and historical and temporal features (Si-
 551 mons, Shoda, and Lindsay 2017). This kind of statement would at least
 552 remind researchers to be humble: experiments are a powerful tool for
 553 understanding how the world works, but there are limits to what any
 554 individual experiment can teach us.

555 *1.4 Anatomy of a randomized experiment*

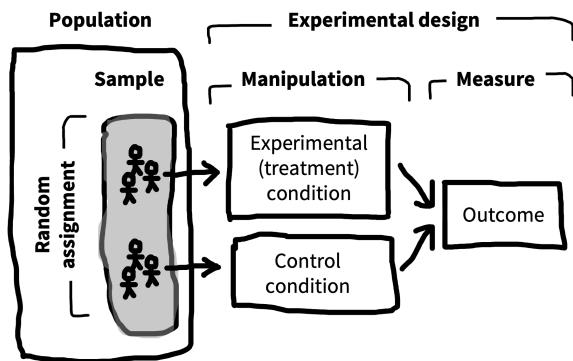


Figure 1.6
Anatomy of a randomized experiment.

556 Now is a good time for us to go back and consolidate the anatomy of
 557 an experiment, since this anatomy is used throughout the book. Fig-
 558 ure 1.6 shows a simple two-group experiment like our possible money-
 559 happiness intervention. A sample is taken from a larger population, and
 560 then participants in the sample are randomly assigned to one of two
 561 conditions (the manipulation)—either the experimental condition, in
 562 which money is provided, or the control condition, in which none is
 563 given. Then an outcome measure—happiness—is recorded for each par-
 564 ticipant.

565 We'll have a lot more to say about all of these components in subsequent
566 chapters. We'll discuss measures in chapter 8, because good measure-
567 ment is the foundation of a good experiment. Then in chapter 9 we'll
568 discuss the different kinds of experimental designs that are possible and
569 their pros and cons. Finally, we'll cover the process of sampling in chap-
570 ter 10.



ACCIDENT REPORT

An experiment with very unclear causal inferences

The Stanford Prison Experiment is one of the most famous studies in the history of psychology. Participants were randomly assigned to play the role of “guards” and “prisoners” in a simulation of prison life inside the Stanford Psychology building ([Zimbardo 1972](#)). Designed to run for two weeks, the simulation had to be ended after six days due to the cruelty of the participants acting as guards, who apparently engaged in a variety of dehumanizing behaviors towards the simulated prisoners. This result is widely featured in introductory psychology textbooks and is typically interpreted as showing the power of situational factors: in the right context, even undergraduate students at Stanford could quickly be convinced to act out the kind of inhumane behaviors found in the worst prisons in the world ([Griggs 2014](#)).

In the years since the study was initially reported, a variety of information has surfaced that makes the causal interpretation of its situational manipu-

lation much less clear (Le Texier 2019). Guards were informed of the objectives of the experiment and given instructions on how to achieve these objectives. The experimenters themselves suggested some harsh punishments whose later use was given as evidence for the emergence of dehumanizing behaviors. Further, both guards and prisoners were coached extensively by the experimenter throughout the study. Some participants have reported that their responses during the study were exaggerated or fabricated (Blum 2018). All of these issues substantially undermine the idea that the assignment of participants' roles (the ostensible experimental manipulation) was the sole cause of the observed behaviors.

The conduct of the study was also unethical. In addition to the question of whether such a study—with all of its risks to the participants—would be ethical at all, a number of features of the study clearly violate the guidelines that we'll learn about in chapter 4. Participants were prevented from exiting the study voluntarily. The guards were deceived into believing that they were research assistants, rather than participants in the study. And to top it off, the study was reported inaccurately, with reports emphasizing the organic emergence of behaviors, the immersive nature of the simulation, and the extensive documentation of the experiment. In fact, the participants were instructed extensively, the simulation was repeatedly interrupted by mundane details of the research environment, and relatively little of the experiment was captured on video and analyzed.

The Prison Experiment is a fascinating and problematic episode in the history of psychology, but it provides very little causal evidence about

the human mind.

573

574 1.5 Chapter summary: Experiments

575 In this chapter, we defined an experiment as a combination of a ma-
576 nipulation and a measure. When combined with randomization, ex-
577 periments allow us to make strong causal inferences, even when we are
578 studying people (who are hard to hold constant). Nonetheless, there are
579 limits to the power of experiments: there are always constraints on the
580 sample, experimental stimuli, and procedure that limit how broadly we
581 can generalize.



DISCUSSION QUESTIONS

1. Imagine that you run a survey and find that people who spend more time playing violent video games tend to be more aggressive (i.e., that there is a positive correlation between violent video games and aggression). Following figure 1.2, list three reasons why these variables may be correlated.
2. Suppose you wanted to run an experiment testing whether playing violent video games causes increases in aggression. What would be your manipulation and what would be your measure? How would you deal with potential confounding by variables like age?
3. Consider an experiment designed to test people's food preferences.

582

The experimenter randomly assigns 30 U.S. preschoolers to be served either asparagus or chicken tenders and then asks them how much they enjoyed their meal. Overall, children enjoyed the meat more; the experimenter writes a paper claiming that humans prefer meat over vegetables. List some constraints on the generalizability of this study. In light of these constraints, is this study (or some modification) worth doing at all?

4. Consider the Milgram study, another classic psychology study (and our case study in chapter 4). Does this study meet our definition of an experiment?

583

READINGS

- A basic introduction to causal inference from a social science perspective: Huntington-Klein, N. (2022). *The Effect: An Introduction to Research Design and Causality*. Chapman & Hall. Available free online at <https://theeffectbook.net>.
- A slightly more advanced treatment, focusing primarily on econometrics: Cunningham, S. (2021). *Causal Inference: The Mixtape*. Yale Press. Available free online at <https://mixtape.scunning.com>.

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2 THEORIES

589



LEARNING GOALS

- Define theories and their components
- Contrast different philosophical views on scientific theories
- Analyze features of an experiment that can lead to strong tests of theory
- Discuss the role of formalization in theory development

590

591 When you do an experiment, sometimes you just want to see what hap-
592 pens, like a kid knocking down a tower made of blocks. And sometimes
593 you want to know the answer to a specific applied question, like “will
594 giving a midterm vs. weekly quizzes lead students in a class to perform
595 better on the final?” But more often, our goal is to create **theories** that
596 help us explain and predict new observations.

597 What is a theory? We’ll argue here that we should think of psycholog-
598 ical theories as sets of proposed relationships among **constructs**, which
599 are variables that we think play causal roles in determining behavior. In

600 this conception of theories, the role of causality is central: theories are
601 guesses about the causal structure of the mind and about the causal re-
602 lationships between the mind and the world. This definition doesn't
603 include everything that gets called a "theory" in psychology. We de-
604 scribe the continuum between theories and **frameworks**—broad sets of
605 ideas that guide research but don't make specific contact with particular
606 empirical observations.

607 We begin this chapter by talking about the specific enterprise of con-
608 structing psychological theories. We'll then discuss how theories make
609 contact with data, reviewing a bit of the philosophy of science, and give
610 some guidance on how to construct experiments that test theories. We
611 end by discussing the relationship between theories and quantitative
612 models. This material touches on several of our book themes, includ-
613 ing GENERALIZABILITY of theories and the need for MEASUREMENT PRE-
614 CISION to make strong tests of theory.

615 2.1 *What is a psychological theory?*

616 The definition we just gave for a psychological theory is that it is a pro-
617 posed set of causal relationships among constructs that helps us explain
618 behavior. Let's look at the ingredients of a theory: the constructs and

619 the relationships between them. Then we can ask about how this defi-
620 nition relates to other things that get called “theories” in psychology.

621 *2.1.1 Psychological constructs*

622 Constructs are the psychological variables that we want our theory to
623 describe, like “money” and “happiness” in the example from last chap-
624 ter. At first glance, it might seem odd that we need a specific name for
625 these variables. But in probing the relationship between money and
626 happiness, we will have to figure out a way to measure happiness. Let’s
627 say we just ask people to answer the question “how happy are you?” by
628 giving ratings on a 1 (miserable) to 10 (elated) scale.

629 Now say someone in the study reports they are an 8 on this scale. Is this
630 *really* how happy they are? What if they weren’t concentrating very
631 hard on the rating, or if they thought the researcher wanted them to
632 be happy? What if they act much less happy in their interactions with
633 family and friends?

634 We resolve this dilemma by saying that the self-report ratings we collect
635 are only a **measure** of a **latent** construct, happiness. The construct is
636 latent because we can never see it directly, but we think it has a causal
637 influence on the measure: happier people should, on average, provide
638 higher ratings. But many other factors can lead to noise or bias in the

639 measurement, so we shouldn't mistake those ratings as actually *being* the
640 construct.

641 The particular question "how happy are you?" is one way of going from
642 the general construct to a specific measure. The general process of go-
643 ing from construct to a specific instantiation that can be measured or
644 manipulated is called **operationalization**. Happiness can be operational-
645 ized by self-report, but it can also be operationalized many other ways,
646 for example through a measure like the use of positive language in a
647 personal essay, or by ratings by friends, family, or a clinician. These de-
648 cisions about how to operationalize a construct with a particular mea-
649 sure are tricky and consequential, and we discuss them extensively in
650 chapter 8. Each different operationalization might be appropriate for a
651 specific study, yet it would require some justification and argument to
652 connect each one to the others.

653 Proposing a particular construct is a very important part of making a
654 theory. For example, a researcher might worry that self-reported hap-
655 piness is very different than someone's well-being as observed by the
656 people around them, and assert that happiness is not a single construct
657 but rather a group of distinct constructs. This researcher would then
658 be surprised to know that self-reports of happiness relate very highly
659 to others' perceptions of a person's well-being ([Sandvik, Diener, and](#)

660 Seidlitz 1993).¹

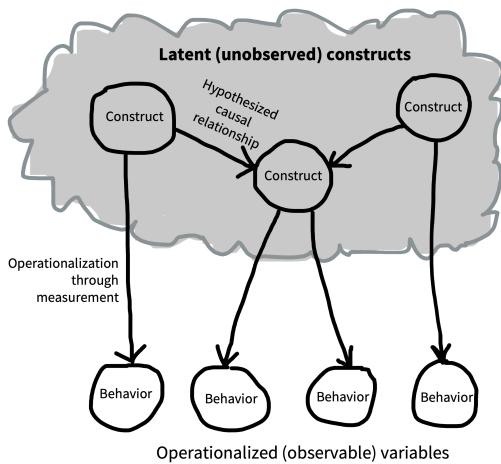
661 Even external, apparently non-psychological variables like money don't
662 have direct effects on people, but rather operate through psychological
663 constructs. People studying money seriously as a part of psychological
664 theories think about perceptions of money in different ways depending
665 on the context. For example, researchers have written about the im-
666 portance of how much money you have on hand based on when in the
667 month your paycheck arrives (Ellwood-Lowe, Foushee, and Srinivasan
668 2022), but have also considered perceptions of long-term accumulation
669 of wealth as a way of conceptualizing people's understanding of the dif-
670 ferent resources available to White and Black families in the United
671 States (Kraus et al. 2019).

672 Finally, a construct can be operationalized through a manipulation: in
673 our money-happiness example, we operationalized "more money" in
674 our theory with a gift of a specific amount of cash. We hope you see
675 through these examples that operationalization is a huge part of the craft
676 of being a psychology researcher—taking a set of abstract constructs that
677 you're interested in and turning them into a specific experiment with a
678 manipulation and a measure that tests your causal theory. We'll have a
679 lot more to say about how this is done in chapter 9.

¹ Sometimes positing the construct *is* the key part of a theory. *g* (general intelligence) is the classic psychological example of a single-construct theory. The idea behind *g* theory is that the best measure of general intelligence is the shared variance between a wide variety of different tests. The decision to theorize about and measure a single unified construct for intelligence—rather than say, many different separate kinds of intelligence—is itself a controversial move.

680 2.1.2 *The relationships between constructs*

681 Constructs gain their meaning in part via their own definitions and op-
 682 erationalizations, but also in part through their causal relationships to
 683 other constructs. Figure 2.1 shows a schematic of what this kind of the-
 684 ory might look like—as you can see, it looks a lot like the DAGs that we
 685 introduced in the last chapter! That’s no accident. The arrows here also
 686 describe hypothesized causal links.²



687 This web of constructs and assumptions is what Cronbach and Meehl
 688 (1955) referred to as a “nomological network”—a set of proposals about
 689 how different entities are connected to one another. The tricky part
 690 is that the key constructs are never observed directly. They are in peo-
 691 ple’s heads.³ So researchers only get to probe them by measuring them
 692 through specific operationalizations.

693 One poetic way of thinking about this idea is that the theoretical system

² Sometimes these kind of diagrams are used in the context of a statistical method called Structural Equation Modeling, where circles represent constructs and lines represent their relationships with one another. Confusingly, structural equation models are also used by many researchers to describe psychological theories. The important point for now is that they are one particular statistical formalism, not a general tool for theory building—the points we are trying to make here are more general.

³ We’re not saying these should correspond to specific brain structures. They could, but most likely they won’t. The idea that psychological constructs are not the same as any particular brain state (and especially not any particular brain region) is called “multiple realizability” by philosophers, who mostly agree that psychological states can’t be reduced to brain states, as much as philosophers agree on anything (Block and Fodor 1972 et seq.).

694 of constructs “floats... above the plane of observation and is anchored to
695 it by the rules of **measurement**.” (Hempel 1952). So, even if your the-
696 ory posits that two constructs (say, money and happiness) are directly
697 related, the best you can do is manipulate one operationalization and
698 measure another operationalization. If this manipulation doesn’t pro-
699 duce any effect, it’s possible that you are wrong and money does not
700 cause happiness—but it is also possible that your operationalizations are
701 poor.

702 Here’s a slightly different way of thinking about a theory. A theory
703 provides a **compression** of potentially complex data into much a smaller
704 set of general factors. If you have a long sequence of numbers, say [2 4 8
705 16 32 64 128 256 ...], then the expression 2^n serves as a compression of
706 this sequence—it’s a short expression that tells you what numbers are in
707 vs. out of the sequence. In the same way, a theory can compress a large
708 set of observations (maybe data from many experiments) into a small set
709 of relationships between constructs. Now, if your data are noisy, say [2.2
710 3.9 8.1 16.1 31.7 ...], then the theory will not be a perfect representation
711 of the data. But it will still be useful.

712 In particular, having a theory allows you to **explain** observed data and
713 **predict** new data. Both of these are good things for a theory to do.
714 For example, if it turned out that the money causes happiness theory

715 was true, we could use it to explain observations such as greater levels
716 of happiness among wealthy people. We could also make predictions
717 about the effects of policies like giving out a universal basic income on
718 overall happiness.⁴ Explanation is an important feature of good theories,
719 but it's also easy to trick yourself by using a vague theory to explain a
720 finding **post-hoc** (after the fact). Thus, the best test of a theory is typi-
721 cally a new prediction, as we discuss below.

722 One final note: Causal diagrams are a very useful formalism, but they
723 leave the generalizability of the causal relationships implicit. For ex-
724 ample, will more money result in more happiness for everyone, or just
725 for people at particular ages or in particular cultural contexts? “Who
726 does this theory apply to?” is an important question to ask about any
727 proposed causal framework.

728 2.1.3 *Specific theories vs. general frameworks*

729 You may be thinking, “psychology is full of theories but they don’t look
730 that much like the ones you’re talking about!” Very few of the theories
731 that bear that label in psychology describe causal relationships linking
732 clearly defined and operationalized constructs. You also don’t see that
733 many DAGs, though these are getting (slightly) more common lately
734 ([Rohrer 2018](#)).

⁴ The relationship between money and happiness is actually much more complicated than what we’re assuming here. For example, Killingsworth, Kahneman, and Mellers ([2023](#)) describes a collaboration between two sets of researchers that had different viewpoints on the connection between money and happiness.

735 Here's an example of something that gets called a theory yet doesn't
 736 share the components described above. Bronfenbrenner (1992)'s Eco-
 737 logical Systems Theory (EST) is pictured in figure 2.2. The key thesis
 738 of this theory is that children's development occurs in a set of nested
 739 contexts that each affect one another and in turn affect the child. This
 740 theory has been immensely influential. Yet if it's read as a causal the-
 741 ory, it's almost meaningless: nearly everything connects to everything
 742 in both directions and the constructs are not operationalized—it's very
 743 hard to figure out what kind of predictions it makes!

744 EST is not really a theory in the sense that we are advocating for in this
 745 chapter—and the same goes for many other very interesting ideas in psy-
 746 chology. It's not a set of causal relationships between constructs that
 747 allow specific predictions about future observations. EST is instead a
 748 broad set of ideas about what sorts of theories are more likely to explain
 749 specific phenomena. For example, it helps remind us that a child's be-
 750 havior is likely to be influenced by a huge range of factors, such that any
 751 individual theory cannot just focus on an individual factor and hope to
 752 provide a full explanation. In this sense, EST is a **framework**: it guides
 753 and inspires specific theories—in the sense we've discussed here, namely
 754 a set of causal relationships between constructs—without being a theory
 755 itself.

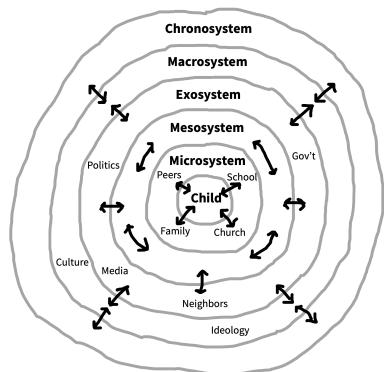


Figure 2.2

The diagram often used to represent Bronfenbrenner's ecological systems theory. Note that circles no longer denote discrete constructs; arrows can be interpreted as causal relationships, but all constructs are assumed to be fully connected.

756 Frameworks like EST are often incredibly important. They can also
757 make a big difference to practice. For example, EST supports a model
758 in social work in which children's needs are considered not only as the
759 expression of specific internal developmental issues but also as stemming
760 from a set of overlapping contextual factors (Ungar 2002). Concretely, a
761 therapist might be more likely to examine family, peer, and school envi-
762 ronments when analyzing a child's situation through the lens of EST.

763 There's a continuum between precisely specified theories and broad
764 frameworks. Some theories propose interconnected constructs but
765 don't specify the relationships between them, or don't specify how
766 those constructs should be operationalized. So when you read a paper
767 that says it proposes a "theory," it's a good idea to ask whether it
768 describes specific relations between operationalized constructs. If it
769 doesn't, it may be more of a framework than a theory.

⭐ ACCIDENT REPORT

The cost of a bad theory

Theory development isn't just about knowledge for knowledge's sake—it has implications for the technologies and policies built off the theories.

One case study comes from Edward Clarke's infamous theory regarding the deleterious effects of education for women (Clarke 1884). Clarke posited that (1) cognitive and reproductive processes relied on the same

fixed pool of energy, (2) relative to men, women's reproductive processes required more energy, and that (3) expending too much energy on cognitive tasks like education depleted women of the energy needed to maintain a healthy reproductive system. Based on case studies, Clarke suggested that education was causing women to become ill, experience fertility issues, and birth weaker children. He thus concluded that "boys must study and work in a boy's way, and girls in a girl's way" (p. 18).

Clarke's work is a chilling example of the implication of a poorly-developed theory. In this scenario, Clarke had neither instruments that allowed him to measure his constructs or experiments to measure the causal connections between them. Instead, he merely highlighted case studies that were consistent with his idea (while simultaneously dismissing cases that were inconsistent). His ideas eventually lost favor—especially as they were subjected to more rigorous tests. But Clarke's arguments were used to attempt to dissuade women from pursuing higher education and hindered educational policy reform.

771

772 2.2 How do we test theories?

773 Our view of psychological theories is that they describe a set of relationships between different constructs. How can we test theories and decide which one is best? We'll first describe **falsificationism**, a historical viewpoint on this issue that has been very influential in the past and

⁷⁷⁷ that connects to ideas about statistical inference presented in chapter 6.

⁷⁷⁸ We'll then turn to a more modern viewpoint, **holism**, that recognizes

⁷⁷⁹ the interconnections between theory and measurement.

⁷⁸⁰ *2.2.1 Falsificationism*

⁷⁸¹ One historical view that resonates with many scientists is the philoso-

⁷⁸² pher Karl Popper's **falsificationism**. In particular, there is a simplistic

⁷⁸³ version of falsificationism that is often repeated by working scientists,

⁷⁸⁴ even though it's much less nuanced than what Popper actually said! On

⁷⁸⁵ this view, a scientific theory is a set of hypotheses about the world that

⁷⁸⁶ instantiate claims like the connection between money and happiness.⁵

⁷⁸⁷ What makes a statement a *scientific* hypothesis is that it can be disproved

⁷⁸⁸ (i.e., it is **falsifiable**) by an observation that contradicts it. For example,

⁷⁸⁹ observing a lottery winner who immediately becomes depressed would

⁷⁹⁰ falsify the hypothesis that receiving money makes you happier.

⁷⁹¹ For the simplistic falsificationist, theories are never **confirmed**. The

⁷⁹² hypotheses that form parts of theories are universal statements. You

⁷⁹³ can never prove them right; you can only fail to find falsifying evidence.

⁷⁹⁴ Seeing hundreds of people get happier when they received money

⁷⁹⁵ would not prove that the money-happiness hypothesis was universally

⁷⁹⁶ true. There could always be a counter-example around the corner.

⁵ Earlier we treated the claim that money caused happiness as a theory. It is one! It's just a very simple theory that has only one hypothesized connection in it.

797 This theory doesn't really describe how scientists work. For example,
798 scientists like to say that their evidence "supports" or "confirms" their
799 theory, and falsificationism rejects this kind of talk. A falsificationist
800 says that confirmation is an illusion; that the theory is simply surviving
801 to be tested another day. This strict falsificationist perspective is unpalat-
802 able to many scientists. After all, if we observe that hundreds of people
803 get happier when they receive money, it seems like this should at least
804 slightly increase our confidence that money causes happiness!⁶

805 2.2.2 *A holistic viewpoint on theory testing*

806 The key issue that leads us to reject strict falsificationism is the obser-
807 vation that no individual hypothesis (a part of a theory) can be falsi-
808 fied independently. Instead, a large series of what are called **auxiliary**
809 **assumptions** (or auxilliary hypotheses) are usually necessary to link an
810 observation to a theory (Lakatos 1976). For example, if giving some
811 individual person money didn't change their happiness, we wouldn't
812 immediately throw out our theory that money causes happiness. In-
813 stead, the fault might be in any one of our auxiliary assumptions, like
814 our measurement of happiness, or our choice of how much money to
815 give or when to give it. The idea that individual parts of a theory can't
816 be falsified independently is sometimes called **holism**.

⁶ An alternative perspective comes from the Bayesian tradition that we'll learn more about in Chapters 5 and 6. In a nutshell, Bayesians propose that our subjective belief in a particular hypothesis can be captured by a probability, and that our scientific reasoning can then be described by a process of normative probabilistic reasoning (Strevens 2006). The Bayesian scientist distributes probability across a wide range of alternative hypotheses; observations that are more consistent with a hypothesis increase the hypothesis's probability (Sprenger and Hartmann 2019).

817 One consequence of holism is that the relationship between data and
818 theory isn't always straightforward. An unexpected observation may
819 not cause us to give up on a main hypothesis in our theory—but it will
820 often cause us to question our auxiliary assumptions instead (e.g., how
821 we operationalize our constructs). Thus, before abandoning our theory
822 of money causing happiness, we might want to try several happiness
823 questionnaires!

824 The broader idea of holism is supported by historical and sociological
825 studies of how science progresses, especially in the work of Kuhn (1962).
826 Examining historical evidence, Kuhn found that scientific revolutions
827 didn't seem to be caused by the falsification of a theoretical statement via
828 an incontrovertible observation. Instead, Kuhn described scientists as
829 mostly working within **paradigms**: sets of questions, assumptions, meth-
830 ods, phenomena, and explanatory hypotheses.

831 Paradigms allow for activities Kuhn described as **normal science**—that is,
832 testing questions within the paradigm, explaining new observations or
833 modifying theory to fit these paradigms. But normal science is punctu-
834 ated by periods of **crisis** when scientists begin to question their theory
835 and their methods. Crises don't happen just because a single observa-
836 tion is inconsistent with the current theory. Rather, there will often be
837 a holistic transition to a new paradigm, typically because of a striking

838 explanatory or predictive success—often one that's outside the scope of
 839 the current working theory entirely.

840 In sum, the lesson of holism is that we can't just put our theories in
 841 direct contact with evidence and think that they will be supported or
 842 overturned. Instead, we need to think about the scope of our theory
 843 (in terms of the phenomena and measures it is meant explain), as well
 844 as the auxiliary hypotheses—operationalizations—that link it to specific
 845 observations.

846 2.3 Designing experiments to test theory

847 One way of looking at theories is that they let us make *bets*. If we bet
 848 on a spin of the roulette wheel in figure 2.3 that it will show us red
 849 as opposed to black, we have almost a 50% chance of winning the bet.

850 Winning such a bet is not impressive. But if we call a particular number,
 851 the bet is riskier because we have a much smaller chance of being right.

852 Cases where a theory has many chances to be wrong are called **risky tests**
 853 (Meehl 1978).⁷

854 Much psychology consists of verbal theories. Verbal theories make
 855 only qualitative predictions, so it is hard convincingly show them to
 856 be wrong (Meehl 1990). In our discussion of money and happiness,

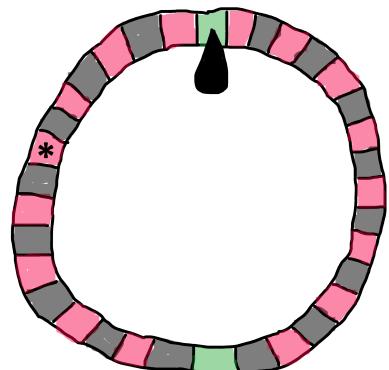


Figure 2.3

A roulette wheel. Betting on red is not that risky, but betting all your chips on a particular value (*) is much riskier.

⁷ Even if you're not a *falsificationist* like Popper, you can still think it's useful to try and falsify theories! Although a single observation is not always enough to overturn a theory, it's still a great research strategy to look for those observations that are most inconsistent with the theory.

857 we just expected happiness to go up as money increased. We would
858 have accepted *any* increase in happiness (even if very small) as evidence
859 confirming our hypothesis. Predicting that it does is a bit like betting
860 on red with the roulette wheel—it's not surprising or impressive when
861 you win. And in psychology, verbal theories often predict that multiple
862 factors interact with one another. With these theories, it's easy to say
863 that one or the other was “dominant” in a particular situation, meaning
864 you can predict almost any direction of effect.

865 To test theories, we should design experiments to test conditions
866 where our theories make “risky” predictions. A stronger version of the
867 money-happiness theory might suggest that happiness increases linearly
868 in the logarithm of income ([Killingsworth, Kahneman, and Mellers](#)
869 [2023](#)). This specific mathematical form for the relationship—as well
870 as the more specific operationalization of money as income—creates
871 opportunities for making much riskier bets about new experiments.
872 This kind of case is more akin to betting on a specific number on the
873 roulette wheel: when you win this bet, it is quite surprising!¹⁸

874 Testing theoretical predictions also requires precise experimental mea-
875 surements. As we start to measure the precision of our experimental
876 estimates in chapter 6, we'll see that the more precise our estimate is,
877 the more values are inconsistent with it. In this sense, a risky test of a

¹⁸ Theories are often developed iteratively. It's common to start with a theory that is less precise and hence, that has fewer opportunities for risky tests. But by collecting data and testing different alternatives, it's often possible to refine the theory so that it is more specific and allows riskier tests. As we discuss below, formalizing theories using mathematical or computational models is one important route to making more specific predictions and creating riskier tests.

878 theory requires both a very specific prediction and a precise measurement. (Imagine spinning the roulette wheel but seeing such a blurry
879 image of the result that you can't really tell where the ball is. Not very
880 useful.)

882 Even when theories make precise predictions, they can still be too flexible to be tested. When a theory has many **free parameters**—numerical
883 values that can be fit to a particular dataset, changing the theories predictions on a case-by-case basis—then it can often predict a wide range
884 of possible results. This kind of flexibility reduces the value of any particular experimental test, because the theorist can always say after the
885 fact that the parameters were wrong but not the theory itself (Roberts
886 and Pashler 2000).

890 One important way to remove this kind of flexibility is to make predictions in advance, holding all parameters constant. A preregistration is a
891 great way to do this—the experimenter derives predictions and specifies in advance how they will be compared to the results of the experiment.
892 We'll talk much more about the process of preregistration in
893 chapter 11.

896 We've been focusing mostly on testing a single theory. But the best state
897 of affairs is if a theory can make a very specific prediction that other
898 theories don't make. If competing theories both predict that money

899 increases happiness to the same extent, then data consistent with that
900 predicted relationship don't differentiate between the theories, no mat-
901 ter how specific the prediction might be. The experiment that teaches
902 us the most is going to be the one where a very specific pattern of data
903 is predicted according to one theory and another.⁹

904 Given all of this discussion, as a researcher trying to come up with a
905 specific research idea, what do you do? Our advice is: *follow the theories*.
906 That is, for the general topic you're interested in—whether it's money
907 and happiness, bilingualism, the nature of concepts, or depression—try
908 to get a good sense of the existing theories. Not all theories will make
909 specific, testable predictions, but hopefully some will! Then ask, what
910 are the “risky bets” that these theories make? Do different theories
911 make different bets about the same effect? If so, that's the effect you
912 want to measure!

913 2.4 Formalizing theories

914 Say we have a set of constructs we want to theorize about. How do we
915 describe our ideas about the relationships between them so that we can
916 make precise predictions that can be compared with other theories? As
917 one writer noted, mathematics is “unreasonably effective” as a vocab-
918 ular for the sciences (Wigner 1990). Indeed, there have been calls for

⁹ We can use this idea, which comes from Bayesian statistics, to try to figure out what the *right* experiment is by considering which specific experimental conditions derive differences between theories. In fact, the idea of choosing experiments based on the predictions that different theories make has a long history in statistics (Lindley 1956); it's now called **optimal experiment design** (Myung, Cavagnaro, and Pitt 2013). The idea is, if you have two or more theories spelled out mathematically or computationally, you can simulate their predictions across a lot of conditions and pick the most informative conditions to run as an actual experiment.

⁹¹⁹ greater formalization of theory in psychology for at least the last 50 years

⁹²⁰ (Harris 1976).

DEPTH

A universal law of generalization?

How do you take what you know and apply it to a new situation? One answer is that you use the same answer that has worked in similar situations. To do this kind of extrapolation, however, you need a notion of similarity. Early learning theorists tried to measure similarity by creating an association between a stimulus—say a projected circle of light of a particular size—and a reward by repeatedly presenting them together. After this association was learned, they would test generalization by showing circles of different sizes and measuring the strength of the expectation for a reward. These experiments yielded generalization curves: the more similar the stimulus, the more people and other animals would give the same response, signaling generalization.

Shepard (1987) was interested in unifying the results of these different experiments. The first step in this process was establishing a **stimulus space**. He used a procedure called “multidimensional scaling” to infer how close stimuli were to each other on the basis of how strong the generalization between them was. When he plotted the strength of the generalization by the distance between stimuli within this space (their similarity), he found an incredibly consistent pattern: generalization decreased exponentially as similarity decreased.

He argued that this described a “universal law” that governed the relationship between similarity and generalization for almost any stimulus, whether it was the size of circles, the color of patches of light, or the similarity between speech sounds. Later work has even extended this same framework to highly abstract dimensions such as the relationships between numbers of different types [e.g., being even, being powers of 2, etc.; Tenenbaum (2000)].

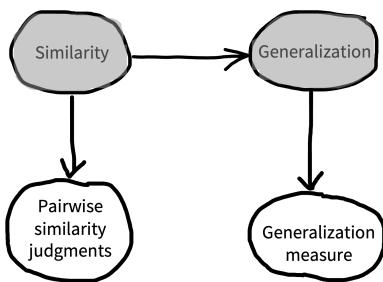


Figure 2.4
The causal theory of similarity and generalization posited by Shepard (1987).

The pattern shown in Shepard’s work is an example of **inductive theory building**. In the vocabulary we’re developing, Shepard ran (or obtained the data from) randomized experiments in which the manipulation was stimulus dimension (e.g., circle size) and the measure was generalization strength. Then the theory that Shepard proposed was that manipulations of stimulus dimension acted to change the perceived similarity between the stimuli. His theory thus linked two constructs: stimulus similarity and generalization strength (figure 2.4). Critically the causal relationship he described was not just a qualitative relationship but instead a specific mathematical form.

Shepard wrote in the conclusion of his 1987 paper, “Possibly, behind the diverse behaviors of humans and animals, as behind the various motions of planets and stars, we may discern the operation of universal laws.” While Shepard’s dream is an ambitious one, it defines an ideal for psychological theorizing.

923

924 There is no one approach that will be right for theorizing across all ar-
925 eas of psychology (Oberauer and Lewandowsky 2019; Smaldino 2020).
926 Mathematical theories [such as Shepard (1987); see Depth box] have
927 long been one tool that allows for precise statements of particular rela-
928 tionships.

929 Computational or formal artifacts are not themselves psychological the-
930 ories, but they can be used to create psychological theories via the map-
931 ping of constructs onto entities in the model and the use of the principles
932 of the formalism to instantiate psychological hypotheses or assumptions
933 (Guest and Martin 2021).¹⁰ Yet stating such clear and general laws feels
934 out of reach in many cases. If we had more Shepard-style theorists or
935 theories, perhaps we’d be in a better place. Or perhaps such “universal
936 laws” are simply out of reach for most of human behavior.

937 An alternative approach creates statistical models of data that incorpo-
938 rate substantive assumptions about the structure of the data. We use
939 such models all the time for data analysis. The trouble is, we often

940 don't interpret them as having substantive assumptions about the struc-
941 ture of the data, even when they do (Fried 2020)! But if we examine
942 these assumptions explicitly, even the simplest statistical models can be
943 productive tools for building theories.

944 For example, if we set up a simple linear regression model to estimate
945 the relationship between money and happiness, we'd be positing a linear
946 relationship between the two variables—that an increase in one would
947 always lead to a proportional increase in the other.¹¹ If we fit the model
948 to a particular dataset, we could then look at the weights of the model.
949 Our theory might then then be something like “giving people \$100
950 causes 0.2 points of increase in happiness on a self-report scale.”

951 Obviously, this regression model is not a very good theory of the broader
952 relationship between money and happiness, since it posits that every-
953 one's happiness would be at the maximum on the 10 point scale if you
954 gave them (at most) \$4500. It also doesn't tell us how this theory would
955 generalize to other people, other measures of happiness, or other as-
956 pects of the psychological representation of money such as income or
957 wealth.

958 From our viewpoint, these sorts of questions are not distractions—they
959 are the critical work of moving from experiment to theory (Smaldino
960 2020)! In chapter 7, we try to draw out this idea further, reconstruing

¹¹ Linear models are ubiquitous in the social sciences because they are convenient to fit, but as theoretical models they are deeply impoverished. There is a lot you can do with a linear regression, but in the end, most interesting processes are not linear combinations of factors!

961 common statistical tests as models that can be repurposed to express con-
962 tentful scientific hypotheses while recognizing the limitations of their
963 assumptions.

964 One of the strengths of modern cognitive science is that it provides a
965 very rich set of tools for expressing more complex statistical models
966 and linking them to data. For example, the modern Bayesian cogni-
967 tive modeling tradition grew out of work like Shepard's; in these mod-
968 els, a system of equations defines a probability distribution that can be
969 used to estimate parameters, predict new data, or make other inferences
970 (Goodman, Tenenbaum, and Contributors 2016). And neural network
971 models—which are now fueling innovations in artificial intelligence—
972 have a long history of being used as substantive models of human psy-
973 chology (Elman, Bates, and Johnson 1996). One way to think about
974 all these alternatives is as being on a gradient from the general, inspira-
975 tional frameworks we described above all the way down through com-
976 putational models and then to statistical models that can be fit to specific
977 datasets (figure 2.5).

978 In our discussion, we've presented theories as static entities that are
979 presented, tested, confirmed, and falsified. That's a simplification that
980 doesn't take into account the ways that theories—especially when in-
981 stantiated as formal models—can be flexibly adjusted to accommodate

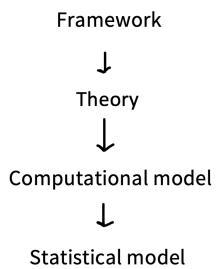


Figure 2.5

A gradient of specificity in theoretical tools. Figure inspired by Guest and Martin (2021).

982 new data (Navarro 2019). Most modern computational theories are
983 more like a combination of core principles, auxiliary assumptions, and
984 supporting empirical assumptions. The best theories are always being
985 enlarged and refined in response to new data.¹²

986 2.5 Chapter summary: Theories

987 In this chapter, we characterized psychological theories as a set of causal
988 relationships between latent constructs. The role of experiments is to
989 measure these causal relationships and to adjudicate between theories
990 by identifying cases where different theories make different predictions
991 about particular relationships.

¹² In the thinking of the philosopher Imre Lakatos, a “productive” research program is one where the core principles are gradually supplemented with a limited set of additional assumptions to explain a growing base of observations. In contrast, a “degenerate” research program is one in which you are constantly making ad-hoc tweaks to the theory to explain each new datapoint (Lakatos 1976).



DISCUSSION QUESTIONS

1. Identify an influential theory in your field or sub-field. Can you draw the “nomological network” for it? What are the key constructs and how are they measured? Are the links between constructs just directional links or is there additional information about what type of relationship exists? Or does our description of a theory in this chapter not fit your example?
2. Can you think of an experiment that falsified a theory in your area of psychology? To what extent is falsification possible for the kinds of theories that you are interested in studying?



READINGS

- A fabulous introduction to issues in the philosophy of science can be found in: Godfrey-Smith, P. (2009). *Theory and reality*. University of Chicago Press.
- Bayesian modeling has been very influential in cognitive science and neuroscience. A good introduction in cognitive science comes from: Lee, M. D. & Wagenmakers, E. J. (2013). *Bayesian Cognitive Modeling: A Practical Course*. Cambridge University Press. Much of the book is available free online at <https://faculty.sites.uci.edu/mdlee/bgm/>.
- A recent introduction to Bayesian modeling with a neuroscience focus: Ma, W. J., Kording, K. P., & Goldreich, D. (2022). *Bayesian models of perception and action: An introduction*. MIT Press. Free online at <https://www.cns.nyu.edu/malab/bayesianbook.html>.

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⁹⁹⁹ 3 REPLICATION



LEARNING GOALS

- Define and distinguish reproducibility and replicability
- Synthesize the meta-scientific literature on replication and the causes of replication failures
- Reason about the relation of replication to theory building

¹⁰⁰⁰

¹⁰⁰¹ In the previous chapters, we introduced experiments, their connection
¹⁰⁰² with causal inference, and their role in building psychological theory. In
¹⁰⁰³ principle, repeated experimental work combined with theory building
¹⁰⁰⁴ should yield strong research programs that explain and predict phenom-
¹⁰⁰⁵ ena with increasing scope.

¹⁰⁰⁶ Yet in recent years there has been an increasing recognition that this ide-
¹⁰⁰⁷ alized view of science might not be a good description of what we actu-
¹⁰⁰⁸ ally see when we look at the psychology literature. Many classic findings
¹⁰⁰⁹ may be wrong, or at least overstated. Their statistical tests might not be

1010 trustworthy. The actual numbers are even wrong in many papers! And
 1011 even when experimental findings are “real,” they may not generalise
 1012 broadly to different people and different situations.

1013 How do we know about these problems? A burgeoning field called
 1014 **metascience** is providing the evidence. metascience is research *about re-*
 1015 *search*, for example investigating how often findings in a literature can be
 1016 successfully built on, or trying to figure out how widespread some neg-
 1017 ative practice is. metascience allows us to go beyond one-off anecdotes
 1018 about a particular set of flawed results or rumors about bad practices.
 1019 Perhaps the most obvious sign that something is wrong is that when in-
 1020 dependent scientists team up in metascience projects and try to repeat
 1021 previous studies, they often do not get the same results.

1022 Before we begin reviewing this evidence, let’s discuss the different ways
 1023 in which a scientific finding can be repeated. Figure 3.1 gives us a basic
 1024 starting point for our definitions. For a particular finding in a paper, if
 1025 we take the same data, do the same analysis, and get the same result, we
 1026 call that finding **reproducible** (sometimes, **analytically** or **computation-**
 1027 **ally reproducible**). If we collect *new* data using the same methods, do
 1028 the same analysis, and get the same result, we call that a **replication** and
 1029 say that the finding is **replicable**. If we do a different analysis with the
 1030 same data, we call this a **robustness check** and if we get a similar result,

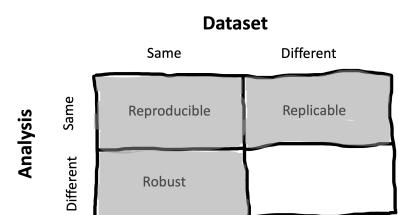


Figure 3.1
 A framework for understanding different terms related to the repeatability of scientific findings (based on Whitaker 2017).

1031 we say that the finding is **robust**.¹ We leave the last quadrant empty be-
1032 cause there's no specific term for it in the literature—the eventual goal
1033 is to draw **generalizable** conclusions but this term means more than just
1034 having a finding that is reproducible and replicable.

1035 In this chapter, we'll primarily discuss reproducibility and replicability
1036 (we'll talk about robustness a bit in chapter 11). We'll start out by re-
1037 viewing key concepts around reproducibility and replicability as well
1038 as some important metascience findings. This literature suggests that
1039 when you read an average psychology paper, your default expectation
1040 should be that it might not replicate!

1041 We'll then discuss some of the main reasons *why* findings might not
1042 replicate—especially **analytic flexibility** and **publication bias**. We end
1043 by taking up the issue of how reproducibility and replicability relate to
1044 theory building in psychology, and the role of **open science** in this dis-
1045 cussion. This discussion focuses on the key role of **TRANSPARENCY** (one
1046 of our major book themes) in supporting theory building.

1047 3.1 Reproducibility

1048 Scientific papers are full of numbers: sample sizes, measurements, statis-
1049 tical results, and visualizations. For those numbers to have meaning, and

¹ You might have observed that a lot of work is being done here by the word “same.” How do we operationalize same-ness for experimental procedures, statistical analyses, samples, or results? These are difficult questions that we'll touch on below. Keep in mind that there's no single answer and so these terms are always going to helpful guides rather than exact labels.

1050 for other scientists to be able to verify them, we need to know where
1051 they came from (their **provenance**). The chain of actions that scientists
1052 perform on the raw data, all the way through to reporting numbers in
1053 their papers, is sometimes called the *analysis pipeline*. For much of his-
1054 tory, scientific papers have only provided a verbal, description of the
1055 analysis pipeline, usually with little detail.²

1056 Moreover, researchers typically do not share key research objects from
1057 this pipeline, such as the analysis scripts or the raw data (Hardwicke,
1058 Thibault, et al. 2021).³ Without code and data, the numbers reported
1059 in scientific papers are often not reproducible—an independent scientist
1060 cannot repeat all of the steps in the analysis pipeline and get the same
1061 results as the original scientists.

1062 Reproducibility is desirable for a number of reasons. Without it:

- 1063 – Errors in calculation or reporting could lead to disparities
1064 between the reported result and the actual result,
- 1065 – Vague verbal descriptions of analytic computations could keep
1066 readers from understanding the computations that were actually
1067 performed,
- 1068 – The robustness of data analyses to alternative model specifications
1069 cannot be checked, and

² The situation is nicely summed up by a prescient quote from Buckheit and Donoho (1995): “... a scientific publication is not the scholarship itself, it is merely advertising of the scholarship. The actual scholarship is the complete software development environment and the complete set of instructions which generated the figures.”

³ For many years, professional societies, like the American Psychological Association, have mandated data sharing (<https://www.apa.org/ethics/code>), but only for purposes of verification, and only “on request”—in other words, scientists could keep data hidden by default and it was their responsibility to share if another scientist requested access. In practice, this kind of policy does not work; data are rarely made available on request (Wicherts et al. 2006). We believe this situation is untenable. We provide a longer argument justifying data sharing in chapter 4 and discuss some of the practicalities of sharing in chapter 13.

1070 – Synthesizing evidence across studies, a key part of building a cu-
1071 mulative body of scientific knowledge, is much more difficult.

1072 From this list, error detection and correction is probably the most press-
1073 ing issue. But are errors common? There are plenty of individual in-
1074 stances of errors that are corrected in the published literature (e.g., some
1075 of us found an error in [Cesana-Arlotti et al. 2018](#)), and we ourselves
1076 have made significant analytic errors (e.g., [Frank et al. 2013](#)). But
1077 these kinds of experiences don't tell us about the frequency of errors
1078 more generally (or the consequences of error for the conclusions that
1079 researchers draw).⁴

1080 Estimating the frequency of errors is a meta-scientific issue that
1081 researchers have attempted to answer over the years. If errors are
1082 frequent, that would suggest a need for changes in our policies and
1083 practices to reduce their frequency! Unfortunately, the lack of data
1084 availability creates a problem: it's hard to figure out if calculations are
1085 wrong if you can't check them in the first place. Here's one clever
1086 approach to this issue. In standard American Psychological Association
1087 (APA) reporting format, inferential statistics must be reported with
1088 three pieces of information: the test statistic, the degrees of freedom
1089 for the test, and the p -value (e.g., $t(18) = -0.74, p = 0.47$). Yet
1090 these pieces of information are redundant with one another. Thus,

⁴ There is a very interesting discussion of the pernicious role of scientific error on theory building in Gould (1996)'s "The Mismeasure of Man." Gould examines research on racial differences in intelligence and documents how scientific errors that supported racial differences were often overlooked. Errors are often caught asymmetrically; we are more motivated to double-check a result that contradicts our biases.

1091 reported statistics can be checked for consistency simply by evaluating
1092 whether they line up with one another—that is, whether the p -value
1093 recomputed from the t and degrees of freedom matches the reported
1094 value.

1095 Bakker and Wicherts (2011) performed this kind of statistical consis-
1096 tency analysis on a sample of 281 papers, and found that around 18%
1097 of statistical results were incorrectly reported. Even more worrisome,
1098 around 15% of articles contained at least one decision error—that is, a
1099 case where the error changed the direction of the inference that was
1100 made (e.g., from significant to insignificant).⁵ Nuijten et al. (2016) used
1101 an automated method called “statcheck”⁶ to confirm and extend this
1102 analysis. They checked p -values for more than 250,000 psychology pa-
1103 pers in the period 1985–2013 and found that around half of all papers
1104 contained at least one incorrect p -value!

1105 These findings provide a lower bound on the number of errors in the
1106 literature and suggest that reproducibility of analyses is likely very im-
1107 portant. However, they only address the consistency of statistical re-
1108 porting. What would happen if we tried to repeat the entire analysis
1109 pipeline from start to finish? It’s rather difficult to answer this question
1110 at a large scale: firstly, it takes a long time to run a reproducibility check;
1111 and secondly, the lack of access to raw data means that for most scientific

⁵ Confirming Gould’s speculation (see note above), most of the reporting errors that led to decision errors were in line with the researchers’ own hypotheses.

⁶ Statcheck is now available as a web app (<http://statcheck.io>) and an R package so that you can check your own manuscripts!

1112 papers, checking reproducibility is impossible.

1113 Nevertheless, a few years ago a group of us spotted an opportunity

1114 to check reproducibility by examining studies published in two jour-

1115 nals that either required or encouraged data sharing. Hardwicke et al.

1116 (2018) and Hardwicke, Bohn, et al. (2021) first identified studies that

1117 shared data, then narrowed those down to studies that shared *reusable*

1118 data (the data were accessible, complete, and comprehensible). For 60

1119 of these articles, we then attempted to reproduce numerical values re-

1120 lated to a particular statistical result in the paper. The process was in-

1121 credibly labor-intensive, with articles typically requiring 5–10 hours

1122 of work each. And the results were concerning: the targeted values in

1123 only about a third of articles were completely reproducible without help

1124 from the original authors! In many cases, after—sometimes extensive—

1125 correspondence with the original authors, they provided additional in-

1126 formation that was not reported in the original paper. After author con-

1127 tact, the reproducibility success rate improved to 62% (figure 3.2). The

1128 remaining papers appeared to have some values that neither we, nor

1129 the original authors, could reproduce. Importantly, we didn’t identify

1130 any patterns of non-reproducibility that seriously undermined the con-

1131 clusions drawn in the original articles; however, other reproducibility

1132 studies have found a distressingly high number of decision errors (Artner

1133 et al. 2020), albeit with a slightly higher success rate overall.

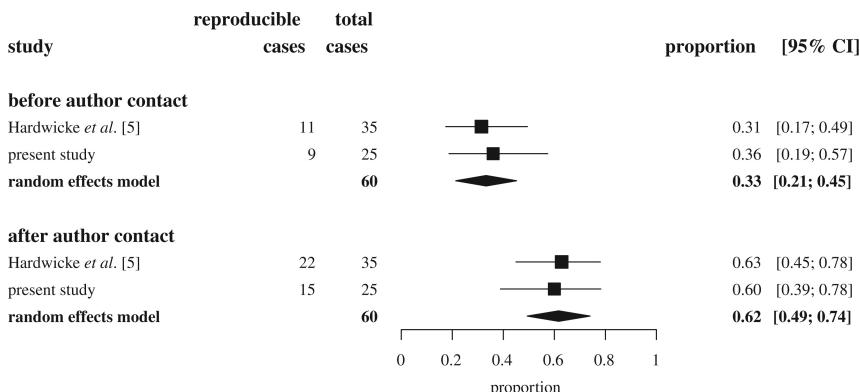


Figure 3.2

Analytic reproducibility of results from open-data articles in *Cognition* and *Psychological Science*. From Hardwicke, Bohn, et al. (2021), Figure 1 (licensed under CC BY 4.0).

1134 In sum: transparency is a critical imperative for decreasing the frequency of errors in the published literature. Reporting and computation
 1135 errors are frequent in the published literature, and the identification of
 1136 these errors depends on the findings being reproducible. If data are not
 1137 available, then errors usually cannot be found.
 1138

CASE STUDY

The Open Science Collaboration

Around 2011, we were teaching our Experimental Methods course for the first time, based on a course model that we had worked on with Rebecca Saxe (Frank and Saxe 2012). The idea was to introduce students to the nuts and bolts of research by having them run replications. A guy named Brian Nosek was on sabbatical nearby, and over coffee we learned that he was starting up an ambitious project to replicate a large sample of studies published in top psychology journals in 2008.

In the course that year we chose replication projects from the sample that Nosek had told us about. Four of these projects were executed very

well and were nominated by the course TAs for inclusion in the broader project. A few years later, when the final group of 100 replication studies was completed, we got a look at the results, shown in figure 3.3.

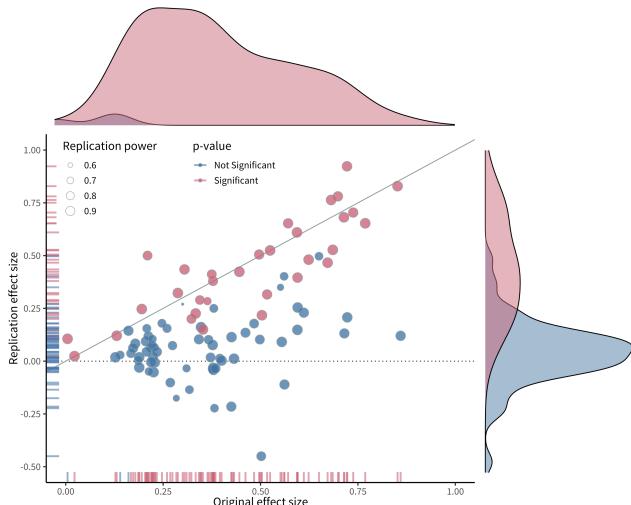


Figure 3.3
Results from the Open Science Collaboration (2015). Each point represents one of the studies in the sample, with the horizontal position giving the original effect size and the vertical position giving the replication effect size. Dot size represents estimated statistical power. The grey line represents a perfect replication.

The resulting metascience paper, which we and others refer to as the “replication project in psychology” (RPP), made a substantial impression on both psychologists and the broader research community, defining both a field of psychology metascience studies and providing a template for many-author collaborative projects (Open Science Collaboration 2015). But the most striking thing was the result: disappointingly, only around a third of the replications had similar findings to the original studies. The others yielded smaller effects that were not statistically significant in the replication sample (almost all of the original studies were significant). RPP provided the first large-scale evidence that there were systematic

issues with replicability in the psychology literature.

RPP's results—and their interpretation—were controversial, however, and much ink was spilled on what these data showed. In particular, critics pointed to different degrees of fidelity between the original studies and the replications; insufficient levels of statistical power and low evidential value in the replications; non-representative sampling of the literature; and difficulties identifying specific statistical outcomes for replication success (Gilbert et al. 2016; Anderson et al. 2016; Etz and Vandekerckhove 2016). In our view, many of these critiques have merit, and you can't simply interpret the results of RPP as an unbiased estimate of the replicability of results in the literature, contra the title.

And yet, RPP's results are still important and compelling, and they undeniably changed the direction of the field of psychology. Many good studies are like this—they have flaws but they inspire follow up studies that can address those problems. For several of us personally, working on this project was also transformative in that it showed us the power of collaborative work. Together we could do a study that no one of us had any hope of completing on our own, and potentially make a difference in our field.

1141

3.2 Replication

1142 Beyond verifying a paper's original analysis pipeline, we are often in-

1143 terested in understanding whether the study can be replicated—if we

1145 repeat the study methods and obtain new data, do we get similar re-
1146 sults? To quote from Popper (2005), “the scientifically significant... ef-
1147 fect may be defined as that which can be regularly [replicated] by anyone
1148 who carries out the appropriate experiment in the way prescribed.”

1149 Replications can be conducted for many reasons (Schmidt 2009). One
1150 goal can be to verify that the results of an existing study can be obtained
1151 again if the study is conducted again in exactly the same way, to the
1152 best of our abilities. A second goal can be to gain a more precise esti-
1153 mate of the effect of interest by conducting a larger replication study, or
1154 combining the results of a replication study with the existing study. A
1155 third goal can be to investigate whether an effect will persist when, for
1156 example, the experimental manipulation is done in a different, but still
1157 theory-consistent, manner. Alternatively, we might want to investigate
1158 whether the effect persists in a different population. Such replications
1159 are often efforts to “replicate and extend,” and are common both when
1160 the same research team wants to conduct a sequence of experiments
1161 that each build on one another or when a new team wants to build on
1162 a result from a paper they have read (Rosenthal 1990).

1163 Much of the metascience literature (and attendant debate and discus-
1164 sion) has focused on the first goal—simple verification. This focus has
1165 been so intense that the term “replication” has become associated with

¹¹⁶⁶ skepticism or even attacks on the foundations of the field. This dynamic
¹¹⁶⁷ is at odds with the role that replication is given in a lot of philosophy of
¹¹⁶⁸ science, where it is assumed to be a typical part of “normal science.”

¹¹⁶⁹ *3.2.1 Conceptual frameworks for replication*

¹¹⁷⁰ The key challenge of replication is **invariance**—Popper’s stipulation that
¹¹⁷¹ a replication be conducted “in the way prescribed” in the quote above.
¹¹⁷² That is, what are the features of the world over which a particular obser-
¹¹⁷³ vation should be relatively constant, and what are those that are specified
¹¹⁷⁴ as the key ingredients for the effect? Replication is relatively straightfor-
¹¹⁷⁵ ward in the physical and biological sciences, in part because of presup-
¹¹⁷⁶ posed theoretical background that allows us to make strong inferences
¹¹⁷⁷ about invariance. If a biologist reports an observation about a particular
¹¹⁷⁸ cell type from an organism, the color of the microscope is presumed not
¹¹⁷⁹ to matter to the observation.

¹¹⁸⁰ These invariances are far harder to state in psychology, for both the pro-
¹¹⁸¹ cedure of an experiment and its sample. Procedurally, should the color
¹¹⁸² of the experimental stimulus matter to the measured effect? In some
¹¹⁸³ cases yes, in some cases no.⁷ Yet the task of postulating how a scientific
¹¹⁸⁴ effect should be invariant to lab procedures pales in comparison to the

⁷ A fascinating study by Baribault et al. (2018) proposes a method for em-
pirically understanding psychological in-
variances. Treating a subliminal priming
effect as their model system, they sam-
pled thousands of “micro-experiments”
in which small parameters of their exper-
imental procedure were randomly sam-
pled. These parameters allowed for mea-
surement of their effect of interest, aver-
aging across this irrelevant variation. In
their case, it turned out that color did not
matter.

1185 task of postulating how the effect should be invariant across different
1186 human populations!⁸

1187 A lot is at stake in this discussion. If Dr. Frog publishes a finding with
1188 US undergraduates and Dr. Toad then “replicates” the procedure in
1189 Germany, to what extent should we be perturbed if the effect is differ-
1190 ent in magnitude or absent?⁹ Meta-researchers have made a number of
1191 replication taxonomies to try and quantify the degree of methodologi-
1192 cal consistency between two experiments.

1193 Some researchers have tried to distinguish “direct replications”¹⁰ and
1194 “conceptual replications”. Direct replications are those that attempt to
1195 reproduce all of the salient features of the prior study, up to whatever in-
1196 variances the experimenters believe are present (e.g., color of the paint,
1197 gender of the experimenter, etc.). In contrast, conceptual replications
1198 are typically paradigms that attempt to test the same hypothesis via dif-
1199 ferent operationalizations of the manipulation and/or the measure. We
1200 agree with Zwaan et al. (2018): labeling this second type of experiment
1201 as a “replication” is a little misleading. Rather, so-called “conceptual
1202 replications” are actually different tests of the same part of your theory.
1203 Such tests can be extremely valuable, but they serve a different goal than
1204 replication.

⁸ In some sense, the research program of some branches of the social sciences amounts to an understanding of invariances across human cognition.

⁹ Presumably not very much if Dr. Toad gave the original instructions in English instead of in German—that’s another one of these pesky invariances that we are always worrying about!

¹⁰ These also get called **exact** replica-
tions sometimes. We think this term is misleading because similarity between two different experiments is always going to be on a gradient, and where you cut this continuum is always going to be a theory-laden decision. One person’s “exact” is another’s “inexact.”

💥 ACCIDENT REPORT

“Small Telescopes”

We've been discussing the question of invariance with respect to procedure and sample, but we haven't really discussed invariance with respect to the studies' statistical results. To what extent can we consider two statistical results to be “the same”? Several obvious metrics, including those used by RPP, have important limitations (Simonsohn 2015). For example, if one finding is statistically significant and the other isn't, they still could have effect sizes that are actually quite close to one another, in part because one might have a larger sample size than the other. Or you could have two significant findings that nevertheless have very different effect sizes.

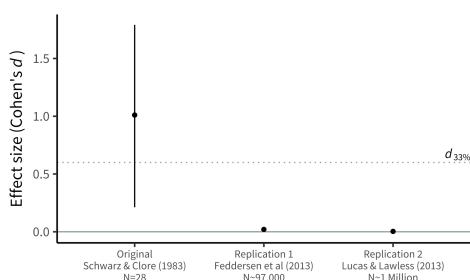


Figure 3.4

The original finding by Schwarz and Clore (1983) and two replications with much larger samples. All three estimates include a 95% confidence interval, but the confidence intervals are very small for the two replication studies. The blue dotted line shows the smallest effect that the original study could reasonably have detected. Based on Simonsohn (2015).

In a classic study, Schwarz and Clore (1983) reported that participants ($N=28$) rated their life satisfaction as higher on sunny days than rainy days, suggesting that they mis-attributed temporary happiness about the

weather to longer-term life satisfaction. However, when two more recent studies examined very large samples of survey responses, they yielded estimates of the effect that were much smaller. (All of these effects have been standardized so they are on the same scale using a metric called Cohen's d that we will introduce more formally in chapter 5). In one survey, the effect was statistically significant but extremely small; in the other it was essentially zero (figure 3.4). Using statistical significance as the metric of replication success, you might be tempted to say that the first of these studies was a successful replication and the second was a failed replication.

Simonsohn points out that this interpretation doesn't make sense, using the analogy of a study's sample size as a telescope. Following this analogy, Schwarz and Clore had a very small telescope (i.e., a small sample size), and they pointed it in a particular direction and claimed to have observed a planet (i.e., a nonzero effect). Now it might turn out that there *was* a planet at that location when you look with a much larger telescope (first replication), and it might turn out that there *wasn't* (second replication). Regardless, however, the original small telescope was simply not powerful enough to have seen whatever was there. Both studies fail to replicate the original observation, regardless of whether their observed effect was in the same direction.

Following Simonsohn's example, numerous metrics for replication success have been proposed (Mathur and VanderWeele 2020). The best of these move away from the idea that there is a binary test of whether an individual replication was successful and towards a comparison of the two

effects and whether they appear consistent with the same theory. Gelman (2018) suggests the “time reversal” heuristic—rather than thinking of a replication as a success or a failure, consider the alternative world in which the replication study had been performed first and the original study followed it.

If we leave behind the idea that the original study has precedence, it makes much more sense to consider the sum total of the evidence across multiple experiments. Using this approach, it seems pretty clear that the weather mis-attribution effect is, at best, a tiny factor in people’s overall judgments of their life satisfaction, even if a small study once found a larger effect.

1207

1208 3.2.1 *The metascience of replication*

1209 In RPP, replication teams reported subjectively that 39% of replications
1210 were successful, with 36% reporting a significant effect in the same di-
1211 rection as the original. How generalizable is this estimate—and how
1212 replicable *is* psychological research more broadly? Based on the discus-
1213 sion above, we hope we’ve made you skeptical that this is a well-posed
1214 question, at least without additional qualifiers. Any answer is going to
1215 have to provide details about the scope of this claim, the definition of
1216 replication being used, and the metric for replication success. On the
1217 other hand, *versions* of this question have led to a number of empirical

1218 studies that help us better understand the scope of replication issues.

1219 Many subsequent empirical studies of replication have focused on par-
1220 ticular subfields or journals, with the goal of informing particular field-
1221 specific practices or questions. For example, Camerer et al. (2016) repli-
1222 cated all of the between-subject laboratory articles published in two top
1223 economics journals in the period 2011–2014. They found a replication
1224 rate of 61% of significant effects in the same direction of the original,
1225 higher than the rate in RPP but lower than the naive expectation based
1226 on their level of statistical power. Another study attempted to replicate
1227 all 21 behavioral experiments published in the journals *Science* and *Na-*
1228 *ture* from 2010–2015, finding a replication rate of 62% significant effects
1229 (Camerer et al. 2018). This study was notable because they followed
1230 a two-step procedure—after an initial round of replications, they fol-
1231 lowed up on the failures by consulting with the original authors and
1232 pursuing extremely large sample sizes. The resulting estimate thus is
1233 less subject to many of the critiques of the original RPP paper. While
1234 these types of studies do not answer all the questions that were raised
1235 about RPP, they suggest that replication rates for top experiments are
1236 not as high as we’d like them to be, even when care is taken with the
1237 sampling and individual study protocols.

1238 Other scientists working in the same field can often predict when an ex-

periment will fail to replicate. Dreber et al. (2015) showed that prediction markets (where participants bet small sums of real money on replication outcomes) made fairly accurate estimates of replication success in the aggregate. This result has itself now been replicated several times (e.g., in the Camerer et al., 2018 study described earlier). Maybe even more surprisingly, there's some evidence that machine learning models trained on the text of papers can predict replication success (Yang, Youyou, and Uzzi 2020; Youyou, Yang, and Uzzi 2023), though more work still needs to be done to validate these models and understand the features they use. More generally, these two lines of research suggest the possibility of isolating consistent factors that lead to replication success or failure. (In the next section we consider what these factors are in more depth.)

Although more work still needs to be done to get generalizable estimates of replicability, taken together, the metascience literature does provide some clarity on what we should expect. Altogether, the chance of a significant finding in a (well-powered) replication study of a generic experiment in social and cognitive psychology is likely somewhere around 56%. Furthermore, the replication effect will likely be on average 53% as large (Nosek et al. 2021).

On the other hand, these large-scale replication studies have substantial

1260 limitations as well. With relatively few exceptions, the studies chosen
1261 for replication used short, computerized tasks that mostly would fall
1262 into the categories of social and cognitive psychology. Further, and per-
1263 haps most troubling from the perspective of theory development, they
1264 tell us only whether a particular experimental effect can be replicated.
1265 They tell us much less about whether the construct that the effect was
1266 meant to operationalize is in fact real! We'll return to the difficult issue
1267 of how replication and theory construction relate to one another in the
1268 final section of this chapter.

1269 Some have called the narrative that emerges from the sum of these meta-
1270 science studies the “replication crisis.” We think of it as a major temper-
1271 ing of expectations with respect to the published literature. Your naive
1272 expectation might reasonably be that you could read a typical journal ar-
1273 ticle, select an experiment from it, and replicate that experiment in your
1274 own research. The upshot of this literature is, unfortunately, if you try
1275 selecting and replicating an exeriment, you might well be disappointed
1276 by the result.

INCIDENT REPORT

Consequences for the study, consequences for the person

“Power posing” is the idea that adopting a more open and expansive phys-
ical posture might also change your confidence. Carney, Cuddy, and Yap

(2010) told 42 participants that they were taking part in a study of physiological recording. They then held two poses, each for a minute. In one condition, the poses were expansive (e.g., legs out, hands on head); in another condition, the poses were contractive (e.g., arms and legs crossed). Participants in the expansive pose condition showed increases in testosterone and decreases in salivary cortisol (a stress marker), they took a greater number of risk in a gambling task, and they reported that they were more “in charge” in a survey. This result suggested that a two-minute manipulation could lead to striking physiological and psychological changes—in turn leading to power posing becoming firmly enshrined as part of the set of recommended strategies in business and elsewhere. The original publication contributed to the rise of the researchers’ careers, including becoming a principal piece of evidence in a hugely-popular TED talk by Amy Cuddy, one of the authors.

Followup work has questioned these findings, however. A replication study with a larger number of participants ($N=200$) failed to find evidence for physiological effects of power-posing, even as it did find some effects on participants’ own beliefs (Ranehill et al. 2015). And a review of the published literature suggested that many findings appeared to be the result of some sort of publication bias, as far too many of them had p -values very close to the .05 threshold (Simmons and Simonsohn 2017). In light of this evidence, the first author of the replication study bravely made a public statement that she does not believe that “power pose” effects are real (Carney 2016).

From the scientific perspective, it's very tempting to take this example as a case in which the scientific ecosystem corrects itself. Although many people continue to cite the original power posing work, we suspect the issues are well-known throughout the social psychology community, and overall interest from the lay public has gone down. But this narrative masks the very real human impacts of the self-correction process, which can raise ethical questions about the best way to address issues in the scientific record.

The process of debate and discussion around individual findings can be bruising and complicated. In the case of power posing, Cuddy herself was tightly associated with the findings and many critiques of the findings became critiques of the individual. Several commentators used Cuddy's name as a stand-in for low-quality psychological results, likely because of her prominence and perhaps because of her gender and age as well. These comments were harmful to Cuddy personally and her career more generally.

Scientists should critique, reproduce, and replicate results—these are all parts of the progress of normal science. But it's important to do this in a way that's sensitive to the people involved. Here are a few guidelines for courteous and ethical conduct:

- Always communicate about the work, never the person. Try to use language that is specific to the analysis or design being critiqued, rather than the person who did the analysis or thought up the design.

- Avoid using language that assumes negative intentions, e.g. “the authors misleadingly state that …”
- Ask someone to read your paper, email, blogpost, or tweet before you hit send. It can be very difficult to predict how someone else will experience the tone of your writing; a reader can help you make this judgement.
- Consider communicating personally before communicating publicly.
As Joe Simmons, one critic in the power-posing debate said, “I wish I’d had the presence of mind to pick up the phone and call [before publishing my critique]” (Dominus 2017). Personal communication isn’t always necessary (and can be difficult due to asymmetries of power or status), but it can be helpful.

As we will argue in the next chapter, we have an ethical duty as scientists to promote good science and critique low quality science. But we also have a duty to our colleagues and communities to be good to one another.

1280

¹²⁸¹ 3.3 *Causes of replication failure*

⊕ DEPTH

Context, moderators, and expertise

There are many explanations for failed replications. The wonderful thing about metascience is that these explanations can be tested empirically!

Let’s start with the idea that specific experimental operationalizations of a

1282

theory might be “context sensitive,” especially in subfields, like social psychology, whose theories inherently refer to environmental context (Van Bavel et al. 2016). Critics brought this issue up for RPP, where there were several studies in which the original experimental materials were tailored to one cultural context but then were deployed in another context, potentially leading to failure due to mismatch (Gilbert et al. 2016).

Context sensitivity seems like a great explanation because in some sense, it *must* be right. If the context of an experiment includes the vast network of learned associations, practices, and beliefs that we all hold, then there’s no question that an experiment’s materials tap into this context to one degree or another. For example, if your experiment relies on the association between *doctor* and *nurse* concepts, you would expect this experiment to work differently in the past when *nurse* meant something more like *nanny* (Ramscar 2016).

On the other hand, as an explanation of specific replication failures, context sensitivity has not fared very well. The “Many Labs” projects were a series of replication projects in which *multiple* labs independently attempted to replicate several original studies. (In contrast, in RPP and similar studies, a single replication was conducted for each original study.) Some of the Many Labs projects assessed variation in replication success across different labs. In ManyLabs 2, Klein et al. (2018) replicated 28 findings, distributed across 125 different samples and more than 15,000 participants. ManyLabs 2 found almost no support for the context sensitivity hypothesis as an explanation of replication failure. In general, when

effects failed to replicate, they did so when conducted in person as well as when conducted online, and these failures were consistent across many cultures and labs.

On the other hand, a review of several Many Labs-style replication projects indicated, on re-analysis, that population effects differed across replication labs even when the replication protocols were very similar to one another (Olsson-Collentine, Wicherts, and Assen 2020; Errington et al. 2021). So context sensitivity is almost certainly present—and we'll return to the broader issues of generalizability, context, and invariance in the next section—but so far we have not identified specific forms of context sensitivity that reliably affect replication success.

These observations—that 1) direct replications vary in how successful they are, but 2) we cannot identify specific contextual moderators—together suggest the possible presence of “hidden moderators.” That is, when faced with a successful original study and a failed replication, there may be some unknown factor(s) that moderates the effect.

We've personally had several experiences that corroborate the idea that there are hidden moderators. For example, in Lewis and Frank (2016), we were unsuccessful in replicating a simple categorization experiment. We then made a series of iterative changes to the stimuli and instructions, for example changing the color and pattern of the stimuli (figure 3.5), eventually resulting in a larger (and statistically significant) effect—though still much smaller than the original. Critically, however, each alteration that

we made to the procedure yielded a very small change in the effect, and it would have taken us many thousands of participants to figure exactly which alteration made the difference. (If you’re keeping score, here’s a case where stimulus color *did* matter to the outcome of the experiment!).

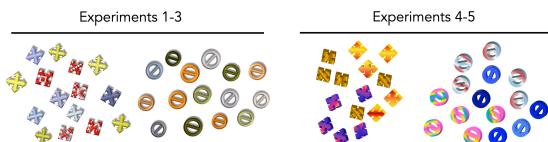


Figure 3.5
Stimuli from Lewis and Frank (2016) (<https://github.com/mllewis/xtSamp>).

Another explanation for replication failure that is often cited is experimenter expertise (e.g., Schwarz and Strack 2014). On this hypothesis, replications fail because the researchers performing the replication do not have sufficient expertise to execute the study. Like context sensitivity, this explanation is almost certainly true for some replications. In our own work, we have repeatedly performed experiments that failed due to our own incompetence!

Yet as an explanation of the pattern of metascience findings, the expertise hypothesis hasn’t been supported empirically. First, team expertise was not a predictor of replication success in RPP (cf. Bench et al. 2017).

More convincingly, Many Labs 5 selected ten findings from RPP with unsuccessful replications and systematically evaluated whether formal expert peer review of the protocols, including by the authors of the original study, would lead to a larger effect sizes. Despite a massive sample size and extremely thorough review process, there was little to no change in the effects for the vetted protocols relative to the original protocol used

in RPP (Ebersole et al. 2020).

Context, moderators, and expertise seem like reasonable explanations for individual replication failures. Certainly, we should expect them to be explanatory! But for these hypotheses to be operationalized in such a way that they carry weight in our evaluation of the meta-scientific evidence, they must be evaluated empirically rather than accepted uncritically. When such evaluations have been carried out, they have failed to support a large role for these factors.

1286

1287 The general argument of this chapter is that everything is not all
1288 right in experimental psychology, and hence that we need to change
1289 our methodological practices to avoid negative outcomes like irre-
1290 producible papers and unreplicable results. Towards that goal, we
1291 have been presenting meta-scientific evidence on reproducibility and
1292 replicability. But this evidence has been controversial, to say the
1293 least! Do large-scale replication studies like RPP—or for that matter,
1294 smaller-scale individual replications of effects like “power posing”—
1295 really lead to the conclusion that our methods require changes? Or are
1296 there reasons why a lower replication rate is actually consistent with a
1297 cumulative, positive vision of psychology?

1298 One line of argument addresses this question through the dynamics of
1299 scientific change. There are many versions, but one is given by Wilson,

1300 Harris, and Wixted (2020). The idea is that progress in psychology con-
1301 sists of a two-step process by which candidate ideas are “screened” by
1302 virtue of small, noisy experiments that reveal promising but tentative
1303 ideas that can then be “confirmed” by large-scale replications. On this
1304 kind of view, it’s business as usual to find that many randomly-selected
1305 findings don’t hold up in large-scale replications and so we shouldn’t be
1306 distressed by results like those of RPP. The key to progress is to find-
1307 ing a small set that *do* hold up, which will lead to new areas of inquiry.
1308 We’re not sure this is view is either a good description of current prac-
1309 tice or a good normative goal for scientific progress, but we won’t focus
1310 on that critique of Wilson et al.’s argument here. Instead, since book is
1311 written for experimenters-in-training, we assume that *you* do not want
1312 your experiment to be a false positive from a noisy screening procedure,
1313 regardless of your feelings about the rest of the literature!

1314 In RPP and subsequent metascience studies, original studies with lower
1315 *p*-values, larger effect sizes, and larger sample sizes were more likely
1316 to replicate successfully (Yang, Youyou, and Uzzi 2020). From a the-
1317 oretical perspective, this result is to be expected, because the *p*-value
1318 literally captures the probability of the data (or any “more extreme”)
1319 under the null hypothesis of no effect. So a lower *p*-value should indi-
1320 cate a lower probability of a spurious result.¹¹ In some sense, the funda-
1321 mental question about the replication metascience literature is why the

¹¹ In chapter 6 we will have a lot more to say about $p < .05$ but for now we’ll mostly just treat it as a particular research outcome.

1322 *p*-values aren't better predictors of replicability! For example, Camerer
1323 et al. (2018) computes an expected number of successful replications
1324 on the basis of the effects and sample sizes—and their proportion of suc-
1325 cessful replications is substantially lower than that number.¹²

1326 One explanation is that the statistical evidence presented in papers often
1327 dramatically overstates the true evidence from a study. That's because
1328 of two pervasive and critical issues: **analytic flexibility** (also known as
1329 **p-hacking** or **questionable research practices**) and **publication bias**.¹³

1330 Publication bias refers to the relative preference (of scientists and other
1331 stakeholders, like journals) for experiments that "work" than those that
1332 do not, where "work" is typically defined as yielding a significant result
1333 at $p < .05$. Because of this preference, it is typically easier to publish
1334 positive (statistically significant) results. The relative absence of negative
1335 results leads to biases in the literature. Intuitively, this bias will lead to a
1336 literature filled with papers where $p < .05$. Negative findings will then
1337 remain unpublished, living in the proverbial "file drawer" (Rosenthal
1338 1979).¹⁴ In a literature with a high degree of publication bias, many
1339 findings will be spurious because experimenters got lucky and published
1340 the study that "worked" even if that success was due to chance variation.
1341 In this situation, these spurious findings will not be replicable and so the
1342 overall rate of replicability in the literature will be lowered.¹⁵

¹² This calculation, as with most other metrics of replication success, assumes that the underlying population effect is exactly the same for the replication and the original. This is a limitation because there could be unmeasured moderators that could produce genuine substantive differences between the two estimates.

¹³ These terms basically mean the same thing and are not used very precisely in the literature. *p*-hacking is an informal term that sounds like you know you are doing something bad; sometimes people do, and sometimes they don't. Questionable research practices is a more formal-sounding term that is in principle vague enough to encompass many ethical failings but in practice gets used to talk about *p*-hacking. Unless *p*-hacking intent is crystal clear, we favor two clunkier terms: "data-dependent decision-making" and "undisclosed analytic flexibility" describe the actual practices more precisely: trying many different things after looking at data, typically without reporting all of them.

1343 It's our view that publication bias and its even more pervasive cousin,
1344 analytic flexibility, are likely to be key drivers of lower replicability. We
1345 admit that the meta-scientific evidence for this hypothesis isn't unam-
1346 biguous, but that's because there's no sure-fire way to diagnose analytic
1347 flexibility in a particular paper—since we can almost never reconstruct
1348 the precise choices that were made in the data collection and analysis
1349 process! On the other hand, it is possible to analyze indicators of publi-
1350 cation bias in specific literatures and there are several cases where pub-
1351 lication bias diagnostics appear to go hand in hand with replication fail-
1352 ure. For example, in the “power posing” example described above, Sim-
1353 mons and Simonsohn (2017) noted strong evidence of analytic flexibility
1354 throughout the literature, leading them to conclude that there was no
1355 evidential value in the literature. And in the case of “money priming”
1356 (incidental exposures to images or text about money that were hypoth-
1357 esized to lead to changes in political attitudes), strong evidence of pub-
1358 lication bias (Vadillo, Hardwicke, and Shanks 2016) was accompani-
1359 ed by a string of failed replications (Rohrer, Pashler, and Harris 2015).

¹⁴ One estimate is that 96% of (non-preregistered) papers report positive findings (Scheel, Schijen, and Lakens 2021)! We'll have a lot more to say about analytic flexibility and publication bias in Chapters 11 and 16, respectively.

¹⁵ The mathematics of the publication bias scenario strikes some observers as implausible: most psychologists don't run dozens of studies and report only one out of each group (Nelson, Simmons, and Simonsohn 2018). Instead, a more common scenario is to conduct many different analyses and then report the most successful, creating some of the same effects as publication bias—a promotion of spurious variation—without a file drawer full of failed studies.

❖ ACCIDENT REPORT

Analytic flexibility reveals a fountain of eternal youth

The way they tell it, Joseph Simmons, Leif Nelson, and Uri Simonsohn wrote their paper on “false positive psychology” (Simmons, Nelson, and

Simonsohn 2011) as an attempt at catharsis (Simmons, Nelson, and Simonsohn 2018). They were fed up with work that they felt exploited flexibility in data analysis to produce findings blessed with $p < .05$ but likely did not reflect replicable effects. They called this practice **p-hacking**: trying different things to get your p -value to be below .05.

Their paper reported on a simple experiment: they played participants either the Beatles song, “when I’m 64,” or a control song and then asked them to report their date of birth (Simmons, Nelson, and Simonsohn 2011). This manipulation resulted in a significant one and a half year rejuvenation effect. Listening to the Beatles seemed to have made their participants younger!

This result is impossible, of course. But the authors produced a statistically significant difference between the groups that, by definition, was a **false positive**—a case where the statistical test indicated that there was a difference between groups despite no difference existing. In essence, they did so by trying many possible analyses and “cherry-picking” the one that produced a positive result. This practice of course invalidates the inference that the statistical test is supposed to help you make. Several of the practices they followed included:

- Selectively reporting dependent measures (e.g., collecting several measures and reporting only one)
- Selectively dropping manipulation conditions
- Conducting their statistical test and then testing extra participants if

they did not see a significant finding

- Adjusting for gender as a covariate in their analysis if doing so resulted in a significant effect

Many of the practices that the authors followed in their rejuvenation study were (and maybe still are!) commonplace in the research literature.

John, Loewenstein, and Prelec (2012) surveyed research psychologists on the prevalence of what they called **questionable research practices**. Most participants admitted to following some of these practices—including exactly the same practices followed by the rejuvenation study.

For many in the field, “false positive psychology” was a galvanizing moment, leading them to recognize how common practices could lead to completely spurious (or even impossible) conclusions. As Simmons, Nelson, and Simonsohn wrote in their 2018 article, “Everyone knew [p-hacking] was wrong, but they thought it was wrong the way it is wrong to jaywalk. We decided to write ‘False-Positive Psychology’ when simulations revealed that it was wrong the way it is wrong to rob a bank.”

1362

3.4 Replication, theory building, and open science

¹³⁶³ Empirical measures of reproducibility and replicability in the experi-

¹³⁶⁵ mental psychology literature are low—lower than we may have naively

¹³⁶⁶ suspected and lower than we want. How do we address these issues?

¹³⁶⁷ And how do these issues interact with the goal of building theories?

1368 In this section, we discuss the relationship between replication and
1369 theory—and the role that open and transparent research practices can
1370 play.

1371 *3.4.1 Reciprocity between replication and theory*

1372 Analytic reproducibility is a prerequisite for theory building because if
1373 the twin goals of theories are to explain and to predict experimental
1374 measurements, then an error-ridden literature undermines this goal. If
1375 some proportion of all numerical values reported in the literature were
1376 simple, unintentional typos, this situation would create an extra level of
1377 noise—irrelevant random variation—impeding our goal of getting pre-
1378 cise enough measurements to distinguish between theories. But the
1379 situation is likely worse: errors are much more often in the direction
1380 that favors authors' own hypotheses. Thus, irreproducibility not only
1381 decreases our precision, it also increases the bias in the literature, creat-
1382 ing obstacles to the fair evaluation of theories with respect to data.

1383 Replicability is also foundational to theory building. Across a range of
1384 different conceptions of how science works, scientific theories are eval-
1385 uated with respect to their relationship to the world. They must be sup-
1386 ported, or at least fail to be falsified, by specific observations. It may be

1387 that some observations are by their nature un-repeatable (e.g., a partic-
1388 ular astrophysical event might be observed once a human lifetime). But
1389 for laboratory sciences—and experimental psychology can be counted
1390 among these, to a certain extent at least—the independent and skeptical
1391 evaluation of theories requires repeatability of measurements.

1392 Some authors have argued (following the philosopher Heraclitus), “you
1393 can’t step in the same river twice” (McShane and Böckenholdt 2014)—
1394 meaning, the circumstances and context of psychological experiments
1395 are constantly changing and no observation will be identical to another.

1396 This is of course technically true from a philosophical perspective. But
1397 that’s where theory comes in! As we discussed above, our theories pos-
1398 tulate the invariances that allow us to group together similar observa-
1399 tions and generalize across them.

1400 In this sense, replication is critical to theory, but theory is also critical
1401 to replication. Without a theory of “what matters” to a particular out-
1402 come, we really are stepping into an ever-changing river. But a good
1403 theory can concentrate our expectations on a much smaller set of causal
1404 relationships, allowing us to make strong predictions about what factors
1405 should and shouldn’t matter to experimental outcomes. To return to an
1406 example we discussed earlier, should stimulus color matter to the out-
1407 come of an experiment? Our theory could tell us that it shouldn’t mat-

1408 ter for a priming experiment (Baribault et al. 2018) but that it should

1409 for a generalization experiment (Lewis and Frank 2016).

1410 *3.4.2 Deciding when to replicate to maximize epistemic value*

1411 As a scientific community, how much emphasis should we place on

1412 replication? In the words of Newell (1973), “you can’t play 20 ques-

1413 tions with nature and win”. A series of well-replicated measurements

1414 does not itself constitute a theory. Theory construction is its own impor-

1415 tant activity. We’ve tried to make the case here that a reproducible and

1416 replicable literature is a critical foundation for theory building. That

1417 doesn’t necessarily mean you have to do replications all the time.

1418 More generally, any scientific community needs to trade off between

1419 exploring new phenomena and confirming previously reported effects.

1420 In a thought-provoking analysis, Oberauer and Lewandowsky (2019)

1421 suggest that perhaps replications also aren’t the best test of theoretical

1422 hypotheses. In their analysis, if you don’t have a theory then it makes

1423 sense to try and discover new phenomena and then to replicate them.

1424 If you *do* have a theory, you should expend your energy in testing new

1425 predictions rather than repeating the same test across multiple replica-

1426 tions. Analyses such as Oberauer and Lewandowsky (2019) can provide

1427 a guide to our allocation of scientific effort.

1428 Our goal in this book is somewhat different than the general goal of
1429 metascientists considering how science should be conducted. Once *you*
1430 as a researcher decide to do a particular experiment, we think you will
1431 want to maximize its scientific value and so you will want it to be repli-
1432 cable. But we aren't suggesting that you should necessarily do a replica-
1433 tion study. There are many concerns that go into whether to replicate—
1434 including not only whether you are trying to gather evidence about a
1435 particular phenomenon, but also whether you are trying to master tech-
1436 niques and paradigms related to it. As we said at the beginning of this
1437 chapter, not all replication is for the purpose of verification, and you as
1438 a researcher can make an informed decision about what experimental
1439 strategy is best for you.

1440 3.4.3 Open science

1441 The **open science movement** is, in part, a response—really a set of
1442 responses—to the challenges of reproducibility and replicability. The
1443 open science (and now the broader **open scholarship**) movement is a
1444 broad umbrella (figure 3.6), but in this book we take open science to be
1445 a set of beliefs, research practices, results, and policies that are organized
1446 around the central roles of transparency and verifiability in scientific
1447 practice.¹⁶ The core of this movement is the idea of “nullius in verba”

¹⁶ Another part of the open science um-
brella involves a democratization of the
scientific process through efforts to open
access to science. This process involves
both removal of barriers to access the
scientific literature but also efforts to
remove barriers to scientific training—
especially to groups historically under-
represented in the sciences. The hope
is that these processes increase both the
set of people and the range of perspec-
tives contributing to science. We view
these changes as no less critical than the
transparency aspects of the open science
movement, though more indirectly re-
lated to the current discussion of repro-
ducibility and replicability.

¹⁴⁴⁸ (the motto of the British Royal Society, which roughly means “take
¹⁴⁴⁹ no one’s word for it.”¹⁷

¹⁴⁵⁰ Transparency initiatives are critical for ensuring reproducibility. As we
¹⁴⁵¹ discussed above, you cannot even evaluate reproducibility in the ab-
¹⁴⁵² sence of data sharing. Code sharing can go even further towards help-
¹⁴⁵³ ing reproducibility, as code makes the exact computations involved in
¹⁴⁵⁴ data analysis much more explicit than the verbal descriptions that are
¹⁴⁵⁵ the norm in papers (Hardwicke et al. 2018). Further, as we will discuss
¹⁴⁵⁶ in chapter 13, the set of practices involved in preparing materials for
¹⁴⁵⁷ sharing can themselves encourage reproducibility by leading to better
¹⁴⁵⁸ organizational practices for research data, materials, and code.

¹⁴⁵⁹ Transparency also plays a major role in advancing replicability. This
¹⁴⁶⁰ point may not seem obvious at first—why would sharing things openly
¹⁴⁶¹ lead to more replicable experiments?—but it is one of the major theses
¹⁴⁶² of this book, so we’ll unpack it a bit. Here are a couple of routes by
¹⁴⁶³ which transparent practices lead to greater replication rates.

- ¹⁴⁶⁴ 1. Sharing of experimental materials enables replications that closely
- ¹⁴⁶⁵ follow the original study’s methods. One critique of many repli-
- ¹⁴⁶⁶ cations has been that they differ in key respects from the originals.
- ¹⁴⁶⁷ Sometimes those deviations were purposeful, but in other cases

¹⁷ At least that’s a reasonable para-phrase; there’s some interesting discussion about what this quote from Horace really means in a letter by Gould (1991).

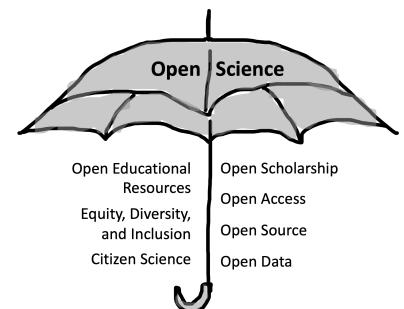


Figure 3.6
The broad umbrella of open science
(adapted from an image created for the Stanford Lane Library Blog).

1468 they were simply because the replicators could not use the origi-
1469 nal experimental materials. Sharing materials solves this problem.

1470 2. Sharing sampling and analysis plans allows replication of key as-
1471 pects of design and analysis that may not be clear in verbal de-
1472 scriptions, for example exclusion criteria or details of data pre-
1473 processing.

1474 3. Sharing of analytic decision-making via preregistration can lead
1475 to a decrease in *p*-hacking and other practices that can introduce
1476 bias. The strength of statistical evidence in the original study is a
1477 predictor of replicability in subsequent studies. If original studies
1478 are preregistered, they are more likely to report effects that are not
1479 subject to inflation via questionable research practices.

1480 4. Preregistration can also clarify the distinction between confirma-
1481 tory and exploratory findings, helping subsequent experimenters
1482 to make a more informed judgment about which effects are likely
1483 to be good targets for replication.

1484 For all of these reasons, we believe that open science practices can play
1485 a critical role in increasing reproducibility and replicability.

1486 3.4.4 *A crisis?*

1487 So, is there a “replication crisis”? The common meaning of “crisis” is
1488 “a difficult time.” The data we reviewed in this chapter suggest that
1489 there are real problems in the reproducibility and replicability of the
1490 psychology literature. But there’s no evidence that things have gotten
1491 worse. If anything, we are optimistic about the changes in practices that
1492 have happened in the last ten years. So in that sense, we are not sure
1493 that a crisis narrative is warranted.

1494 On the other hand, for Kuhn (1962), the term “crisis” had a special
1495 meaning: it is a period of intense uncertainty in a scientific field brought
1496 on by the failure of a particular paradigm (chapter 2). A crisis typically
1497 heralds a shift in paradigm, in which new approaches and phenomena
1498 come to the fore.

1499 In this sense, the replication crisis narrative isn’t mutually exclusive with
1500 other crisis narratives, including the “generalizability crisis” (Yarkoni
1501 2020) and the “theory crisis” (Oberauer and Lewandowsky 2019). All
1502 of these are symptoms of discontent with the status quo. We share
1503 this discontent! We are writing this book to encourage further changes
1504 in experimental methods and practices to improve reproducibility and
1505 replicability outcomes—many of them driven by the broader set of ideas
1506 referred to as “open science.” These changes may not lead to a paradigm

1507 shift in the Kuhnian sense, but we hope that they lead to eventual im-
1508 provements. In that sense, we think agree with those who say that the
1509 “replication crisis” has led to a “credibility revolution” (Vazire 2018).

1510 3.5 *Chapter summary: Replication*

1511 In this chapter we introduce the notions of reproducibility—getting the
1512 same numbers from the same analysis—and replicability—getting the
1513 same conclusions from a new dataset. Both of these are critical pre-
1514 requisites of a cumulative scientific literature, yet the metascience liter-
1515 ature has suggested that the rate of both reproducibility and replicability
1516 in the published literature is quite a bit lower than we would hope. A
1517 strong candidate explanation for low reproducibility is simply that code
1518 and data are rarely shared alongside published research. Lowered repli-
1519 cability is more difficult to explain, but our best guess is that analytic
1520 flexibility (“*p*-hacking”) is at least partially to blame. On our account,
1521 replication is a meta-scientific tool for understanding the status of the
1522 scientific literature rather than an end in itself. Instead, we see the open
1523 science movement, a movement focused on the role of transparency in
1524 the scientific process, as a promising response to issues of reproducibility
1525 and replicability.



DISCUSSION QUESTIONS

1. How would you design a measure of the context sensitivity of an experiment? Think of a measure you could apply *post hoc* to a description of an experiment (e.g., from reading a paper) so that you could take a group of experiments and annotate how context-sensitive they are on some scale.
2. Take the measure you designed above. How would you test that this measure really captured context sensitivity in a way that was not circular? What would be an “objective measure” of context sensitivity?
3. What proportion of reproducibility failures do you think are due to questionable practices by experimenters vs. just plain errors? How would you test your hypothesis?

1526



READINGS

- Still a very readable and entertaining introduction to the idea of p-hacking: Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2011). False-Positive Psychology: Undisclosed Flexibility in Data Collection and Analysis Allows Presenting Anything as Significant. *Psychological Science*, 22(11), 1359-1366. <https://doi.org/10.1177/0956797611417632>.
- A recent review of issues of replication in psychology: Nosek, B. et al. (2022). Replicability, Robustness, and Reproducibility in Psychological Science. *Annual Review of Psychology*, 73, 719-748. <https://doi.org/10.1146/annurev-psych-072020-010540>

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1538 4 ETHICS

 LEARNING GOALS

- Distinguish between consequentialist, deontological, and virtue ethics frameworks
- Identify key ethical issues in performing experimental research
- Discuss ethical responsibilities in analysis and reporting of research
- Describe ethical arguments for open science practices

1539

1540 The fundamental thesis of this book is that experiments are the way
1541 to estimate causal effects, which are the foundations of theory. And
1542 as we discussed in chapter 1, the reason why experiments allow for
1543 strong causal inferences is because of two ingredients: a manipulation—
1544 in which the experimenter changes the world in some way—and ran-
1545 domization. Put a different way, experimenters learn about the world
1546 by randomly deciding to do things to their participants! Is that even
1547 allowed?

We have placed this chapter in the

Foundations section of the book

because we think it's critical to start the

1548 Experimental research raises a host of ethical issues that deserve consid-
1549 eration. What can and can't we do to participants in an experiment,
1550 and what considerations do we owe to them by virtue of their deci-
1551 sion to participate? To facilitate our discussion of these issues, we start
1552 by briefly introducing the standard philosophical frameworks for eth-
1553 ical analysis. We then use those to discuss problems of experimental
1554 ethics, first from the perspective of participants and then second from
1555 the perspective of the scientific ecosystem more broadly. We end with
1556 an ethical argument for TRANSPARENCY.



CASE STUDY

Shock treatment

A decade after surviving prisoners were liberated from the last concentration camp, Adolf Eichmann, one of the Holocaust's primary masterminds, was tried for his role in the mass genocide (Baade 1961). While reflecting on his rationale for forcibly removing, torturing, and eventually murdering millions of Jews, an unrepentant Eichmann claimed that he was "merely a cog in the machinery that carried out the directives of the German Reich" and therefore was not directly responsible (Kilham and Mann 1974). This startling admission gave a young researcher an interesting idea: "Could it be that Eichmann and his million accomplices in the Holocaust were just following orders? Could we call them all accomplices?" (Milgram 1974).

Stanley Milgram aimed to make a direct test of whether people would comply under the direction of an authority figure no matter how uncomfortable or harmful the outcome. He invited participants into the laboratory to serve as a teacher for an activity (Milgram 1963). Participants were told that they were to administer electric shocks of increasing voltage to another participant, the student, in a nearby room whenever the student provided an incorrect response. In reality, there were no shocks, and the student was an actor who was in on the experiment and only pretended to be in pain when the ‘shocks’ were administered. Participants were encouraged to continue administering shocks despite clearly audible pleas from the student to stop. In one of Milgram’s studies, nearly 65% of participants administered the maximum voltage to the student.

This deeply unsettling result has become, as Ross and Nisbett (2011) say, “part of our society’s shared intellectual legacy,” informing our scientific and popular conversation in myriad different ways. At the same time, modern re-analyses of archival materials from the study have called into question whether the deception in the study was effective, casting doubt on its central findings (Perry et al. 2020).

Regardless of its scientific value, Milgram’s study blatantly violates modern ethical norms around the conduct of research. Among other violations, the procedure involved **coercion** that undermined participants’ right to withdraw from the experiment. This coercion appeared to have negative consequences: Milgram noted that a number of his participants displayed anxiety symptoms and nervousness. This observation was dis-

tressing and led to calls for this sort of research to be declared unethical (e.g., Baumrind 1964). The ethical issues surrounding Milgram's study are complex, and some are relatively specific to the particulars of his study and moment (Miller 2009). But the controversy around the study was an important part of convincing the scientific community to adopt stricter policies that protect study participants from unnecessary harm.

1559

1560 4.1 Ethical frameworks

1561 Was Milgram's experiment (see Case Study) really ethically wrong—in
1562 the sense that it should not have been performed? You might have the
1563 intuition that it was unethical, due to the harms that the participants
1564 experienced or the way they were (sometimes) deceived by the experi-
1565 menter. Others might consider arguments in defense of the experiment,
1566 perhaps that what we learned from it was sufficiently valuable to justify
1567 its being conducted. Beyond simply arguing back and forth, how could
1568 we approach this issue more systematically?

1569 Ethical frameworks offer tools for analyzing such situations. In this sec-
1570 tion, we'll introduce three of the most commonly used frameworks and
1571 discuss how each of these could be applied to Milgram's paradigm.

1572 4.1.1 *Consequentialist theories*

1573 Ethical theories provide principles for what constitute good actions.

1574 The simplest theory of good actions is the **consequentialist theory**: good

1575 actions lead to good results. The most famous consequentialist position

1576 is the **utilitarian position**, originally defined by the philosopher John

1577 Stuart Mill (Flinders 1992). This view emphasizes decision-making

1578 based on the “greatest happiness principle”, or the idea that an action

1579 should be considered morally good based on the degree of happiness

1580 or pleasure people experience because of it, and likewise that an action

1581 should be considered morally bad based on the degree of unhappiness

1582 or pain people experience by the same action (Mill 1859).

1583 A consequentialist analysis of Milgram’s study considers the study’s neg-

1584 ative and positive effects and weighs these against one another. Did the

1585 study cause harm to its participants? On the other hand, did the study

1586 lead to knowledge that prevented harm or caused positive benefits?

1587 Consequentialist analysis can be a straightforward way to justify the risks

1588 and benefits of a particular action, but in the research setting it is unsat-

1589 isfying. Many horrifying experiments would be licensed by a conse-

1590 quentialist analysis and yet feel untenable to us. Imagine a researcher

1591 forced you to undergo a risky and undesired medical intervention be-

1592 cause the resulting knowledge might benefit thousands of others. This

1593 experiment seems like precisely the kind of thing our ethical framework
1594 should rule out!

1595 *4.1.2 Deontological approaches*

1596 Harmful research performed against participants' will or without their
1597 knowledge is repugnant; we consider the Tuskegee Syphilis Exper-
1598 iment, a horrifying example of such research (Case Study, below).

1599 Considering such cases, a few rules seem obvious, for example: "re-
1600 searchers must ask participants' permission before conducting research
1601 on them." Principles like this one are now formalized in all ethical
1602 codes for research. They exemplify an approach called **deontological**
1603 (or duty-based) ethics.

1604 Deontology emphasizes the importance of taking ethically permissible
1605 actions, regardless of their outcome (Biagetti, Gedutis, and Ma 2020).

1606 In general, university ethics boards take a deontological approach to
1607 ethics (Boser 2007). In the context of research, there are four primary
1608 principles being applied:

1609 (1) **Respect for autonomy.** This principle requires that people par-
1610 ticipating in research studies can make their own decisions about
1611 their participation, and that those with diminished autonomy

(children, neuro-divergent people, etc.) should receive equal protections (Beauchamp, Childress, et al. 2001). Respecting someone's autonomy also means providing them with all the information they need to make an informed decision about whether to participate in a research study (giving **consent**) and giving them further context about the study they have participated in after it is done (**debriefing**).

(2) **Beneficence.** This principle means that researchers are obligated to protect the well-being of participants for the duration of the study. Beneficence has two parts. The first is to do no harm. Researchers must take steps to minimize the risks to participants and to disclose any known risks at the onset. If risks are discovered during participation, researchers must notify participants of their discovery and make reasonable efforts to mitigate these risks, even if that means stopping the study altogether. The second is to maximize potential benefits to participants.¹

(3) **Nonmaleficence.** This principle is similar to beneficence (in fact, beneficence and nonmaleficence were a single principle when they were first introduced in the Belmont Report, which we'll discuss later) but differs in its emphasis on doing/causing no harm. In general, harm is bad—but deontology is about intent,

¹ In practice, this doesn't mean compensating participants with exorbitant amounts of money or gifts, which might cause other issues, like exerting an undue influence on low-income participants to participate. Instead “maximizing benefits” is interpreted as identifying all possible benefits of participation in the research and making them available where possible.

1633 not impact, so harm is sometimes warranted when the intent
1634 is morally good. For example, administering a vaccine may
1635 cause some discomfort and pain, but the intent is to protect the
1636 patient from developing a deadly virus in the future. The harm
1637 is justifiable under this framework.

1638 (4) **Justice.** This principle means that both the benefits and risks of
1639 a study should be equally distributed among all participants. For
1640 example, participants should not be systematically assigned to one
1641 condition over another based on features of their identity such as
1642 socioeconomic status, race and ethnicity, or gender.

1643 Analyzed from the perspective of these principles, Milgram's study
1644 raises several red flags. First, Milgram's study reduced participants'
1645 autonomy by making it difficult for them to voluntarily end their
1646 involvement (participants were told up to four times to continue
1647 administering shocks even after they expressed clear opposition).

1648 Second, the paradigm was designed in a way that it was likely to cause
1649 harm to its participants by putting them in a very stressful situation.

1650 Further, Milgram's study may have induced *unnecessary* harm on certain
1651 participants by failing to screen participants for existing mental health
1652 issues before beginning the session.

 DEPTH

Was Milgram justified?

Was the harm done in Milgram's experiment justifiable given that it informed our understanding of obedience and conformity? We can't say for sure. What we can say is that in the 10 years following the publication of Milgram's study, the number of papers on (any kind of) obedience increased and the nature of these papers expanded from a focus on religious conformity to a broader interest in social conformity, suggesting that Milgram changed the direction of this research area. Additionally, in a followup that Milgram conducted, he reported that 84% of participants in the original study said they were happy to have been involved (Milgram 1974). On the other hand, given concerns about validity in the original study, perhaps its influence on the field was not warranted (Perry et al. 2020).

Many researchers believe there was no ethical way to conduct Milgram's experiment while also protecting the integrity of the research goals, but some have tried. One study recreated a portion of the original experiment, with some critical changes (Burger 2007). Before enrolling in the study, participants completed both a phone screening for mental health concerns, addiction, or extreme trauma, and a formal interview with a licensed clinical psychologist, who identified signs of depression or anxiety. Those who passed these assessments were invited into the lab for a Milgram-type learning study. Experimenters clearly explained that par-

ticipation was voluntary and the decision to participate could be reversed at any point, either by the participant themselves or by a trained clinical psychologist who was present for the duration of the session. Additionally, shock administration never exceeded 150 volts (compared to 450 volts in the original study), and experimenters debriefed participants extensively following the end of the session. This modified replication study found similar patterns of obedience as Milgram's; further, one year later, no participants expressed any indication of stress or trauma associated with their involvement in the study.

1654

1655 4.1.1 *Virtue-based Approaches*

1656 A final way that we can approach ethical dilemmas is through a virtue
1657 framework. A **virtue** is a trait, disposition, or quality that is thought to
1658 be a moral foundation (Annas 2006). Virtue ethics suggests that people
1659 can learn to be virtuous by observing those actions in others they admire
1660 (Morris and Morris 2016). Proponents of virtue ethics say this works for
1661 two reasons: (1) people are generally good at recognizing morally good
1662 traits in others and (2) people receive some fulfillment from living virtu-
1663 ously. Virtue ethics differs from deontology and utilitarianism because
1664 it focuses on a person's character rather than on the nature of a rule or
1665 the consequences of an action.

1666 From a research perspective, virtue ethics tells us that in order to behave

1667 virtuously, we must make decisions that consider the context surround-
1668 ing the experiment (Dillern 2021). In other words, researchers should
1669 evaluate how their studies might influence a participant's behaviors, es-
1670 pecially when those behaviors deviate from typical expectations. This
1671 process is also meant to be adaptive, meaning that researchers must be
1672 vigilant about both the changing mental states of their participants dur-
1673 ing the experimental session and whether the planned procedure is no
1674 longer acceptable.

1675 How can we apply this ethical framework to Milgram's experiment?
1676 Many virtue ethicists would probably conclude that Milgram's ap-
1677 proach was neither appropriate (for participants) nor adaptive. Upon
1678 noticing increasing levels of participant distress, an experimenter
1679 following the virtue ethics framework should have chosen to end the
1680 session early or—even better—to have minimized participant distress
1681 from the beginning.

1682 *4.2 Ethical responsibilities to research participants*

1683 Milgram's shock experiment was just one of dozens of unethical hu-
1684 man subjects studies that garnered the attention and anger of the public
1685 in the United States. In 1978, the US National Commission for the
1686 Protection of Human Services of Biomedical and Behavioral Research

1687 released the **Belmont Report**, which described protections for the rights
1688 of human subjects participating in research studies (Adashi, Walters, and
1689 Menikoff 2018). Perhaps the most important message found in the re-
1690 port was the notion that “investigators should not have sole responsibil-
1691 ity for determining whether research involving human subjects fulfills
1692 ethical standards. Others, who are independent of the research, must
1693 share the responsibility.” In other words, ethical research requires both
1694 transparency and external oversight.

1695 4.2.1 *Institutional review boards*

1696 The creation of **institutional review boards** (IRBs) in the United States
1697 was an important result of the Belmont Report. While regulatory frame-
1698 works and standards vary across national boundaries, ethical review of
1699 research is ubiquitous across countries. In what follows, we focus on
1700 the US regulatory framework as it has been a model for other ethical
1701 review systems but we use the clearer label “ethics review boards” for
1702 IRBs.

1703 An ethics board is a committee of people who review, evaluate, and
1704 monitor human subjects research to make sure that participants’ rights
1705 are protected when they participate in research (Oakes 2002). Ethics
1706 boards are local; every organization that conducts human subjects or

1707 animal research is required to have its own ethics board or to contract
1708 with an external one. If you are based at a university, yours likely has
1709 its own, and its members are probably a mix of scientists, doctors, pro-
1710 fessors, and community residents.²

1711 When a group of researchers have a research question they are interested
1712 in pursuing with human subjects, they must receive approval from their
1713 local ethics board before beginning any data collection. The ethics board
1714 reviews each study to make sure:

1715 1. A study poses no more than **minimal risk** to participants. This
1716 means the anticipated harm or discomfort to the participant is
1717 not greater than what would be experienced in everyday life. It is
1718 possible to perform a study that poses **greater than minimal risk**,
1719 but it requires additional monitoring to detect any adverse events
1720 that may occur.

1721 2. Researchers obtain **informed consent** from participants before col-
1722 lecting any data. This requirement means experimenters must dis-
1723 close all potential risks and benefits so that participants can make
1724 an informed decision about whether or not to participate in the
1725 study. Importantly, informed consent does not stop after partic-
1726 ipants sign a consent form. If researchers discover any new po-

² The local control of ethics boards can lead to very different practices in ethical review across institutions, which is obviously inconsistent with the idea that ethical standards should be uniform! In addition, critics have wondered about the structural issue that institutional ethics boards have an incentive to decrease liability for the institution, while private boards have an incentive to provide approvals to the researchers who pay them (Lemmens and Freedman 2000).

1727 tential risks or benefits along the way, they must disclose these
1728 discoveries to all participants (see chapter 12).

1729 3. Sensitive information remains **confidential**. Although regulatory
1730 frameworks vary, researchers typically have an obligation to their
1731 participants to protect all identifying information recorded during
1732 the study (see chapter 13).

1733 4. Participants are recruited **equitably** and without **coercion**. Be-
1734 fore ethics boards became standard, researchers often coercively
1735 recruited marginalized and vulnerable populations to test their
1736 research questions, rather than making participation in research
1737 studies voluntary and providing equitable access to the opportu-
1738 nity to participate.



CASE STUDY

The Tuskegee Syphilis Study

In 1929, The United States Public Health Service (USPHS) was perplexed by the effects of syphilis in Macon County, Alabama, an area with an overwhelmingly Black population (Brandt 1978). Syphilis is a sexually transmitted bacterial infection that can either be in a visible and active stage or in a latent stage. At the time of the study's inception, roughly 36% of Tuskegee's adult population had developed some form of syphilis, one of the highest infection rates in America (White 2006).

The USPHS recruited 400 Black males from 25–60 years of age with latent syphilis and 200 Black males without the infection to serve as a control group to participate (Brandt 1978). The USPHS sought the help of the Macon County Board of Health to recruit participants with the promise that they would provide treatment for community members with syphilis. The researchers sought poor, illiterate Black people and, instead of telling them that they were being recruited for a research study, merely informed them that they would be treated for “bad blood”.

Because the study was interested in tracking the natural course of latent syphilis without any medical intervention, the USPHS had no intention of providing any care to its participants. To assuage participants, the USPHS distributed an ointment that had not been shown to be effective in the treatment of syphilis, and only small doses of a medication actually used to treat the infection. In addition, participants underwent a spinal tap which was presented to them as another form of therapy and their “last chance for free treatment.”

By 1955, just over 30% of the original participants had died from syphilis complications. It took until the 1970s before the final report was released and (the lack of) treatment ended. In total, 128 participants died of syphilis or complications from the infection, 40 wives became infected, and 19 children were born with the infection (Katz and Warren 2011). The damage rippled through two generations, and many never actually learned what had been done to them.

The Tuskegee experiment violates nearly every single guideline for research described above—indeed in its many horrifying violations of research participants' agency, it provides a blueprint for future regulation to prevent any aspect of it from being repeated: Investigators did not obtain informed consent. Participants were not made aware of all known risks and benefits involved with their participation. Instead, they were deceived by researchers who led them to believe that diagnostic and invasive exams were directly related to their treatment.

Perhaps most shocking, participants were denied appropriate treatment following the discovery that penicillin was effective at treating syphilis (Mahoney, Arnold, and Harris 1943). The USPHS requested that medical professionals overseeing their care outside of the research study not offer treatment to participants so as to preserve the study's methodological integrity. This intervention violated participants' rights to equal access to care, which should have taken precedence over the results of the study.

Finally, recruitment was both imbalanced and coercive. Not only were participants selected from the poorest of neighborhoods in the hopes of finding vulnerable populations with little agency, but they were also bribed with empty promises of treatment and a monetary incentive (payment for burial fees, a financial obstacle for many sharecroppers and tenant farmers at the time).

1742 4.2.1 *Risks and benefits*

1743 Imagine that you were approached about participating in a research
1744 study at your local university. You were only told you would be paid
1745 \$25 in exchange for completing an hour of cognitive tasks on a com-
1746 puter. Now imagine that halfway through the session, the experimenter
1747 revealed they would also need to collect a blood sample, “which should
1748 only take a couple of minutes and which will really help the research
1749 study.” Would you agree to the sample? Would you feel uncomfortable
1750 in any way?

1751 Participants need to understand the risks and benefits of participation in
1752 an experiment before they give consent. To do otherwise compromises
1753 their autonomy (a key deontological principle). In the case of this hy-
1754 pothetical experiment, a new and unexpected invasive component of
1755 an experiment is coercive: participants would have to choose to forfeit
1756 their expected compensation to opt out. They also might feel that they
1757 have been deceived by the experimenter.

1758 In human subjects research, **deception** is a specific technical term that
1759 refers to cases when (1) experimenters withhold any information about
1760 its goals or intentions, (2) experimenters hide their true identity (such
1761 as when using actors), (3) some aspects of the research are under- or
1762 overstated to conceal information, or (4) participants receive any false

1763 or misleading information. The use of deception requires special con-
1764 sideration from a human subjects perspective (Kelman 2017; Baumrind
1765 1985).

1766 Even assuming they are disclosed properly without coercion or decep-
1767 tion, the risks and benefits of a study must be assessed from the per-
1768 spective of the *participant*, not the experimenter. By doing so, we allow
1769 participants to make an informed choice. In the case of the blood sam-
1770 ple, the risks to the participant were not disclosed, and the benefits were
1771 stated in terms of the research project (and the experimenter).

1772 The benefits of participation in research can either be direct or indi-
1773 rect, and it is important to specify which type participants may receive.
1774 While some clinical studies and interventions may offer some direct ben-
1775 efit due to participation, many of the benefits of basic science research
1776 are indirect. Both have their place in science, but participants must ul-
1777 timately determine the degree to which each type of benefit motivates
1778 their own involvement in a study (Shatz 1986).

1779 4.3 Ethical responsibilities in analysis and reporting of
1780 research

 ACCIDENT REPORT

What data?

Dutch social psychologist Diederick Stapel contributed to more than 200 articles on social comparison, stereotype threat, and discrimination, many published in the most prestigious journals. Stapel reported that affirming positive personal qualities buffered against dangerous social comparison, that product advertisements related to a person's attractiveness changed their sense of self, and that exposure to intelligent in-group members boosted a person's performance on future tasks (Stapel and Linde 2012; Trampe, Stapel, and Siero 2011; Gordijn and Stapel 2012). These findings were fresh and noteworthy at the time of publication, and Stapel's papers were cited thousands of times. The only problem? Stapel's data were made up.

Stapel has admitted that when he first began fabricating data, he would make small tweaks to a few data points (Stapel 2012). Changing a single number here and there would turn a flat study into an impressive one. Having achieved comfortable success (and having aroused little suspicion from journal editors and others in the scientific community), Stapel eventually began creating entire data sets and passing them off as his own. Several colleagues began to grow skeptical of his overwhelming success, however, and brought their concerns to the Psychology Department at

Tilburg University. By the time the investigation of his work concluded, 58 of Stapel's papers were **retracted**, meaning that the publishing journal withdrew the paper after discovering that its contents were invalid.

Everyone agrees that Stapel's behavior was deeply unethical. But should we consider cases of falsification and fraud to be different in kind from other ethical violations in research? Or is fraud merely the endpoint in a continuum that might include other practices like *p*-hacking? Lawyers and philosophers grapple with the precise boundary between sloppiness and neglect, and it can be difficult to know which one is at play when a typo or coding mistake changes the conclusion of a scientific paper. Similarly, if a researcher engages in so-called "questionable research practices," at what point should they be considered to have made an ethical violation as opposed to simply performing their research poorly?

The ethical frameworks above provide a framework for thinking about this topic. For the consequentialist, sloppy science can lead to good outcomes for the scientist (quicker publication) but bad outcomes for the rest of the scientific community who have to waste time and effort on papers that may not be correct. For the deontologist, the scientist's intention plays a key role: it is not a generally acceptable principle to knowingly use sub-standard practices. And for the virtue ethicist, sloppiness is not a morally good trait. On all analyses, researchers have a duty to pursue their work carefully.

1785 also responsible for what we do with our data and for the kinds of con-
1786 clusions we draw. Cases like Stapel's (see Accident Report) seem stun-
1787 ning, but they are part of a continuum. Codes of professional ethics for
1788 organizations like the American Psychological Association encourage
1789 researchers to take care in the management and analysis of their data so
1790 as to avoid errors and misstatements (Association 2022).

1791 Researchers also have an obligation not to suppress findings based on
1792 their own beliefs about the right answer. One unfortunate way that
1793 this suppression can happen is when researchers selectively report their
1794 research, leading to **publication bias**, as you learned in chapter 3. Re-
1795 searchers' own biases can be another (invalid) rationale for not publish-
1796 ing: it's also an ethical violation to suppress findings that contradict your
1797 theoretical commitments.

1798 Importantly, researchers don't have an obligation to publish *everything*
1799 they do. Publishing in the peer-reviewed literature is difficult and time-
1800 consuming. There are plenty of reasons not to publish an experimental
1801 finding! For example, there's no reason to publish a result if you believe
1802 it is truly uninformative because of a confound in the experimental de-
1803 sign. You also aren't typically committing an ethical violation if you de-
1804 cide to quit your job in research and so you don't publish a study from
1805 your dissertation.³ The primary ethical issue arises when you use the

³ On the other hand, if your dissertation contains the cure to a terrible disease, you do have a duty to publish it!

¹⁸⁰⁶ result of a study—and how it relates to your own beliefs or to a threshold

¹⁸⁰⁷ like $p < .05$ —to decide whether to publish it or not.

¹⁸⁰⁸ As we'll discuss again and again in this book, the preparation of research

¹⁸⁰⁹ reports must also be done with care and attention to detail (see chap-

¹⁸¹⁰ ter 14). Sloppiness in writing up results can lead to imprecise or over-

¹⁸¹¹ broad claims; and if that sloppiness extends to the reporting of data, and

¹⁸¹² analysis, it may lead to irreproducibility as well.

¹⁸¹³ Further, professional ethics dictate that published contributions to the

¹⁸¹⁴ literature be original. In general, the text of a paper must not be pla-

¹⁸¹⁵ giarized (copied) from the text of other reports whether by you or by

¹⁸¹⁶ another author without attribution. Copying from others outside of a

¹⁸¹⁷ direct, attributed quotation is obviously an ethical violation because it

¹⁸¹⁸ leads to credit for text being given to you rather than the true author.

¹⁸¹⁹ But self-plagiarism is also not acceptable—it is a violation to receive

¹⁸²⁰ credit multiple times for the same product.⁴

¹⁸²¹ 4.4 Ethical responsibilities to the broader scientific ¹⁸²² community

¹⁸²³ The open science principles that we will describe throughout this book

¹⁸²⁴ are not only important correctives to issues of reproducibility and repli-

⁴ Standards on this issue differ from field to field. Our sense is that the rule on self-plagiarism applies primarily to duplication of content between journal papers. So, for example, barring any specific policy of the funder or journal, it is acceptable to use text from one of your own grant proposals in a journal paper. It is also typically acceptable to reuse text from a conference abstract or preregistration (that you wrote, of course) when prepare a journal paper.

1825 capability, they are also ethical duties.

1826 The sociologist Robert Merton described a set of norms that science
1827 is assumed to follow: communism—that scientific knowledge belongs
1828 to the community; universalism—that the validity of scientific results
1829 is independent of the identity of the scientists; disinterestedness—that
1830 scientists and scientific institutions act for the benefit of the overall en-
1831 terprise; and organized skepticism—that scientific findings must be crit-
1832 ically evaluated ([Merton 1979](#)).

1833 If the products of science aren't open, it is very hard to be a scientist
1834 by Merton's definition. To contribute to the communal good, papers
1835 need to be openly available. And to be subject to skeptical inquiry, ex-
1836 perimental materials, research data, analytic code, and software must
1837 be all available so that analytic calculations can be verified and experi-
1838 ments can be reproduced. Otherwise, you have to accept arguments on
1839 authority rather than by virtue of the materials and data.

1840 Openness is not only definitionally part of the scientific enterprise, it's
1841 also good for science and individual scientists ([Gorgolewski and Pol-](#)
1842 [drack 2016](#)). Open access publications are cited more ([Eysenbach 2006;](#)
1843 [Gargouri et al. 2010](#)). Open data also increases the potential for ci-
1844 tation and reuse, and maximizes the chances that errors are found and
1845 corrected.

1846 But these benefits mean that researchers have a responsibility to their
1847 funders to pursue open practices so as to seek the maximal return on
1848 funders' investments. And by the same logic, if research participants
1849 contribute their time to scientific projects, the researchers also owe it to
1850 these participants to maximize the impact of their contributions (Brake-
1851 wood and Poldrack 2013). For all of these reasons, individual scientists
1852 have a duty to be open—and scientific institutions have a duty to pro-
1853 mote transparency in the science they support and publish.

1854 How should these duties be balanced against researchers' other respon-
1855 sibilities? For example, how should we balance the benefit of data shar-
1856 ing against the commitment to preserve participant privacy? And, since
1857 transparency policies also carry costs in terms of time and effort, how
1858 should researchers consider those costs against other obligations?

1859 First, open practices should be a default in cases where risks and costs
1860 are limited. For example, the vast majority of journals allow authors to
1861 post accepted manuscripts in their un-typeset form to an open reposi-
1862 tory. This route to “green” open access is easy, cost free, and—because
1863 it comes only after articles are accepted for publication—confers essen-
1864 tially no risks of scooping. As a second example, the vast majority of
1865 analytic code can be posted as an explicit record of exactly how analy-
1866 ses were conducted, even if posting data is sometimes more complicated

1867 due to privacy restrictions. These kinds of “incentive compatible” ac-
1868 tions towards openness can bring researchers much of the way to a fully
1869 transparent workflow, and there is no excuse not to take them.

1870 Second, researchers should plan for sharing and build a workflow that
1871 decreases the costs of openness. As we discuss in chapter 13, while it
1872 can be costly and difficult to share data after the fact if they were not
1873 explicitly prepared for sharing, good project management practices can
1874 make this process far simpler (and in many cases completely trivial).

1875 Finally, given the ethical imperative towards openness, institutions like
1876 funders, journals, and societies need to use their role to promote open
1877 practices and to mitigate potential negatives (Nosek et al. 2015). Schol-
1878 arly societies have an important role to play in educating scientists about
1879 the benefits of openness and providing resources to steer their members
1880 towards best practices for sharing their publication and other research
1881 products. Similarly, journals can set good defaults, for example by re-
1882 quiring data and code sharing except in cases where a strong justification
1883 is given. Funders of research can—and increasingly, do—signal their in-
1884 terest in openness through data sharing mandates.

1885 4.5 *Chapter summary: Ethics*

1886 In this chapter, we discussed three ethical frameworks and evaluated
1887 how they can be applied to our own research through the lens of Mil-
1888 gram's famous obedience experiment. Studies like Milgram's prompted
1889 serious conversations about how best to reconcile experimenter goals
1890 with participant well-being. The publication of the Belmont Report
1891 and later creation of ethics boards in the United States standardized
1892 the way scientists approach human subjects research, and created much-
1893 needed accountability. We also addressed our ethical responsibilities to
1894 the scientific community, both in how we report our data and how we
1895 distribute it. We hope that we have convinced you that careful, open
1896 science is an ethical imperative for researchers!



DISCUSSION QUESTIONS

1. The COVID-19 pandemic led to an immense amount of “rapid response” research in psychology that aimed to discover—and influence—the way people reasoned about contagion, vaccines, masking, and other aspects of the public health situation. What are the specific ethical concerns that researchers should be aware of for this type of research? Are there reasons for more caution in this kind of research than in other “run of the mill” research?
2. Think of an argument against open science practices—for example, that following open science practices is especially burdensome for re-

searchers with more limited resources (you can make up another if you want!). Given our argument that researchers have an ethical duty to openness, how would you analyze this argument under the three different ethical frameworks we discussed?

1898

READINGS

- The Belmont Report has shaped US research ethics policy from its publication to the present day. It's also short and quite readable: <https://www.hhs.gov/ohrp/regulations-and-policy/belmont-report/index.html>.
- A rich reference with several case studies on science misconduct and with strong arguments for open science: Ritchie, S. (2020). *Science fictions: How fraud, bias, negligence, and hype undermine the search for truth*. Metropolitan Books.

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1900

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1901

STATISTICS

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5 ESTIMATION

1907

LEARNING GOALS

- Estimate the causal effect of a manipulation
- Discuss differences between frequentist and Bayesian estimation
- Reason about standardized effect sizes and their strengths and weaknesses
- Quantify the relationship between variables

1908

1909 “In every quantitative paper we read, every quantitative
1910 talk we attend, and every quantitative article we write, we
1911 should all ask one question: *what is the estimand?* The es-
timand is the object of inquiry—it is the precise quantity
1912 about which we marshal data to draw an inference. Yet,
1913 too often social scientists skip the step of defining the esti-
1914 mand. Instead, they leap straight to describing the data they
1915 analyze and the statistical procedures they apply. Without
1916

1917 a statement of the estimand, it becomes impossible for the
1918 reader to know whether those procedures were appropri-
1919 ate.” (Lundberg, Johnson, and Stewart 2021)

1920 In the first section of this book, our goal was to set up some of the the-
1921 oretical ideas that motivate our approach to experimental design and
1922 planning. We introduced our key thesis, namely that experiments are
1923 about measuring causal effects. We also began to discuss our key themes,

1924 TRANSPARENCY, MEASUREMENT PRECISION, BIAS REDUCTION, and GENER-
1925 ALIZABILITY.

1926 In this next section of the book—treating statistical topics—we will inte-
1927 grate these ideas with an analytic toolkit for estimating effects and quan-
1928 tifying their size (this chapter), making inferences about how these esti-
1929 mates relate to a population (chapter 6), and building models for estima-
1930 tion and inference in more complex settings (chapter 7). Although this
1931 book does not provide an extensive treatment of statistics, we hope that
1932 these chapters provide a foundations—and an opinionated perspective—
1933 for beginning the statistical analysis of your experimental data, with a
1934 focus on MEASUREMENT PRECISION.



CASE STUDY

The Lady Tasting Tea

The birth of modern statistical inference arose from the age old conundrum of how to best make a cup of tea. The statistician Ronald Fisher was apparently at an afternoon tea party when a lady declared that she could tell the difference when tea was added to milk vs. milk to tea. Rather than taking her at her word, Fisher devised an experimental and data analysis procedure to test her claim.

The lady would have to judge a set of six new cups of tea and sort them into milk-first vs. tea-first sets. Her data would then be analyzed to determine whether her level of correct choice exceeded that expected by chance. While this process now sounds like a quotidian experiment that might be done on a cooking reality show, it seems unremarkable in hindsight only because it set the standard for the way science was done going forward.

The important and unusual element of the experiment was its treatment of potential design confounds such which cup of tea was prepared first, which cup of tea was presented first, or the material that the cups were made out of. Prior experimental practice would have been to try to equate all of the cups as closely as possible, decreasing the influence of confounds. Fisher recognized that this strategy was insufficient because of the presence of unobserved confounders. Only by randomizing all other aspects of the experiment could he make strong causal inferences about the

treatment (milk then tea vs. tea then milk). We discussed the causal power of random assignment in chapter 1—the Lady Tasting Tea experiment is a key touchstone in the popularization of randomized experiments!

1936

1937 5.1 Estimating a quantity

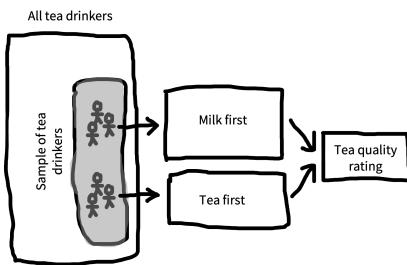


Figure 5.1
The structure of our tea tasting experiment.

1938 If experiments are about estimating effects, how do we actually use our
 1939 experimental data to make these estimates? For our example we'll de-
 1940 sign a slightly more modern version of Fisher's experiment, shown in
 1941 figure 5.1.

1942 Our causal theory is that the tea quality is affected by milk-tea ordering,
 1943 so we'll test that by rating tea quality both milk-first and tea-first, rep-
 1944 resented by a DAG like the one in figure 5.2. Our intended population
 1945 to generalize to is the set of all tea drinkers, and towards that goal we
 1946 sample a set of tea-drinkers. In practice, we might do a field trial in a
 1947 cafe in which we approach patrons and ask them to participate in our
 1948 experiment in exchange for a free cup of tea. Although this sample size

An important piece of context for the work of Ronald Fisher, Karl Pearson, and other early pioneers of statistical inference is that they were all strong proponents of eugenics. Fisher was the founding Chairman of the Cambridge Eugenics Society. Pearson was perhaps even worse, an avowed Social Darwinist who believed fervently in Eugenic legislation. These views are repugnant and provide important context for their statistical contributions.

1949 is almost certainly too small to get precise estimates, for the purpose of
 1950 this example, we'll sample 18 tea drinkers—nine in each condition.

1951 As our manipulation, we follow Fisher in randomly assigning partici-
 1952 pants (who of course should give consent to participate) into to one of
 1953 our two conditions: milk-first and tea-first.¹ This design is a between-
 1954 participants design, so each participant gets only one cup of tea. They
 1955 receive their cup of tea and taste it. Then as our measure, we ask for
 1956 a rating of the tea on a continuous scale from 1 (terrible) to 7 (deli-
 1957 cious).²

1958 An example dataset from our experiment is shown in figure 5.3. Eventu-
 1959 ally, we'll want to estimate the effect of milk-first preparation on quality
 1960 ratings (our effect of interest). But for now, our goal will be to estimate
 1961 the quality of the tea when it is milk-first [which some data suggest is
 1962 actually the better way, at least for British tea drinkers; Kennedy (2003)].
 1963 More formally, we want to use our sample of 9 milk-first tea judgments
 1964 to estimate a number that we can't directly observe, namely the true per-
 1965 ceived quality of all possible milk-first cups. We'll call this number a
 1966 **population parameter** for reasons that will become clear in a moment.

1967 We'll try to go easy on notation but some amount will hopefully make
 1968 things clearer. We will use θ_M ("theta") to denote the parameter we

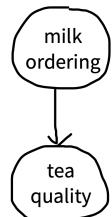


Figure 5.2
 A directed acyclic graph representing our causal theory of tea quality.

¹ Technically, randomized experiments were not invented by Fisher. Perhaps the earliest example of a (somewhat) randomized experiment was a trial of scurvy treatments in the 1700s (Dunn 1997). Peirce and Jastrow (1884) also report a strikingly modern use of randomized stimulus presentation (via shuffling cards). Nevertheless, Fisher's statistical work popularized randomized experiments throughout the sciences, in part by integrating them with a set of analytic methods.

¹⁹⁶⁹ want to estimate (the population parameter) and $\hat{\theta}_M$, its sample esti-
¹⁹⁷⁰ mate.³

¹⁹⁷¹ 5.1.1 Maximum likelihood estimation

¹⁹⁷² OK, you are probably saying, if we want our estimate of milk-first qual-
¹⁹⁷³ ity, shouldn't we just take the average rating across the 9 cups of milk-
¹⁹⁷⁴ first tea? The answer is yes. But let's unpack that choice: taking the
¹⁹⁷⁵ sample mean as our estimate $\hat{\theta}_M$ is an example of an estimation approach
¹⁹⁷⁶ called **maximum likelihood estimation**. In general terms, maximum
¹⁹⁷⁷ likelihood estimation is a two-step process.

¹⁹⁷⁸ First, we assume a **model** for how the data were generated.⁴ This model
¹⁹⁷⁹ is specified in terms of certain population parameters. In our example,
¹⁹⁸⁰ the model is as simple as they come: we just assume there is some aver-
¹⁹⁸¹ age level of tea quality and that the measurements vary around it. Let's
¹⁹⁸² take a look at the data from the milk-first condition, shown in figure 5.4.
¹⁹⁸³ Our observations are clustered around the mean, but they also show
¹⁹⁸⁴ some variation. Some are higher and some are lower. Variation of this
¹⁹⁸⁵ type is a feature of every data set. This variation can be summarized
¹⁹⁸⁶ via a **probability distribution**, a mathematical entity that describes the
¹⁹⁸⁷ properties of possible datasets.

² Right now we're going to assume that our ratings are just simple numerical values and not worry about the fact that they come from a rating scale that is bounded (e.g., can't go above 7). If you're curious about **Likert scales** (the name for discrete numerical rating scales; pronounced LICK-ERT), we'll talk a bit more about them in chapter 8.

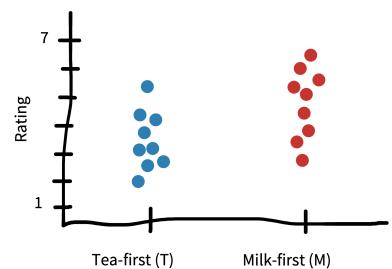


Figure 5.3
Schematic data from the tea tasting experiment.

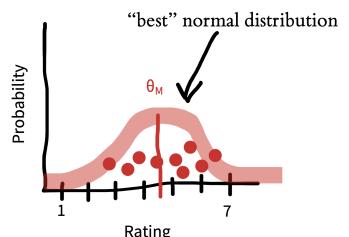
³ Statisticians use "hats" like this to denote estimates from a specific sample. One way to remember this is that the "person in the hat" is wearing a hat to dress up as the actual quantity.

1988 The only probability distribution we'll discuss here is the ubiquitous
 1989 **normal distribution** (also sometimes called a "Gaussian distribution"). A
 1990 normal distribution has two **parameters** (numbers that define its shape),
 1991 a **mean** and a **standard deviation**. These two parameters define the shape
 1992 of the curve. The mean (θ_M) describes where its center goes, and the
 1993 standard deviation describes how wide it is. Technically, the mean is
 1994 the **expected value** for new samples from the distribution. Our best
 1995 guess about the value of these new samples is that they are at the mean.
 1996 We can write this more formally by introducing $E[M]$ to denote the
 1997 expectation of the variable M .

1998 The standard deviation σ_M is then a way of describing the expected
 1999 *variation* in these samples. A bigger standard deviation means that we
 2000 expect samples to be on average further from the mean. We can write
 2001 this formally as $\sigma_M = \sqrt{E[(M - \theta_M)^2]}$: the standard deviation is the
 2002 expected absolute distance between individual samples and the mean,
 2003 with the square and square root being necessary to compute distance.

2004 Using a probability distribution to describe our dataset gives us a way of
 2005 summarizing our observations through the parameters of the distribu-
 2006 tion and encoding an assumption about what future observations might
 2007 look like. How do we fit a normal distribution to our data? We try
 2008 to find the values of the population parameters that make our observed

⁴ This sense of "model" is actually a formal instantiation of the type of causal model we discussed in chapter 1. As you get deeper into causal modeling, typically what you do is define a causal "story" for the statistical process that generated a dataset, using both DAGs and the kinds of probability distributions we define below.



θ_M is the mean of the best-fitting normal distribution

Figure 5.4
The best-fitting normal distribution for data from the milk-first condition.

2009 data as likely as possible. Let's start with the mean.

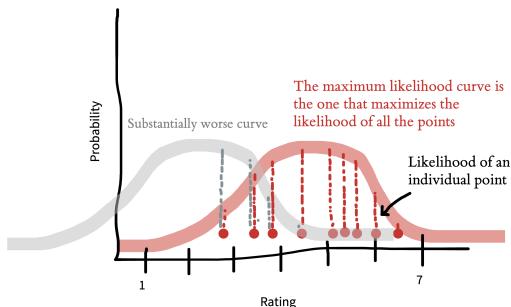


Figure 5.5

Comparison of the best-fitting normal distribution and a substantially worse curve.

2010 For example, if our sample mean is $\hat{\theta}_M = 4.5$, what underlying value

2011 of θ_M would make these data most likely to occur? Well, suppose the

2012 underlying parameter were $\theta_M = 2.5$. Then it would be pretty unlikely

2013 that our sample mean would be so much bigger. So $\hat{\theta}_M = 2.5$ is a poor

2014 estimate of the population parameter based on these data (figure 5.5).

2015 Conversely, if the parameter were $\theta_M = 6.5$, it would be a bit unlikely

2016 that our sample mean would be so much *smaller*. The value of $\hat{\theta}_M$ that

2017 makes these data most likely is just 4.5 itself: the sample mean! That

2018 is why the sample mean in this case is the maximum likelihood esti-

2019 mate.

2020 5.1.2 Bayesian estimation

2021 The maximum likelihood estimation example above describes a

2022 common approach to estimating parameters, where the researcher

2023 completely puts aside their prior expectations about what these values

2024 might be. This approach is an example of a **frequentist** statistical

2025 approach, an approach that focuses on the long-run performance of
2026 estimation procedures.

2027 Often this approach makes sense, especially when we have no prior ex-
2028 pectations about the values we are estimating. But sometimes we *do*
2029 have relevant beliefs about the value. For example, before we perform
2030 our tea experiment, we don't know exactly what θ_M will be, but it seems
2031 a bit unlikely that tea would be consistently rated as either horrible (1)
2032 or perfect (7). We have what you might call *weak prior expectations* about
2033 the kinds of ratings we'll receive.

2034 These kind of expectations are most useful when we have a very small
2035 amount of data. Remember that our goal is to estimate a population
2036 parameter using the sample data, and small data sets can be rather noisy.

2037 Taking into account our prior expectations can help to temper the in-
2038 fluence of noise. For example, if our very first participant in the ex-
2039 periment rated their tea as terrible, we wouldn't want to jump to the
2040 conclusion that the tea was actually bad. Instead, we might speculate
2041 that the participant was having a bad day or just brushed their teeth.

2042 On the other hand, if all of our participants gave bad ratings to their tea,
2043 the data would be more persuasive; in that case, we might want to tell
2044 the cafe that they are serving substandard tea. The extent to which our
2045 prior expectations should moderate our conclusions should vary with

2046 the amount of sample data; with only a little data, our prior expecta-
 2047 tions should have more influence, but as we gather more, we should
 2048 put greater weight on the data.

2049 How do we quantify this tradeoff between our prior expectations and
 2050 our current observations? We can do this via **Bayesian estimation** of
 2051 $\hat{\theta}_M$. Bayesian estimation provides a principled framework for integrating
 2052 prior beliefs and data. These estimation techniques can be very helpful
 2053 in cases where data are sparse or prior beliefs are strong.

2054 In Bayesian estimation, we observe some data d , consisting of the set
 2055 of responses in the experiment. Now we can use **Bayes' rule**, a tool
 2056 from basic probability theory, to estimate this number (figure 5.6). Each
 2057 part of this equation has a name, and it's worth becoming familiar with
 2058 them. The thing we want to compute, $p(\theta_M|data)$, is called the **poste-**
 2059 **rior probability**—it tell us what we should believe about the population
 2060 parameter on tea quality, given the data we observed.⁵

2061 The first part of the numerator is $p(data|\theta_M)$, the probability of the data
 2062 we observed given our hypothesis about the participant's ability. This
 2063 part is called the **likelihood**.⁶ This term tells us about the relationship
 2064 between our hypothesis and the data we observed—so if we think the
 2065 tea is of high quality (say $\theta_M = 6.5$) then the probability of observing a
 2066 bunch of low quality ratings will be fairly low.

$$\text{posterior} \quad \text{likelihood} \quad \text{prior}$$

$$p(\theta_M|data) = \frac{p(data|\theta_M) p(\theta_M)}{p(data)}$$

Figure 5.6
Bayes rule, annotated.

⁵ We're making the posterior purple to indicate the combination of likelihood (red) and prior (blue).

⁶ Speaking informally, “likelihood” is just a synonym for probability, but in Bayesian estimation, “likelihood” is a technical term specifically referring to probability of the data given our hypothesis. This ambiguity can get a bit confusing.

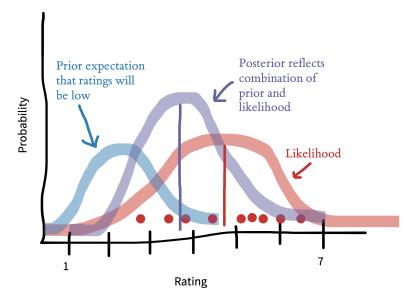


Figure 5.7
Bayesian inference about tea ratings with a strong prior on low values.

2067 The second term in the numerator, $p(\theta_M)$, is called the **prior**. This term
 2068 encodes our beliefs about the likely distribution of tea quality. Intu-
 2069 itively, if we think that the tea is likely of high quality, we should re-
 2070 quire more evidence to convince us that it's bad. In contrast, if we think
 2071 it's probably bad, a few examples of low ratings might serve to convince
 2072 us.

2073 figure 5.7 gives an example of the combination of prior and data. In
 2074 this example, we look at what difference the prior makes after observ-
 2075 ing 9 ratings. If we go in assuming that the tea is likely to be bad, the
 2076 posterior mean (purple line) will be pushed downward relative to the
 2077 maximum likelihood estimate (red line). This prior is operating only
 2078 over on ratings—estimates of tea quality. Later on when we talk about
 2079 comparing milk-first and tea-first ratings to get an estimate of the ex-
 2080 perimental effect, we could consider putting a prior on tea *discrimination*
 2081 (e.g., the experimental effect).

2082 Priors aren't usually as strong as the one shown above. Figure 5.8 shows
 2083 how the picture shifts when we have a weaker prior reflecting a flatter,
 2084 more widely spread belief about the distribution of ratings. Now the
 2085 posterior mean (purple) is closer to the maximum likelihood mean (red).
 2086 This situation is more common—the prior encodes a weak assumption
 2087 that ratings won't cluster around the ends of the scale.

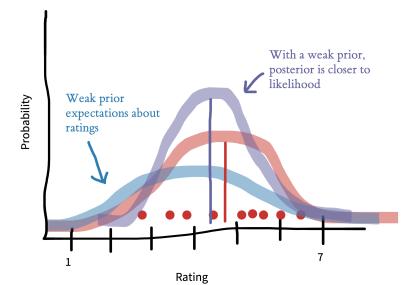


Figure 5.8
 Bayesian inference about tea ratings with a weak prior on low values.

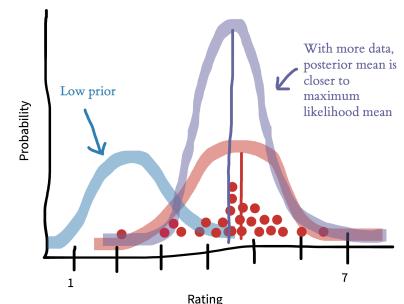


Figure 5.9
 Bayesian inference about tea ratings with a strong prior on low values and more data.

2088 The effect of the prior is also decreased when you have more data. Take
2089 a look at figure 5.9. The prior is the same as in figure 5.7, but we
2090 have more data. As a result, the posterior distribution is much more
2091 peaked and also much closer to the data—the prior makes much less
2092 difference.

2093 Bayesian estimation is most important when you have strong beliefs
2094 and not a lot of data. That can be a case where you have just a few
2095 participants in your experiment, but it's also good—and perhaps more
2096 common—to use Bayesian methods when you have a lot of data, but
2097 maybe not that much data about particular units that you care about.
2098 For example, you might have a large dataset about the effects of an ed-
2099 ucational intervention but not that much data about how it affects a
2100 particular subgroup. Bayesian estimates and maximum likelihood esti-
2101 mates will exactly coincide either under a flat prior (a prior that makes
2102 any value equally likely) or as the amount of data goes to infinity.

2103 5.2 Estimating and comparing effects

2104 We've now covered estimating a single parameter (the mean for people
2105 who had milk-first tea) using both frequentist and Bayesian methods.
2106 But recall that what we really wanted to do was to estimate the *causal*
2107 *effect* we were interested in, namely the milk-first vs. tea-first effect. In

2108 this section, we'll discuss how to estimate the effect, and then how to
 2109 use **effect size** measures to compare effects across experiments (as well
 2110 as some of the pros and cons of doing so).⁷

2111 5.2.1 Estimating the treatment effect

2112 Let's refer to the causal effect we care about as our **treatment effect**.⁸

2113 In practice, estimating β (a parameter describing the treatment effect) is
 2114 going to be a pretty straightforward extension to what we did before.

2115 In the maximum likelihood framework, we could posit that ratings in
 2116 each group (milk-first and tea-first) follow a normal distribution, but
 2117 that these normal distributions might have different means and standard
 2118 deviations. Extending the notation introduced above, let's term the pa-
 2119 rameters for the tea-first group θ_T (the mean) and σ (the standard devia-
 2120 tion). To estimate the treatment effect, we are positing a **model** in which
 2121 the milk-first ratings are normally distributed with mean $\theta_M = \theta_T + \beta$
 2122 and with standard deviation σ .⁹ This equation says that milk-first ratings
 2123 have the same distribution as tea-first ratings, except that their average
 2124 is shifted by β . Setting our model up this way then lets us compute $\hat{\beta}$,
 2125 our estimate of the treatment effect in our sample.

2126 As in the one-sample case (i.e., estimating the mean of just the milk-
 2127 first group), maximum likelihood estimation would then proceed by

⁷ This method doesn't have to be used only with a causal effect, it can be any between-group difference. In the current example, we can say with certainty that this effect is a causal because our experiment uses random assignment.

⁸ This is the effect of our manipulation—what we sometimes call an “intervention” as well. “Treatment” is a term that comes from medical statistics but is used more broadly in statistics now.

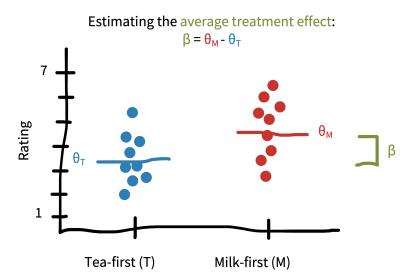


Figure 5.10
 Estimating the average treatment effect from the tea-tasting data.

⁹ For simplicity, we're assuming that the standard deviations in each tea group are equal.

²¹²⁸ finding the value of β that makes the data most likely under the assumed
²¹²⁹ model. As you'd probably expect, this estimate $\hat{\beta}$ turns out to be simply
²¹³⁰ the difference in sample means, $\hat{\theta}_M - \hat{\theta}_T$. You can see this difference
²¹³¹ pictured in figure 5.10.

²¹³² In the Bayesian framework, we would again specify a prior $p(\beta)$ that
²¹³³ encodes our prior beliefs about the size and direction of the treatment
²¹³⁴ effect. If we have no prior beliefs at all, then we could specify a flat prior,
²¹³⁵ $p(\beta) \propto 1$.¹⁰ If we believe the treatment effect is likely to favor milk-
²¹³⁶ first pouring ($\beta > 0$), we could specify the prior is a normal distribution
²¹³⁷ centered at some positive value (e.g., $\beta = 0.5$); the standard deviation of
²¹³⁸ this prior would encode how certain we are about our prior beliefs. And
²¹³⁹ if we have no prior beliefs about the direction of the treatment effect,
²¹⁴⁰ but we think it is unlikely to be very large, we could specify a normal
²¹⁴¹ prior centered at 0, which has the effect of "shrinking" the estimates
²¹⁴² closer to 0.¹¹

²¹⁴³ As in our example above, maximum likelihood estimates and Bayesian
²¹⁴⁴ estimates are going to be pretty similar if we have a lot of data or weak
²¹⁴⁵ priors. They will only diverge when we have strong priors or relatively
²¹⁴⁶ little data. The reason we are setting up these two different frameworks,
²¹⁴⁷ however, is that they provide very different inferential tools, as we'll see
²¹⁴⁸ in the next chapter.

¹⁰ This equation says that the probability of any value of β is "proportional to" 1, meaning that it's constant ("flat") regardless of what value β takes.

¹¹ The measures of variability that we discuss here account for statistical uncertainty reflecting the fact that we have only a finite sample size. If the sample size were infinite, there would be no uncertainty of this kind. Statistical uncertainty is only one kind of uncertainty, though. A more holistic view of the overall credibility of an estimate should also account for other things outside of the model, like study design issues and bias.

2149 5.2.2 *Measures of effect size*

2150 Once we have measured something, we need to make a decision about
2151 how to describe this effect to others. Sometimes we are working with
2152 fairly intuitive relationships that are easy to describe. A researcher might
2153 say, for example, that people who received milk-first tea drank the tea,
2154 on average, 5 minutes quicker than people who received tea-first tea
2155 (i.e., that $\hat{\beta} = 5$ minutes). Time is measured in units like minutes and
2156 seconds and so we all have a shared understanding of what 5 minutes
2157 means.

2158 But what about our participants' ratings of tea quality, which were pro-
2159 vided on an arbitrary 7-point rating scale that we devised? What does it
2160 mean to that participants who drank milk-first tea rated it 1 point higher
2161 than participants who drank tea-first tea (i.e., that $\hat{\beta} = 1$ point)? And
2162 how is this difference comparable to, for instance, a 1-point change on
2163 a scale that has similar anchors ("terrible" and "delicious") but uses a
2164 100-point rating system?

2165 To provide a common language for describing these relationships, some
2166 researchers use **standardized effect sizes**. A common standardized effect
2167 size is Cohen's d , which provides a standardized estimate of the differ-
2168 ence between two means. There are many different ways to calculate

²¹⁶⁹ Cohen's d (Lakens 2013), but all approaches are usually some variant of

²¹⁷⁰ the following formula:

$$d = \frac{\theta_M - \theta_T}{\sigma_{\text{pooled}}}$$

²¹⁷¹ where the difference between means (θ_T and θ_M) is divided by the

²¹⁷² pooled standard deviation σ_{pooled} . Intuitively, what you're doing is

²¹⁷³ taking the study effect (β) and dividing it—scaling it—by the variation

²¹⁷⁴ we saw between individuals in the study.

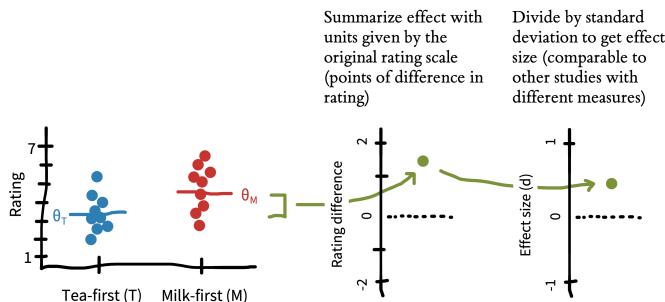


Figure 5.11
Schematic effect size computation.

²¹⁷⁵ Let's compute this measure for our tea-drinking study. We can just

²¹⁷⁶ plug in the estimates we see in figure 5.10 and compute the standard

²¹⁷⁷ deviation of our observed data:

$$\hat{d} = \frac{\hat{\theta}_M - \hat{\theta}_T}{\hat{\sigma}_{\text{pooled}}} = \frac{4.5 - 3.5}{1.25} = \frac{1}{1.25} = 0.80$$

²¹⁷⁸ In other words, the effect size of the difference between the two con-

²¹⁷⁹ ditions is .8 standard deviations. This process is shown graphically in

2180 figure 5.11.¹²

2181 We previously said that people who drank milk-first tea had quality
2182 ratings that were, on average, 1 point higher on a 7-point scale ($\beta = 1$
2183 point). Cohen's d translates the arbitrary units of our rating scale into
2184 a **unit-less** effect size that is measured in terms of the variation in the
2185 data. You may find yourself wondering: "why would I ever describe
2186 things in terms of standard deviations?" The key benefit is that it allows
2187 us to compare the size of the effect between studies that use different
2188 measures.

2189 Let's say that we ran a replication of our tea study with two changes:
2190 (1) we studied patrons in a US cafe instead of a UK cafe, and (2) we
2191 used a 100-point quality rating scale instead of a 7-point scale. Imagine
2192 that, just as we found that participants in the UK rated the milk-first
2193 tea 1-point higher on a 7-point quality scale, US participants rated the
2194 milk-first tea 1-point higher on a *100-point* quality scale. It seems clear
2195 that these effects are different because of the difference in scale. But
2196 how different?

2197 It might at first seem reasonable just to normalize by the length of the
2198 scale. So maybe the UK experimental participants showed a 1/7 rating
2199 effect and the US participants showed a 1/100 rating effect. The trouble

¹² Cohen's d , also referred to as a **standardized mean difference** (SMD), can be tricky to apply to more complex experimental designs, such as when you have within-participant designs and multiple measurements of each participant. For some guidance on this topic, see Lakens (2013).

2200 with this move is that it presupposes that participants from two differ-
2201 ent populations are using two different scales in exactly the same way!
2202 For example, maybe US participants made very clumpy judgments that
2203 were mostly centered around 50 (perhaps because of a lack of milk tea
2204 experience). Standardized effect sizes get around this kind of issue by
2205 scaling according to the variability of the data.

2206 Let's compute the effect size for the cross-cultural replication. We'll
2207 imagine that participants who drank milk-first tea gave an average rat-
2208 ing of 50/100 and participants who drank tea-first tea rated it 49 on
2209 average. But if their variability was also relatively lower, perhaps the
2210 standard deviation of their ratings was only 5. Using the formula above,
2211 we find

$$\hat{d}_{US} = \frac{\hat{\theta}_M - \hat{\theta}_T}{\hat{\sigma}_{\text{pooled}}} = \frac{50 - 49}{5} = \frac{1}{5} = 0.2$$

2212 A Cohen's d of .2 means that US cafe patrons rated their tea .2 stan-
2213 dard deviations higher when it was milk-first, much smaller than the .8
2214 standard deviation difference in the UK patrons.

2215 There are no hard and fast rules for interpreting what makes a big ef-
2216 fect or a small effect, but people often refer back to a standard suggested
2217 by Cohen (1992). On those standards, $d = 0.8$ is a "large effect", and

2218 $d = 0.2$ is a “small effect.” But these effect size interpretation norms are
2219 somewhat arbitrary. The key point here was that US and UK patrons
2220 had the same raw score change in quality ratings ($\hat{\beta} = 1$) and standard-
2221 izing the differences allowed us to communicate that the difference was
2222 larger among the UK patrons.

2223 Cohen’s d is one of many standardized effect sizes that researchers can
2224 use. Just as Cohen’s d standardizes differences in group means, there
2225 are also generalizations that allow for continuous treatment variables or
2226 covariate adjustment (e.g., Pearson’s r , as we discuss below; r^2 ; or η^2).
2227 And there is a whole other set of effect-size measures for relationships
2228 between binary variables (e.g., odds ratio). We’ll be using effect sizes
2229 throughout the book, but we’ll be using Cohen’s d as our example.¹³

2230 5.2.3 Pros and cons of standardizing effect sizes

2231 Standardizing effect size helps communicate that a 1-point change on
2232 a 7-point scale is not the same as a 1-point change on a 100-point scale.
2233 But is it any better to say that the first change represents a 0.80 stan-
2234 dard deviation difference and the second a 0.08 standard deviation dif-
2235 ference?

2236 Effect sizes allow us to compare results across studies more easily. Across
2237 studies, researchers use different measures, different study designs, and

¹³ If you’d like to learn more about other varieties of effect size, take a look at Fritz, Morris, and Richler (2012) and Lakens (2013).

2238 different populations. Standardization gives us a “common language”
2239 to describe estimated relationships in these varied contexts. This lan-
2240 guage is helpful when we want to aggregate and compare effects across
2241 studies via meta-analysis. And it is also helpful when planning new stud-
2242 ies. When trying to figure out how many participants to run in a study,
2243 almost all techniques for sample size planning use standardized effect
2244 sizes to determine how much data would be needed to reliably detect
2245 an effect.

2246 Standardizing effect sizes has limitations, though. For example, if two
2247 interventions produce the same absolute change in the same outcome
2248 measure, but are studied in different populations in which the variabil-
2249 ity on the outcome differs substantially, the interventions would pro-
2250 duce different standardized mean differences (Baguley 2009) (see the
2251 Depth box “Reliability paradoxes!” in chapter 8).

2252 Imagine we conducted our tea experiment again, but this time with
2253 (decaf) tea, and focusing on children. Maybe milk-first tea tastes the
2254 same amount better than tea-first tea for kids and for adults. But kids
2255 are, as a rule, more variable in their responding than adults. This higher
2256 level of variability would lead us to observe a smaller effect size in kids
2257 vs. adults. Recall that our UK adult SD was 1.25, and our effect size
2258 was $d = .8$. Imagine that children’s SD is 2.5. In this scenario, even if

2259 tea led to the same 1-point absolute change in ratings among adults and

2260 children, the standardized effect size for kids would look half as big:

$$\hat{d}_{kids} = \frac{\hat{\theta}_M - \hat{\theta}_T}{\hat{\sigma}_{pooled}} = \frac{5 - 4}{2.5} = \frac{1}{2.5} = .4$$

2261 This example highlights some of the challenges with standardization. If

2262 we focused on the fact that both adults and children show a 1-point

2263 change in ratings levels ($\hat{\beta} = 1$), we would conclude that milk-first

2264 tea ordering is as much better for adults as kids. If we focused on the

2265 standardized effect sizes, however, we would conclude that the milk

2266 ordering effect is twice as big for adults.

2267 So which is better: describing raw measures or standardized effect sizes?

2268 In general our response is “Why not both?” But if you wanted to pick

2269 one or the other, we recommend considering what type of measure-

2270 ment you are using. With measures that yield common measurement

2271 units that are likely to be reported in many studies already, use raw scores

2272 (Baguley 2009). For example, if your study uses physical units such as

2273 milliseconds (e.g., for reaction times) or counts (e.g., for a study track-

2274 ing an outcome like number of words), these measurements can be quite

2275 useful to compare across studies. Reporting raw measurements also can

2276 allow you to check whether your measurements make sense—for exam-

2277 ple, a reaction time of 70 milliseconds is inhumanly fast, while a reaction
 2278 time of 10 seconds might be extremely slow (at least, for many speeded
 2279 tasks).

2280 In contrast, we recommend using standardized effect sizes for cases
 2281 where the measurement is relatively unlikely to be comparable with
 2282 other studies in its original form, or unlikely to be meaningful on its
 2283 own. For example, reporting the effect of an intervention on raw math
 2284 test scores is only meaningful if the reader knows how many items are
 2285 on the test, how difficult it is, and so forth. In such a case where there
 2286 it is hard for a reader to be “calibrated” to the specific measurement
 2287 units you are using, standardized effect sizes may be the best way to
 2288 report your finding (Kelley and Preacher 2012).

2289 5.3 Estimating the relationship between variables

2290 Our focus up until now has been in estimating individual effects, but
 2291 sometimes we also want to estimate the relationship between two dif-
 2292 ferent variables. Extending our example, figure 5.12 shows the relation-
 2293 ship between the age of the tea taster and their rating of milk-first tea.
 2294 It seems that younger people overall like tea less than older people.¹⁴
 2295 How could we quantify this result?

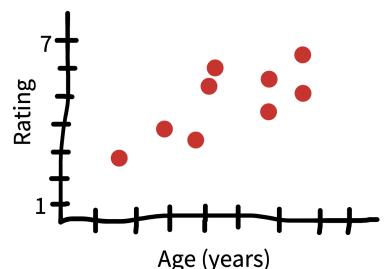


Figure 5.12
 The relationship between age and milk-first tea rating.

¹⁴ Remember, this is a correlational relationship, and there’s no causal inference possible here.

2296 The first concept we need is **covariance**. Covariance captures the de-
 2297 gree to which we expect two variables to deviate from their means in
 2298 the same direction. We're looking at milk-first tea ratings M and partic-
 2299 ipant ages A . We can write the covariance between these two variables
 2300 as

$$\text{Cov}(M, A) = E[(M - \theta_M)(A - \theta_A)]$$

2301 This formula expresses the expected product of how much each ob-
 2302 servation differs from its expectation (mean) along each variable. Fig-
 2303 ure 5.13 shows these differences, which are multiplied together for each
 2304 point to get the covariation.¹⁵

2305 This covariance number gives us an estimate of how much age and rat-
 2306 ings covary, but its units are a bit funny: it's hard to know what to make
 2307 of an expected deviation of 1 point-year. We can do a simple trick to
 2308 standardize its units and make it into a wonderful form of effect size
 2309 called the **correlation coefficient** (denoted r). Remember that to create
 2310 effect sizes above, we divided by the standard deviation of the variable.
 2311 Here all we have to do is divide by the standard deviation of both vari-
 2312 ables.

¹⁵ This looks a little tricky, but it's actually very related to the basic concepts we've already seen. Remember when we introduced the standard deviation, we described it as the expected distance between new samples from a distribution and the mean of that distribution. The covariance is very related: the standard deviation is just $\sqrt{\text{Cov}(X, X)}$, in other words, the square root of the covariance of a variable with itself.

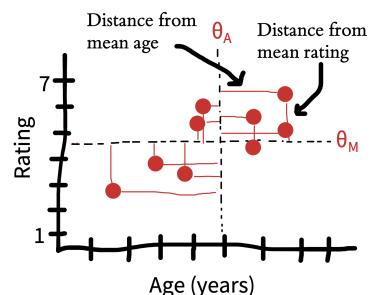


Figure 5.13
 Estimating the covariation between age and milk-first tea rating.

$$r_{M,A} = \frac{Cov(M, A)}{\sigma_M \sigma_A}$$

₂₃₁₃ In other words, the correlation between two variables is the standard-
₂₃₁₄ ized covariation.

₂₃₁₅ The correlation coefficient is the most ubiquitous measure of associa-
₂₃₁₆ tion between variables. It ranges between -1, where two variables co-
₂₃₁₇ vary in exactly the opposite direction, to 1, when two variables covary
₂₃₁₈ perfectly. A correlation means that there is no association between two
₂₃₁₉ variables. A correlation of -1 or 1 doesn't mean that these two vari-
₂₃₂₀ ables have the same scale, however: it just means that they "move to-
₂₃₂₁ gether."

₂₃₂₂ Critically, a correlation is an effect size. Correlations can be compared
₂₃₂₃ across different measures and different studies (including both experi-
₂₃₂₄ mental and observational studies), making it a very valuable scale-free
₂₃₂₅ comparison tool.

This section has described one way of looking at a correlation coefficient: as standardized covariation. For a great discussion of all the different ways of thinking about correlations, see Lee Rodgers and Nicewander (1988).

₂₃₂₆ 5.4 Chapter summary: Estimation

₂₃₂₇ In this chapter, we introduced the idea of estimating both individual
₂₃₂₈ measurements and treatment effects from observed data. These ideas are
₂₃₂₉ simple but they lay the foundations for hypothesis testing and modeling

²³³⁰ (our next two chapters). Further, we set up the distinction between
²³³¹ Bayesian and frequentist approaches, which we will expand in the next
²³³² chapter since these traditions provide different inferential tools.



DISCUSSION QUESTIONS

1. In this chapter you learned about estimation, and in this book more generally, we have argued that the goal of an experiment is to provide a maximally precise estimate of a causal effect. Psychology as a field has often been criticized for focusing too much on inference and too little on estimation. Find an article in the journal *Psychological Science* that reports on an experiment or series of experiments and read the abstract. Does it mention an estimate of any particular quantity? What might be the benefits of reporting estimates in the study abstract?
2. Try the same exercise with a paper in the *New England Journal of Medicine* or *Journal of the American Medical Association*. Find a paper and check if there is a mention of any specific quantity being estimated. (We suspect there will be!) Consider this contrast between the medical article and the psychology article. What do you make of this difference between fields?

²³³³



READINGS

- A great narrative introduction to the history and practice of statistics:
Salsburg, D. (2001). *The lady tasting tea: How statistics revolutionized science in the twentieth century*. Macmillan.

²³³⁴

- An open source statistics textbook that follows a similar approach as Chapters 5–7: Poldrack, R. (2022). *Statistical thinking for the 21st century*. Available free online at <https://statsthinking21.org>.

2335

2336 References

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²³³⁹ 6 INFERENCE



LEARNING GOALS

- Discuss the purpose of statistical inference
- Define p -values and Bayes Factors
- Consider common fallacies about inference (especially for p -values)
- Reason about sampling variability
- Define and reason about confidence intervals

²³⁴⁰

²³⁴¹ We've been arguing that experiments are about measuring effects. The
²³⁴² effects we are interested in are causal effects for a group of people, but
²³⁴³ that group is almost always bigger than the participants in an experi-
²³⁴⁴ ment. **Statistical inference** is the process of going beyond the specific
²³⁴⁵ characteristics of the sample that you measured to make generalizations
²³⁴⁶ about the broader population.

²³⁴⁷ chapter 5 already showed us how to make one simple inference: esti-
²³⁴⁸ mating population parameters using both frequentist and Bayesian tech-

2349 niques. Estimating population parameters is an important first step. But
2350 often we want to make more sophisticated inferences so that we can an-
2351 swer questions such as:

- 2352 1. How likely is it that this pattern of measurements was produced
2353 by chance variation?
- 2354 2. Do these data provide more support for one hypothesis or an-
2355 other?
- 2356 3. How precise is our estimate of an effect?
- 2357 4. What portion of the variation in the data is due to a particular ma-
2358 nipulation (as opposed to variation between participants, stimulus
2359 items, or other manipulations)?

2360 Question (1) is associated with one particular type of statistical infer-
2361 ence method—**null hypothesis significance testing** (NHST) in the fre-
2362 quentist statistical tradition. NHST has become synonymous with data
2363 analysis, such that in the vast majority of research papers (and research
2364 methods courses), all of the reported analyses are tests of this type. Yet
2365 this equivalence is quite problematic.

2366 The move to “go test for significance” before visualizing your data and
2367 trying to understand sources of variation (participants, items, manipula-
2368 tions, etc.) is one of the most unhelpful strategies for an experimenter.

2369 Whether $p < .05$ or not, a test of this sort gives you literally *one bit* of in-
 2370 formation about your data.¹ Considering effect sizes and their variation
 2371 more holistically, including using the kinds of visualizations we advo-
 2372 cate in chapter 15, gives you a much richer sense of what happened in
 2373 your experiment!

2374 In this chapter, we will describe NHST, the conventional method that
 2375 many students still learn (and many scientists still use) as their primary
 2376 method for engaging with data. All practicing experimentalists need
 2377 to understand NHST, both to read the literature and also to apply this
 2378 method in appropriate situations. For example, NHST may be a rea-
 2379 sonable tool for testing whether an intervention leads to a difference
 2380 between a treatment condition and an appropriate control. But we will
 2381 also try to contextualize NHST as a very special case of a broader set of
 2382 statistical inference strategies. Further, we will continue to flesh out our
 2383 account of how some of the pathologies of NHST have been a driver
 2384 of the replication crisis.

2385 If NHST approaches have so many issues, what should replace them?
 2386 figure 6.1 shows one way of organizing different inferential approaches.
 2387 There has been a recent move towards the use of Bayes Factors to quan-
 2388 tify the evidence in support of different candidate hypotheses. Bayes
 2389 Factors can help answer questions like (2). We introduce these tools, and

¹ In the information theoretic sense, as well as the common sense!

	Frequentist	Bayesian
Measurement focused	estimate with confidence interval	posterior distribution with credible interval
Hypothesis focused	p value from null hypothesis significance test	Bayes factor

Figure 6.1

Clarifying the distinctions between Bayesian and Frequentist paradigms and the tools they offer for measurement and hypothesis testing. For many settings, we think the measurement mindset is more useful. Adapted from Kruschke and Liddell (2018).

2390 believe that they have broader applicability than the NHST framework
2391 and should be known by students. On the other hand, Bayes Factors are
2392 not a panacea. They have many of the same problems as NHST when
2393 they are applied dichotomously.

2394 Instead of dichotomous frequentist or Bayesian hypothesis testing, we
2395 follow our thematic emphasis on MEASUREMENT PRECISION and advocate
2396 for a **measurement** strategy, which is more suited towards questions (3)
2397 and (4) (Cumming 2014; Kruschke and Liddell 2018). The goal of these
2398 strategies is to yield an accurate and precise estimate of the relationships
2399 underlying observed variation in the data.

2400 This isn't a statistics book and we won't attempt to teach the full array
2401 of important statistical concepts that will allow students to build good
2402 models of a broad array of datasets. (Sorry!).² But we do want you to
2403 be able to reason about inference and modeling. In this chapter, we'll
2404 start by making some inferences about our tea-tasting example from the
2405 last chapter, using this example to build up intuitions about hypothesis
2406 testing and inference. Then in chapter 7, we'll start to look at more
2407 sophisticated models and how they can be fit to real datasets.

² If you're interested in going deeper, here are two books that have been really influential for us. The first is Gelman and Hill (2006) and its successor Gelman, Hill, and Vehtari (2020), which teach regression and multi-level modeling from the perspective of data description. The second is McElreath (2018), a course on building Bayesian models of the causal structure of your data. Honestly, neither is an easy book to sit down and read (unless you are the kind of person who reads statistics books on the subway for fun) but both really reward detailed study. We encourage you to get together a reading group and go through the exercises in one of these together. It'll be well worth while in its impact on your statistical and scientific thinking.

2408 6.1 Sampling variation

2409 In chapter 5, we introduced Fisher's tea-tasting experiment and dis-
 2410 cussed how to estimate means and differences in means from our ob-
 2411 served data. These so-called "point estimates" represent our best guesses
 2412 about the population parameters given the data—and possibly also given
 2413 our prior beliefs. We can also report how much statistical uncertainty
 2414 is involved in these point estimates.³ Quantifying and reasoning about
 2415 this uncertainty is an important goal: in our original study we only had
 2416 9 participants in each group, which will only provide a low precision
 2417 (i.e., highly uncertain) estimate of the population. By contrast, if we
 2418 repeated the experiment with 200 participants in each group, the data
 2419 would be far less noisy, and we would have much less uncertainty, even
 2420 if the point estimates happened to be identical.

2421 6.1.1 Standard errors

2422 To characterize the uncertainty in an estimate, it helps to picture its
 2423 **sampling distribution**, which is the distribution of the estimate across
 2424 different, hypothetical samples. That is, let's imagine that we conducted
 2425 the tea experiment not just once, but dozens, hundreds, or even thou-
 2426 sands of times. This idea is often called **repeated sampling** as a shorthand.
 2427 For each hypothetical sample, we use similar recruitment methods to

³ As in the previous chapter, we're only capturing *statistical* uncertainty. A holistic view of a particular estimate's credibility also include everything else you know about the study design.

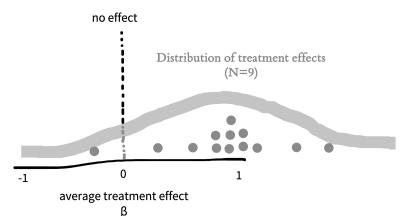


Figure 6.2
 Sampling distribution for the treatment effect in the tea-tasting experiment, given many different repetitions of the same experiment, each with $N=9$ per group. Circles represent average treatment effects from different individual experiments, while the thick line represents the form of the underlying distribution.

2428 recruit a new sample of participants, and we compute $\hat{\beta}$ for that sam-
2429 ple. Would we get exactly the same answer each time? No, simply
2430 because the samples will have some random variability (noise). If we
2431 plotted these estimates, $\hat{\beta}$, we would get the sampling distribution in
2432 figure 6.2.

CODE

In this chapter and the subsequent statistics and visualization chapters of the book, we'll try to facilitate understanding and illustrate how to use these concepts in practice by giving the R code we use in constructing our examples in these code boxes. We'll assume that you have some knowledge of base R and the Tidyverse—to get started with these, go ahead and take a look at appendix D if you haven't already. Although our figures are often drawn by hand, even the hand-drawn ones are based on actual simulation results!

Since we're going to be working with lots of data from the tea tasting example, we wrote a function called `make_tea_data()` that creates a `tibble` with some (made up) data from our modern tea-tasting experiment. You can find the function on GitHub (https://github.com/langcog/experimentology/blob/main/helper/tea_helper.qmd) if you want to follow along.

```
tea_data <- make_tea_data(n_total = 18)
```

Now imagine we also did thousands of repetitions of the experiment with $n = 200$ per group instead of $n = 9$ per group. Figure 6.3 shows what the sampling distribution might look like in that case. Notice how much narrower the sampling distribution becomes when we increase the sample size, showing our decreased uncertainty. More formally, the standard deviation of the sampling distribution itself, called the **standard error**, decreases as the sample size increases.

The sampling distribution is not the same thing as the distribution of tea ratings in a single sample. Instead, it's a distribution of *estimates across samples of a given size*. In essence, it tells us what the mean of a new experiment might be, if we ran it with a particular sample size.

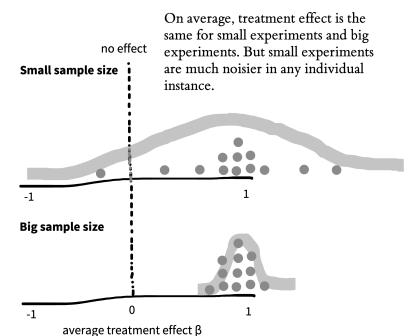


Figure 6.3
Comparing sampling distributions for the treatment effect with smaller and larger size samples.

CODE

To do simulations where we repeat the tea-tasting experiment over and over again, we're using a special tidyverse function from the `purrr` library:

`map()`. `map()` is an extremely powerful function that allows us to run another function (in this case, the `make_tea_data()` function that we introduced last chapter) many times with different inputs. Here we create a tibble made up of a set of 1000 runs of the `make_tea_data()` function.

```
samps <- tibble(sim = 1:1000) |>
  mutate(data = map(sim, \((i) make_tea_data(n_total = 18)))) |>
  unnest(cols = data)
```

Next, we just use the `group_by()` and `summarise()` workflow from appendix D to get the estimated treatment effect for each of these simulations.

```
tea_summary <- samps |>  
  group_by(sim, condition) |>  
  summarise(mean_rating = mean(rating)) |>  
  group_by(sim) |>  
  summarise(delta = mean_rating[condition == "milk first"] -  
            mean_rating[condition == "tea first"])
```

This tibble gives us what we would need to plot the sampling distributions above in figure 6.2 and figure 6.3.

2446

2447 6.1.2 *The central limit theorem*

2448 We talked in the last chapter about the normal distribution, a conve-
2449 nient and ubiquitous tool for quantifying the distribution of measure-
2450 ments. A shocking thing about sampling distributions for many kinds
2451 of estimates—and for *all* maximum likelihood estimates—is that they
2452 become normally distributed as the sample size gets larger and larger.
2453 This result holds even for estimates that are not even remotely normally
2454 distributed in small samples!

2455 For example, say we are flipping a coin and we want to estimate the
 2456 probability that it lands heads (p_H). If we draw samples each consisting
 2457 of only $n = 2$ coin flips, figure 6.4 is the sampling distribution of the
 2458 estimates (\hat{p}_H). This sampling distribution doesn't look normally dis-
 2459 tributed at all—it doesn't have the characteristic "bell curve" shape! In
 2460 a sample of only two coin flips, \hat{p}_H can only take on the values 0, 0.5, or
 2461 1.

2462 But look what happens as we draw increasingly larger samples in fig-
 2463 ure 6.5: We get a normal distribution! This tendency of sampling distri-
 2464 butions to become normal as n becomes very large reflects a deep and
 2465 elegant mathematical law called the **Central Limit Theorem**.

2466 The practical upshot is that the Central Limit Theorem directly helps
 2467 us characterize the uncertainty of sample estimates. For example,
 2468 when the sample size is reasonably large (approximately $n > 30$ in the
 2469 case of sample means) the standard error (i.e., the standard deviation
 2470 of the sampling distribution) of a sample mean is approximately
 2471 $\widehat{SE} = \sigma/\sqrt{n}$. The sampling distribution becomes narrower as the
 2472 sample size increases because we are dividing by the square root of the
 2473 number of observations.

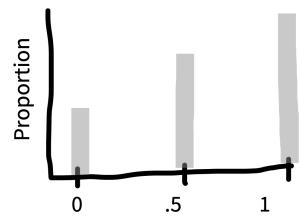


Figure 6.4
Sampling distribution of samples from a biased coin ($N=2$ flips per sample). Bar height is the proportion of flips resulting in a particular mean.

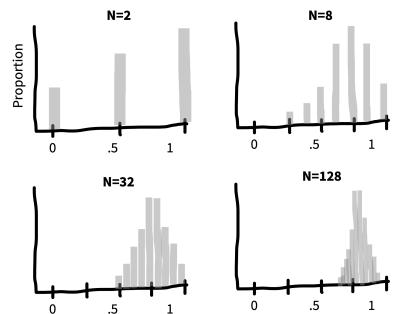


Figure 6.5
Sampling distribution for 2, 8, 32, and 128 flips.

 CODE

Even though our figures are hand-drawn, they're based on real simulations. For our central limit theorem simulations, we again use the `map()` function. We set up a tibble with the different values we want to try (which we call `n_flips`). Then we make use of the `map()` function to run `rbinom()` (random binomial samples) for each value of `n_flips`.

One trick we make use of here is that `rbinom()` takes an extra argument that says how many of these random values you want to generate. Here we generate `nsamps = 1000` samples, giving us 1000 independent replicates at each `n`. But returning an array of 1000 values for a single value of `n_flips` results in something odd: the value for each element of `flips` is an array. To deal with that, we use the `unnest()` function, which expands the array back into a normal tibble.

```
n_samps <- 1000

n_flips_list <- c(2, 8, 32, 128)

sample_p <- tibble(n_flips = n_flips_list) |>
  mutate(flips = map(n_flips, \f) rbinom(n = n_samps, size = f, prob = .7))) |>
  unnest(cols = flips) |>
  mutate(p = flips / n_flips)
```

2475 6.2 From variation to inference

2476 Let's go back to Fisher's tea-tasting experiment. The first innovation
2477 of that experiment was the use of randomization to recover an estimate
2478 of the causal effect of milk ordering. But there was more to Fisher's
2479 analysis than we described.

2480 The second innovation of the tea-tasting experiment was the idea of
2481 creating a model of what might happen during the experiment. Specific-
2482 ically, Fisher described a hypothetical **null model** that would arise if the
2483 lady had chosen cups by chance rather than because of some tea sen-
2484 sitivity. In our tea-rating experiment, the null model describes what
2485 happens when there is no difference in ratings between tea-first and
2486 milk-first cups. Under the null model, the true treatment effect (β) is
2487 zero.

2488 Even with an actual treatment effect of zero, across repeated sampling,
2489 we should see some variation in $\hat{\beta}$, our *estimate* of the treatment effect.
2490 Sometimes we'll get a small positive effect, sometimes a small negative
2491 one. Occasionally just by chance we'll get a big effect. This is just sam-
2492 pling variation as we described above.

2493 Fisher's innovation was to quantify the probability of observing vari-
2494 ous values of $\hat{\beta}$, given the null model. Then, if the observed data that

2495 were very low probability under the null model, we could declare that
2496 the null was rejected. How unlikely must the observed data be, in or-
2497 der to reject the null? Fisher declared that it is “usual and convenient
2498 for experimenters to take 5 percent as a standard level of convenience,”
2499 establishing the .05 cutoff that has become gospel throughout the sci-
2500 ences.⁴

2501 Let’s take a look at what the null model might look like. We already
2502 tried out repeating our tea-tasting experiment thousands of times in our
2503 discussion of sampling above. Now in figure 6.6, we do the same thing
2504 but we assume that the **null hypothesis** of no treatment effect is true.
2505 The plot shows the distribution of treatment effects $\hat{\beta}$ we observe: some
2506 a little negative, some a little positive, and a few substantially positive
2507 or negative, but mostly zero.

2508 Let’s apply the $p < .05$ standard. If our observation has less than a 5%
2509 probability under the null model, then the null model is likely wrong.
2510 The red dashed lines on figure 6.6 show the point below which only
2511 2.5% of the data are found and the point above which only 2.5% of the
2512 data are found. These are called the **tails** of the distribution. Because
2513 we’d be equally willing to accept milk-first tea or tea-first tea being bet-
2514 ter, we consider both positive and negative observations as possible.⁵

⁴ Actually, right after establishing .05 as a cutoff, Fisher then writes that “in the statistical sense, we thereby admit that no isolated experiment, however significant in itself, can suffice for the experimental demonstration of any natural phenomenon... in order to assert that a natural phenomenon is experimentally demonstrable we need, not an isolated record, but a reliable method of procedure. In relation to the test of significance, we may say that a phenomenon is experimentally demonstrable when we know how to conduct an experiment which will rarely fail to give us a statistically significant result.” In other words, Fisher was all for replication!

⁵ Because we’re looking at both tails of the distribution, this is called a “two-tailed” test.

CODE

To simulate our null model, we can do the same kind of thing we did before, just specifying to our `make_tea_data()` function that the true difference in effects is zero!

```
n_sims <- 1000

null_model <- tibble(sim = 1:n_sims, n = 18) |>

  mutate(data = map(sim, \(i) make_tea_data(n_total = n, delta = 0))) |>

  unnest(cols = data)
```

Again we use `group_by()` and `summarise()` to get the distribution of treatment effects under the null hypothesis.

```
null_model_summary <- null_model |>

  group_by(sim, condition) |>

  summarise(mean_rating = mean(rating)) |>

  group_by(sim) |>

  summarise(delta = mean_rating[condition == "milk first"] - 

    mean_rating[condition == "tea first"])
```

2515

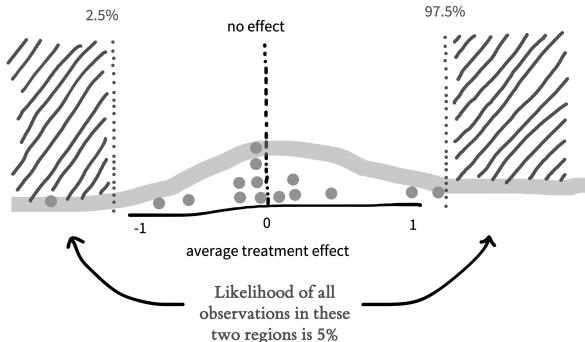


Figure 6.6

One example of the distribution of treatment effects under the null model (with N=9 per group). The red regions indicate the part of the distribution in which less than 5% of observations should fall.

2516 figure 6.6 captures the logic of NHST: if the observed data fall in the
2517 region that has a probability of less than .05 under the null model, then
2518 we reject the null. So then when we observe some particular treatment
2519 effect $\hat{\beta}$ in a single (real) instance of our experiment, we can compute
2520 the probability of these data or any data more extreme than ours under
2521 the null model.⁶ This probability is our p -value, and if it is small, it
2522 gives us license to conclude that the null is false.

2523 As we saw before, the larger the sample size, the smaller the standard
2524 error. That's true for the null model too! figure 6.7 shows the expected
2525 null distribution for a bigger experiment.

⁶ The “more extreme” part deserves a little explanation. Any individual outcome is relatively unlikely by itself, just because it’s surprising that the estimate is that exact value (we’re simplifying here, it gets a bit trickier when you are talking about real numbers). What we care about instead is a *group* of values. The ones that are in the middle of the distribution are, considered as a group, quite likely; the ones on the tails are, as a group, less likely. We want to know if the probability of the group of datapoints that includes our observation and anything even further out on the tails is collectively less than .05.

2526 The more participants in the experiment, the tighter the null distribu-
2527 tion becomes, and hence the smaller the region in which we should
2528 expect a null treatment effect to fall. Because our expectation based on
2529 the null becomes more precise, we will be able to reject the null based
2530 on smaller treatment effects. In this type of hypothesis testing, as with
2531 estimation, our goals matter. If we're merely testing a hypothesis out of
2532 curiosity, perhaps we don't want to measure too many cups of tea. But
2533 if we were designing the tea strategy for a major cafe chain, the stakes
2534 would be higher; in that case, maybe we'd want to do a more extensive
2535 experiment!

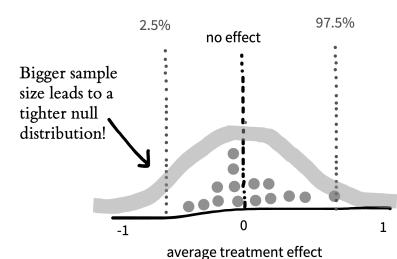


Figure 6.7
Example distribution of treatment effects under the null model for a larger experiment.

CODE

We can do a more systematic simulation of the null regions for different sample sizes by simply adding a parameter to our simulation.

```
n_sims <- 10000

null_model_multi_n <- expand_grid(sim = 1:n_sims, n = c(12, 24, 48, 96)) |>
  mutate(sim_data = map(n, \(n_i) make_tea_data(n_total = n_i, delta = 0))) |>
  unnest(cols = sim_data)

null_model_summary_multi_n <- null_model_multi_n |>
  group_by(n, sim, condition) |>
  summarise(mean_rating = mean(rating)) |>
  group_by(n, sim) |>
  summarise(delta = mean_rating[condition == "milk first"] -
    mean_rating[condition == "tea first"])

null_model_quantiles_multi_n <- null_model_summary_multi_n |>
  group_by(n) |>
  summarise(q_025 = quantile(delta, .025),
    q_975 = quantile(delta, .975))
```

Here is the plotting code to produce a comparable figure to our illustration:

```
ggplot(null_model_summary_multi_n, aes(x = delta)) +  
  facet_wrap(vars(n), nrow = 1, labeller = label_both) +  
  geom_histogram(binwidth = .25) +  
  geom_vline(xintercept = 0, color = pal$grey, linetype = "dotted") +  
  geom_vline(data = null_model_quantiles_multi_n,  
             aes(xintercept = q_025), color = pal$red, linetype = "dotted") +  
  geom_vline(data = null_model_quantiles_multi_n,  
             aes(xintercept = q_975), color = pal$red, linetype = "dotted") +  
  xlim(-2.5, 2.5) +  
  labs(x = "Difference in rating", y = "Frequency")
```

2538

2539 One last note: You might notice an interesting parallel between the
2540 NHST paradigm and Popper's falsificationist philosophy (introduced in
2541 chapter 2). In both cases, you never get to *accept* the actual hypothesis
2542 of interest. The only thing you can do is observe evidence that is incon-
2543 sistent with the null hypothesis. The added limitation of NHST is that
2544 the only hypothesis you can falsify is the null!¹⁷

1989

2545 6.3 Making inferences

2546 In the tea-tasting example we were just considering, we were trying
2547 to make an inference from our sample to the broader population. In
2548 particular, we were trying to test whether milk-first tea was rated as

2549 better than tea-first tea. Our inferential goal was a clear, binary answer:

2550 is milk-first tea better?

2551 By defining a p -value, we got one procedure for giving this answer. If

2552 $p < .05$, we reject the null. Then we can look at the direction of the

2553 difference and, if it's positive, declare that milk-first tea is "significantly"

2554 better. Let's compare this procedure to a different process that builds on

2555 the Bayesian estimation ideas we described in the previous chapter. We

2556 can then come back to examine NHST in light of that framework.

2557 6.3.1 Bayes Factors

2558 Bayes Factors are a method for quantifying the support for one hypoth-

2559 esis over another, based on an observed dataset. They don't tell you the

2560 probability that a particular hypothesis is right, but they let you com-

2561 pare two different ones.

2562 Informally, we've now discussed two different distinct hypotheses

2563 about the tea situation: our participants could have *no* tea discrim-

2564 ination ability—leading to chance performance. We call this H_0 .

2565 Or they could have some non-zero ability—leading to greater than

2566 chance performance. We call this H_1 . The Bayes Factor is simply the

2567 likelihood of the data (in the technical sense used above) under H_1

2568 vs. under H_0 (figure 6.8). The Bayes Factor is a ratio, so if it is greater

$$BF = \frac{p(\text{data}|H_1)}{p(\text{data}|H_0)}$$

↓ ↓

Likelihood of data under hypothesis of non-zero difference in ability Likelihood of data under null hypothesis of zero difference

Figure 6.8
The Bayes Factor (BF).

2569 than 1, the data are more likely under H_1 than they are under H_0 —and
 2570 vice versa for values between 1 and 0. A BF of 3 means there is three
 2571 times as much evidence for H_1 than H_0 , or equivalently 1/3 as much
 2572 evidence for H_0 as H_1 .⁸

CODE

Bayes Factors are delightfully easy to compute using the BayesFactor R package. All we do is feed in the two sets of ratings to the `ttestBF()` function!

```
library(BayesFactor)

tea_bf <- ttestBF(x = filter(tea_data, condition == "milk first")$rating,
                    y = filter(tea_data, condition == "tea first")$rating,
                    paired = FALSE)
```

2573 There are a couple of things to notice about the Bayes Factor. The first
 2574 is that, like a p -value, it is inherently a continuous measure. You can
 2575 artificially dichotomize decisions based on the Bayes Factor by declaring
 2576 a cutoff (say, $\text{BF} > 3$ or $\text{BF} > 10$), but there is no intrinsic threshold at
 2577 which you would say the evidence is “significant.” Some guidelines for
 2578 interpretation (from S. N. Goodman 1999) are shown in table 6.1.⁹ On
 2579 the other hand, cutoffs like $\text{BF} > 5$ or $p < .05$ are not very informative.
 2580 So although we provide this table to guide interpretation, we caution

⁸ Sometimes people refer to the BF in favor of H_1 as the BF_{10} and the BF in favor of H_0 as the BF_{01} . This notation is a bit confusing because the first of these looks like the number 10.

⁹ Some like the guidelines provided by Jeffreys (1961), which include categories such as “barely worth mentioning” ($1 > \text{BF} > 3$).

2582 that you should always report and interpret the actual Bayes Factor, not
 2583 whether it is above or below some cutoff.

Table 6.1
 S. N. Goodman (1999) interpretation guidelines for Bayes Factors.

BF range	Interpretation
< 1	Negative (supports H_0)
1–5	Weak
5–10	Moderate
10–20	Moderate to strong
20–100	Strong to very strong

2584 The second thing to notice about the Bayes Factor is that it doesn't de-
 2585 pend on our prior probability of H_1 vs. H_0 . We might think of H_1 as
 2586 very implausible. But the BF is independent of that prior belief. So that
 2587 means it's a measure of how much the evidence should shift our beliefs
 2588 away from our prior. One nice way to think about this is that the Bayes
 2589 Factor computes how much our beliefs—whatever they are—should be
 2590 changed by the data (Morey and Rouder 2011).

2591 In practice, the thing that is both tricky and good about Bayes Factors
 2592 is that you need to define an actual model of what H_0 and H_1 are. That
 2593 process involves making some assumptions explicit. We won't go into

2594 how to make these models here—this is a big topic that is covered ex-
2595 tensively in books on Bayesian data analysis.¹⁰ The goal here is just to
2596 give a general sense of what Bayes Factors are.

2597 6.3.2 p-values

2598 Now let's turn back to NHST and the *p*-value. We already have a work-
2599 ing definition of what a *p*-value is from our discussion above: it's the
2600 probability of the data (or any data that would be more extreme) under
2601 the null hypothesis. How is this quantity related to either our Bayesian
2602 estimate or the BF? Well, the first thing to notice is that the *p*-value is
2603 very close (but not identical) to the likelihood itself.¹¹

2604 Next we can use a simple statistical test, a *t*-test, to compute *p*-values for
2605 our experiment. In case you haven't encountered one, a *t*-test is a pro-
2606 cedure for computing a *p*-value by comparing the distribution of two
2607 variables using the null hypothesis that there is no difference between
2608 them.¹² The *t*-test uses the data to compute a **test statistic** whose dis-
2609 tribution under the null hypothesis is known. Then the value of this
2610 statistic can be converted to *p*-values for making an inference.

¹⁰ Two good ones beyond the McElreath book mentioned above are Gelman et al. (1995), which is a bit more statistical, and Kruschke (2014), which is a bit more focused on psychological data analysis. An in-prep web-book by Nicenboim et al. (<https://vasishth.github.io/bayescogsci/book/>) also looks great.

¹¹ The likelihood—for both Bayesians and frequentists—is the probability of the data, just like the *p*-value. But unlike the *p*-value, it doesn't include the probability of more extreme data as well.

¹² *t*-tests can also be used in cases where one sample is being compared to some baseline.

CODE

The standard `t.test()` function is built into R via the default `stats` package. Here we simply make sure to specify the variety of test we want by using the flags `paired = FALSE` and `var.equal = TRUE` (denoting the assumption of equal variances).

```
tea_t <- t.test(x = filter(tea_data, condition == "milk first")$rating,
                  y = filter(tea_data, condition == "tea first")$rating,
                  paired = FALSE, var.equal = TRUE)
```

2611

2612 Imagine we conduct a tea-tasting experiment with $N = 48$ and perform
 2613 a t -test on our experimental results. In this case, we see that the differ-
 2614 ence between the two groups is significant at $p < .05$: $t(46) = 2.86$,
 2615 $p = .006$.

2616 The expression $t(46) = 2.86$, $p = .006$ is the standard way to report
 2617 of a t -test according to the American Psychological Association. The
 2618 first part of this report gives the t value, qualified by the **degrees of free-**
 2619 **dom** for the test in parentheses. We won't focus much on the idea of
 2620 degrees of freedom here, but for now it's enough to know that this num-
 2621 ber quantifies the amount of information given by the data, in this case
 2622 48 datapoints minus the two means (one for each of the samples).

2623 Let's compare p values and Bayes Factors (computed using the default

Table 6.2
 Comparison of p -value and BF for several different (randomly-generated) tea-tasting scenarios.

N	Effect size	p-value	BF
12	0.5	> .999	0.5
12	1.0	.076	1.4
12	1.5	.002	18.7
24	0.5	.858	0.4
24	1.0	.061	1.5
24	1.5	.009	5.6
48	0.5	.002	17.7
48	1.0	.033	2.0

2624 setup in the BayesFactor R package). In table 6.2), the rows represent
2625 simulated experiments with varying total numbers of participants (N
2626 and varying average treatment effects. Both p and BF go up with more
2627 participants and larger effects. In general, BFs tend to be a bit more
2628 conservative than p -values, such that $p < .05$ can sometimes translate
2629 to a BF of less than 3 (Benjamin et al. 2018). For example, take a look
2630 at the row with 48 participants and an effect size of 1: the p value is less
2631 than .05, but the Bayes Factor is only 2.0.

2632 The critical thing about p -values, though, is not just that they are a kind
2633 of data likelihoods. It is that they are used in a *specific inferential procedure*.
2634 The logic of NHST is that we make a binary decision about the presence
2635 of an effect. If $p < .05$, the null hypothesis is rejected; otherwise not.

2636 As Fisher (1949) wrote,

2637 It should be noted that the null hypothesis is never proved
2638 or established, but is possibly disproved, in the course of
2639 experimentation. Every experiment may be said to exist
2640 only in order to give the facts a chance of disproving the
2641 null hypothesis. (p. 19)

2642 The main problem with p -values from a scientific perspective is that
2643 researchers are usually interested in not just rejecting the null hypothesis

2644 but also in the evidence for the alternative (the one we are interested in).
 2645 The Bayes Factor is one approach to quantifying positive evidence for
 2646 the alternative hypothesis in a Bayesian framework. This issue with the
 2647 Fisher approach to p -values has been known for a long time, though,
 2648 and so there is an alternative frequentist approach as well.

2649 *6.3.3 The Neyman-Pearson approach*

2650 One way to “patch” NHST is to introduce a decision-theoretic view,
 2651 shown in figure 6.9.¹³ On this view, called the Neyman-Pearson view,
 2652 there is a real H_1 , albeit one that is not specified. Then the true state of
 2653 the world could be that H_0 is true or H_1 is true. The $p < .05$ criterion
 2654 is the threshold at which we are willing to reject the null, and so this
 2655 constitutes our **false positive rate** α . But we also need to define a **false**
 2656 **negative rate**, which is conventionally called β .¹⁴

2657 Setting these rates is a decision problem: If you are too conservative in
 2658 your criteria for the intervention having an effect, then you risk a **false**
 2659 **negative**, where you incorrectly conclude that it doesn’t work. And if
 2660 you’re too liberal in your assessment of the evidence, then you risk a
 2661 **false positive**.¹⁵ In practice, however, people usually leave α at .05 and
 2662 try to control the **false negative rate** by increasing their sample size.

		Inference	
		Reject null (H_0)	Fail to reject null (H_0)
Reality	Null (H_0) is true	False positive α	Correct rejection $1 - \alpha$
	Null (H_0) is false	True positive $1 - \beta$	False negative β

Figure 6.9
Standard decision matrix for the Neyman-Pearson approach to statistical inference.

¹³ A little bit of useful history here is given in Cohen (1990), and we also recommend Gigerenzer (1989) for a broader perspective.

¹⁴ Unfortunately, β is very commonly used for regression coefficients—and for that reason we’ve used it as our symbol for causal effects. We’ll be using these β s in the next chapter as well. Those β s are not to be confused with false negative rates. Sorry, this is just a place where statisticians have used the same Greek letter for two different things.

2663 As we saw in figure 6.6, the larger the sample, the better your chance
2664 of rejecting the null for any given non-null effect. But these chances
2665 will depend also on the effect size you are estimating. This formula-
2666 tion gives rise to the idea of classical power analysis, which we cover in
2667 chapter 10. Most folks who defend binary inference are interested in
2668 using the Neyman-Pearson approach. In our view, this approach has
2669 its place (it's especially useful for power analysis) but it still suffers from
2670 the substantial issues that plague all binary inference techniques.

¹⁵ To make really rational decisions, you could couple this chart to some kind of utility function that assessed the costs of different outcomes. For example, you might think it's worse to proceed with an intervention that doesn't work than to stay with business as usual. In that case, you'd assign a higher cost to a false positive and accordingly try to adopt a more conservative criterion. We won't cover this kind of decision analysis here, but Pratt et al. (1995) is a classic textbook on statistical decision theory if you're interested.

 DEPTH

Nonparametric resampling under the null

Hypothesis testing requires knowing the null distribution. In the examples above, it was easy to use statistical theory to work out the null distribution using knowledge of the binomial or normal distribution. But sometimes we don't know what the null distribution would look like. What if the ratings data from our tea-tasting experiment was very skewed, such that there were many low ratings and a few very high ratings (as in figure 6.10)?

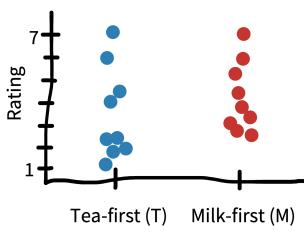


Figure 6.10

A small tea-tasting experiment with a skewed distribution of ratings.

With skewed data like this, we couldn't proceed with a t -test in good conscience because, with only $n = 18$, we can't necessarily trust that the Central Limit Theorem has "kicked in" sufficiently for the test to work despite the skewness. Put another way, we can't be sure that the null distribution is normal (Gaussian) in this case.

An alternative way to approximate a null distribution is through nonparametric resampling. **Resampling** means that we're going to draw new samples *from our existing sample*, and **nonparametric** means that we will

do this in a way that obviates assumptions about the shape of the null distribution—in contrast to **parametric** approaches that do rely on such assumptions). These techniques are sometimes called “bootstrapping” techniques.

The idea is, if the treatment truly had no effect on the outcome, then the observations would be **exchangeable** between the treatment and control groups. That is, there would not be systematic differences between the treatment and control groups. This property may or may not be true in our observed sample (after all, that’s why we’re doing a hypothesis test in the first place), but we can draw new samples from our existing sample in a manner that forces exchangability.

To perform this kind of test with our tea-tasting data, we would randomly shuffle the ratings in our dataset while leaving the condition assignments fixed. If we did this thousands of times and computed the treatment effect in each case, the result would be a null distribution: what we might expect the treatment effect to look like if there was *no* condition effect. In essence we’re using a simulated version of “random assignment” here to *break* the dependency between the condition manipulation and the observed data.

We can then compare our *actual* treatment effect to this nonparametric null distribution. If the actual treatment was smaller than the 2.5th percentile or larger than the 97.5th percentile in the null distribution, we would reject the null with $p < .05$, just the same as if we had used a

t-test.

Resampling-based tests are extremely useful in a wide variety of cases. They can sometimes be less powerful than parametric approaches and they almost always require more computation, but their versatility makes them a great generic tool for data analysis.

2673

2674 *6.4 Inference and its discontents*

2675 In earlier sections of this chapter, we reviewed NHST and Bayesian ap-
2676 proaches to inference. Now it's time to step back and think about some
2677 of the ways that inference practices—especially those related to NHST—
2678 have been problematic for psychology research. We'll begin with some
2679 issues surrounding *p*-values and then give a specific accident report re-
2680 lated to the process of “*p*-hacking” and some general philosophical dis-
2681 cussion of how statistical testing relates to human reasoning.

2682 *6.4.1 Problems with the interpretation of p-values*

2683 *p*-values are basically likelihoods, in the sense we introduced in the pre-
2684 vious chapter.¹⁶ They are the likelihood of the data under the null
2685 hypothesis! This likelihood is a critical number to know—for comput-
2686 ing the Bayes Factor among other reasons. But it doesn't tell us a lot of

2687 things that we might like to know!

2688 For example, p -values don't tell us the probability of the data under a
2689 specific alternative hypothesis that we might be interested in—that's the
2690 posterior probability $p(H_1|\text{data})$. When our tea-tasting t -test yielded
2691 $t(46) = 2.86$, $p = .006$, that p is *not* the probability of the null hypoth-
2692 esis being true! And it's definitely not the probability of milk-first tea
2693 being better.

2694 What can you conclude when $p > .05$? According to the classical logic
2695 of NHST, the answer is “nothing”! A failure to reject the null hypoth-
2696 esis doesn't give you any additional evidence *for* the null. Even if the
2697 probability of the data (or some more extreme data) under H_0 is high,
2698 their probability might be just as high or higher under H_1 .¹⁷ But many
2699 practicing researchers make this mistake. Aczel et al. (2018) coded a
2700 sample of articles from 2015 and found that 72% of negative statements
2701 were inconsistent with the logic of their statistical paradigm of choice—
2702 most were cases where researchers said that an effect was not present
2703 when they had simply failed to reject the null.

2704 These are not the only issues with p -values. In fact, people have so
2705 much trouble understanding what p -values *do* say that there are whole
2706 articles written about these misconceptions. Table 6.3 shows a set of
2707 misconceptions documented and refuted by S. N. Goodman (2008).

¹⁷ Of course, weighing these two against one another brings you back to the Bayes Factor.

2708 Let's take a look at just a few. Misconception 1 is that, if $p = .05$, the
2709 null has a 5% chance of being true. This misconception is a result of
2710 confusing $p(H_0|\text{data})$ (the posterior) and $p(\text{data}|H_0)$ (the likelihood—
2711 also known as the p -value). Misconception 2—that $p > .05$ allows us to
2712 *accept* the null—also stems from this reversal of posterior and likelihood.
2713 And misconception 3 is a misinterpretation of the p -value as an effect
2714 size (which we learned about in the last chapter): a large effect is likely
2715 to be clinically important, but with a large enough sample size, you can
2716 get a small p -value even for a very small effect. We won't go through
2717 all the misconceptions here, but we encourage you to challenge yourself
2718 to work through them (as in the exercise below).

Table 6.3
A “dirty dozen” p -value misconceptions. Adapted from S. N. Goodman (2008).

Misconception
1 “If $p = .05$, the null hypothesis has only a 5% chance of being true.”
2 “A nonsignificant difference (e.g., $p \geq .05$) means there is no difference between groups.”
3 “A statistically significant finding is clinically important.”
4 “Studies with p -values on opposite sides of .05 are conflicting.”
5 “Studies with the same p -value provide the same evidence against the null hypothesis.”
6 “ $p = .05$ means that we have observed data that would occur only 5% of the time under the null hypothesis.”
7 “ $p = .05$ and $p \leq .05$ mean the same thing.”
8 “ p -values are properly written as inequalities (e.g., ‘ $p \leq .02$ ’ when $p = .015$)”

Misconception

- 9 “ $p = .05$ means that if you reject the null hypothesis, the probability of a false positive error is only 5.”
 - 10 “With a $p = .05$ threshold for significance, the chance of a false positive error will be 5.”
 - 11 “You should use a one-sided p -value when you don’t care about a result in one direction, or a difference in that direction is impossible.”
 - 12 “A scientific conclusion or treatment policy should be based on whether or not the p value is significant.”
-

₂₇₁₉ Beyond these misconceptions, there’s another problem. The p -value is
₂₇₂₀ a probability of a certain set of events happening (corresponding to the
₂₇₂₁ observed data or any “more extreme” data, that is to say, data further
₂₇₂₂ from the null). Since p -values are probabilities, we can combine them
₂₇₂₃ together across different events. If we run a “null experiment”—an ex-
₂₇₂₄ periment where the true effect is zero—the probability of a dataset with
₂₇₂₅ $p < .05$ is of course .05. But if we run two such experiments, we can
₂₇₂₆ get $p < .05$ with probability 0.1. By the time we run 20 experiments,
₂₇₂₇ we have an 0.64 chance of getting a positive result.

₂₇₂₈ It would obviously be a major mistake to run 20 experiments and then
₂₇₂₉ report only the positive ones (which, by design, are false positives) as
₂₇₃₀ though these still were “statistically significant.” The same thing applies
₂₇₃₁ to doing 20 different statistical tests within a single experiment. There

2732 are many statistical corrections that can be made to adjust for this prob-
2733 lem, which is known as the problem of **multiple comparisons**.¹⁸ But
2734 the broader issue is one of transparency: unless you *know* what the
2735 appropriate set of experiments or tests is, it's not possible to implement
2736 one of these corrections!¹⁹

❖ ACCIDENT REPORT

Do extraordinary claims require extraordinary evidence?

In a blockbuster paper that may have inadvertently kicked off the replication crisis, Bem (2011) presented nine experiments he claimed provided evidence for precognition— that participants somehow had foreknowledge of the future. In the first of these experiments, Bem showed each of a group of 100 undergraduates 36 two-alternative forced choice trials in which they had to guess which of two locations on a screen would reveal a picture immediately before the picture was revealed. By chance, participants should choose the correct side 50% of the time of course. Bem found that, specifically for erotic pictures, participants' guesses were 53.1% correct. This rate of guessing was unexpected under the null hypothesis of chance guessing ($p = .01$). Eight other studies with a total of more than 1,000 participants yielded apparently supportive evidence, with participants appearing to show a variety of psychological effects even before the stimuli were shown!

¹⁸ The simplest and most versatile one, the Bonferroni correction, just divides .05 (or technically, whatever your threshold is) by the number of comparisons you are making. Using that correction, if you do 20 null experiments, you would have a 3% chance of a false positive.

¹⁹ This issue is especially problematic with p -values because they are so often presented as an independent set of tests, but the problem of multiple comparisons comes up when you compute a lot of independent Bayes Factors as well. “Posterior hacking” via selective reporting of Bayes Factors is perfectly possible (Simonsohn 2014).

Based on this evidence, should we conclude that precognition exists?

Probably not. Wagenmakers et al. (2011) presented a critique of Bem's findings, arguing that 1) Bem's experiments were exploratory (not pre-registered) in nature, 2) that Bem's conclusions were *a priori* unlikely, and 3) that the level of statistical evidence from his experiments was quite low. We find each of these arguments alone compelling; together they present a knockdown case against Bem's interpretation.

First, we've already discussed the need to be skeptical about situations where experimenters have the opportunity for analytic flexibility in their choice of measures, manipulations, samples, and analyses. Flexibility leads to the possibility of cherry-picking those set of decisions from the “garden of forking paths” that lead to a positive outcome for the researcher's favored hypothesis (for more details, see chapter 11). And there is plenty of flexibility on display even in Experiment 1 of Bem's paper. Although there were 100 participants in the study, they may have been combined post hoc from two distinct samples of 40 and 60, each of which saw different conditions. The 40 made guesses about the location of erotic, negative, and neutral pictures; the 60 saw erotic, positive non-romantic, and positive romantic pictures. The means of each of these conditions was presumably tested against chance (at least 6 comparisons, for a false positive rate of 0.26). Had positive romantic pictures been found significant, Bem certainly could have interpreted this finding the same way he interpreted the erotic ones.

Second, as we discussed, a *p*-value close to .05 does not necessarily pro-

vide strong evidence against the null hypothesis. Wagenmakers et al. computed the Bayes Factor for each of experiments in Bem's paper and found that, in many cases, the amount of evidence for H_1 was quite modest under a default Bayesian t -test. Experiment 1 was no exception: the BF was 1.64, giving only "anecdotal" support for the hypothesis of some non-zero effect, even before the multiple-comparisons problem mentioned above.

Finally, since precognition is not supported by any prior compelling scientific evidence (despite many attempts to obtain such evidence) and defies well-established physical laws, perhaps we should assign a low prior probability to Bem's H_1 , a non-zero precognition effect. Taking a strong Bayesian position, Wagenmakers et al. suggest that we might do well to adopt a prior reflecting how unlikely precognition is, say $p(H_1) = 10^{-20}$. And if we adopt this prior, even a very well-designed, highly informative experiment (with a Bayes factor conveying substantial or even decisive evidence) would still lead to a very low posterior probability of precognition.

Wagenmakers et al. concluded that, rather than supporting precognition, the conclusion from Bem's paper should be psychologists should revise how they think about analyzing their data (and avoid p -hacking)!

2740 6.4.1 *Philosophical (and empirical) views of probability*

2741 Up until now we've presented Bayesian and frequentist tools as two dif-
2742 ferent sets of computations. But in fact, these different tools derive from
2743 fundamentally different philosophical perspectives on what a probabili-
2744 ty even is. Very roughly, frequentist approaches tend to believe that
2745 probabilities quantify the long-run frequencies of certain events. So, if
2746 we say that some outcome of an event has probability .5, we're saying
2747 that if that event happened thousands of times, the long run frequency of
2748 the outcome would be 50% of the total events. In contrast, the Bayesian
2749 viewpoint doesn't depend on this sense that events could be exactly re-
2750 peated. Instead, the **subjective Bayesian** interpretation of probability is
2751 that it quantifies a person's degree of belief in a particular outcome.²⁰

2752 You don't have to take sides in this deep philosophical debate about
2753 what probability is. But it's helpful to know that people actually seem
2754 to reason about the world in ways that are well described by the subjec-
2755 tive Bayesian view of probability. Recent cognitive science research has
2756 made a lot of headway in describing reasoning as a process of Bayesian
2757 inference where probabilities describe degrees of belief in different hy-
2758 potheses (for a textbook review of this approach, see **N. D. Goodman,**
2759 **Tenenbaum, and Contributors 2016**). These hypotheses in turn are a lot
2760 like the theories we described in chapter 2: they describe the relation-

²⁰ This is really a very rough description. If you're interested in learning more about this philosophical background, we recommend the Stanford Encyclopedia of Philosophy entry, "Interpretations of Probability" (<https://plato.stanford.edu/entries/probability-interpret/>).

ships between different abstract entities (Tenenbaum et al. 2011). You
might think that scientists are different from lay-people in this regard,
but one of the striking findings from research on probabilistic reasoning
and judgment is that expertise doesn't matter that much. Statistically-
trained scientists—and even statisticians—make many of the same rea-
soning mistakes as their un-trained students (Kahneman and Tversky
1979). Even children seem to reason intuitively in a way that looks a bit
like Bayesian inference (Gopnik 2012).

These cognitive science findings help to explain some of the problems
that people (scientists included) have in reasoning about p -values. If you
are an intuitively Bayesian reasoner, the quantity that you're probably
tracking is how much you believe in your hypothesis (its posterior prob-
ability). So, many people treat the p -value as the posterior probability
of the null hypothesis.²¹ That's exactly what fallacy #1 in table 6.3
states—"If $p = .05$, the null hypothesis has only a 5% chance of being
true." But this equivalence is incorrect! Written in math, $p(\text{data}|H_0)$
(the likelihood that lets us compute the p-value) is not the same thing
as $p(H_0|\text{data})$ (the posterior that we want). Pulling from our accident
report above, even if the *probability of the observed ESP data given the null
hypothesis* is low, that doesn't mean that the *probability of ESP* is high.

²¹ Cohen (1994) is a great treatment of this issue.

2781 6.4.2 *What framework to use?*

2782 The problem with binary inferences is that they enable behaviors that
2783 can introduce bias into the scientific ecosystem. By the logic of statis-
2784 tical significance, either an experiment “worked” or it didn’t. Because
2785 everyone would usually rather have an experiment that worked than
2786 one that didn’t, inference criteria like p -values often become a target
2787 for selection, as we discussed in chapter 3.²²

2788 If you want to quantify evidence for or against a hypothesis, it’s worth
2789 considering whether Bayes Factors address your question better than p -
2790 values. In practice, p -values are hard to understand and many people
2791 misuse them—though to be fair, BFs are misused plenty too. These
2792 issues may be rooted in basic facts about how human beings reason about
2793 probability.

2794 Despite the reasons to be worried about p -values, for many practicing
2795 scientists (at least at time of writing) there is no one right answer about
2796 whether to use them or not. Even if we’d like to be Bayesian all the
2797 time, there are a number of obstacles. First, though new computational
2798 tools make fitting Bayesian models and extracting Bayes Factors much
2799 easier than before, it’s still on average quite a bit harder to fit a Bayesian
2800 model than it is a frequentist one. Second, because Bayesian analyses are

²² More generally, this pattern is probably an example of Goodhart’s law, which states that when a measure becomes a target, it ceases to be a good measure (Strathern 1997). Once the outcomes of statistical inference procedures become targets for publication, they are subject to selection biases— p -hacking, for example—that make them less meaningful.

2801 less familiar, it may be an uphill battle to convince advisors, reviewers,
2802 and funders to use them.

2803 As a group of authors, some of us are more Bayesian than frequentist,
2804 while others are more frequentist than Bayesian—but all of us recog-
2805 nize the need to move between statistical paradigms depending on the
2806 problem we’re working on. Furthermore, a lot of the time we’re not
2807 so worried about which paradigm we’re using. The paradigms are at
2808 their most divergent when making binary inferences, and they often
2809 look much more similar when they are used in the context of quantify-
2810 ing measurement precision.

2811 6.5 Computing precision

2812 Our last section presented an argument against using p -values for mak-
2813 ing *dichotomous* inferences. But we still want to move from what we
2814 know about our own limited sample to some inference about the pop-
2815 ulation. How should we do this?

2816 6.5.1 Confidence intervals

2817 One alternative to binary hypothesis testing is to ask about the precision
2818 of our estimates, in particular how similar an estimate from a particu-

2819 lar sample is to the population parameter of interest. For example, how
2820 close is our tea-tasting effect estimate to the true effect in the popu-
2821 lation? We don't know what the true effect is, but our knowledge of
2822 sampling distributions lets us make some guesses about how precise our
2823 estimate is.

2824 The **confidence interval** is a convenient frequentist way to summarize
2825 the variability of the sampling distribution—and hence how precise our
2826 point estimate is. The confidence interval represents the range of possi-
2827 ble values for the parameter of interest that are plausible given the data.

2828 More formally, a 95% confidence interval for some estimate (call it $\hat{\beta}$, as
2829 in our example) is defined as a range of possible values for β such that,
2830 if we did repeated sampling, 95% of the intervals generated by those
2831 samples would contain the true parameter, β .

2832 Confidence intervals are constructed by estimating the middle 95% of
2833 the sampling distribution of $\hat{\beta}$. Because of our hero, the Central Limit
2834 Theorem, we can treat the sampling distribution as normal for reason-
2835 ably large samples. Given this, it's common to construct a 95% confi-
2836 dence intervals $\hat{\beta} \pm 1.96 \widehat{SE}$.²³ If we were to conduct the experiment
2837 100 times and calculate a confidence interval each time, we should ex-
2838 pect 95 of the intervals to contain the true β , whereas we would expect
2839 the remaining 5 to not contain β .²⁴

²³ This type of CI is called a “Wald” confidence interval.

²⁴ In case you don't have enough tea to do the experiment 100 times to confirm this, you can do it virtually using this nice simulation tool: <https://istats.shinyapps.io/ExploreCoverage>.

2840 Confidence intervals are like betting on the inferences drawn from your
2841 sample. The sample you drew is like one pull of a slot machine that will
2842 pay off (i.e., have the confidence interval contain the true parameter)
2843 95% of the time. Put more concisely: 95% of 95% confidence intervals
2844 contain the true value of the population parameter.

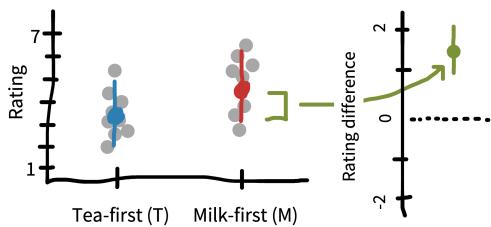


Figure 6.11
Confidence intervals on each of the two condition estimates, as well as on the difference between conditions.

CODE

Computing confidence intervals analytically is pretty easy. Here we first compute the standard error for the difference between conditions. The only tricky bit here is that we need to compute a pooled standard deviation.

```
tea_ratings <- filter(tea_data, condition == "tea first")$rating  
milk_ratings <- filter(tea_data, condition == "milk first")$rating  
  
n_tea <- length(tea_ratings)  
n_milk <- length(milk_ratings)  
sd_tea <- sd(tea_ratings)  
sd_milk <- sd(milk_ratings)  
  
tea_sd_pooled <- sqrt(((n_tea - 1) * sd_tea ^ 2 + (n_milk - 1) * sd_milk ^ 2) /  
(n_tea + n_milk - 2))  
  
tea_se <- tea_sd_pooled * sqrt((1 / n_tea) + (1 / n_milk))
```

Once we have the standard error, we can get the estimated difference between conditions and compute the confidence intervals by multiplying the standard error by 1.96.

```
delta_hat <- mean(milk_ratings) - mean(tea_ratings)  
tea_ci_lower <- delta_hat - tea_se * qnorm(0.975)  
tea_ci_upper <- delta_hat + tea_se * qnorm(0.975)
```

2846

2847 For visualization purposes, we can show the confidence intervals on
2848 individual estimates (left side of figure 6.11). These tell us about the
2849 precision of our estimates of each quantity relative to the population
2850 estimate. But we've been talking primarily about the CI on the treat-

2851 ment effect $\hat{\beta}$ (right side of figure 6.11). This CI allows us to make an
2852 inference about whether or not it overlaps with zero—which is actually
2853 equivalent in this case to whether or not the *t*-test is statistically signifi-
2854 cant.

2855 6.5.2 *Confidence in confidence intervals?*

2856 Confidence intervals are often misinterpreted by students and re-
2857 searchers alike (Hoekstra et al. 2014). Imagine a researcher conducts
2858 an experiment and reports that “the 95% confidence interval for the
2859 mean ranges from 0.1 to 0.4.” All of the statements in table 6.4, though
2860 tempting to make about this situation, are *technically false*.

Table 6.4
Confidence interval misconceptions for a confidence interval [0.1,0.4]. Adapted from
Hoekstra et al. (2014).

Misconception
1 “The probability that the true mean is greater than 0 is at least 95%.”,
2 “The probability that the true mean equals 0 is smaller than 5%.”,
3 “The ‘null hypothesis’ that the true mean equals 0 is likely to be incorrect.”,
4 “There is a 95% probability that the true mean lies between 0.1 and 0.4.”,
5 “We can be 95% confident that the true mean lies between 0.1 and 0.4.”,
6 “If we were to repeat the experiment over and over, then 95% of the time the true mean falls between 0.1 and 0.4.”

2861 The problem with all of these statements is that, in the frequentist frame-

work, there is only one true value of the population parameter, and the variability captured in confidence intervals is about the *samples*, not the parameter itself.²⁵ For this reason, we can't make any statements about the probability of the value of the parameter or of our confidence in specific numbers. To reiterate, what we *can* say is: if we were to repeat the procedure of conducting the experiment and calculating a confidence interval many times, in the long run, 95% of those confidence intervals would contain the true parameter.

The Bayesian analog to a confidence interval is a **credible interval**. Recall that for Bayesians, parameters themselves are considered probabilistic (i.e., subject to random variation), not fixed. A 95% credible interval for an estimate, $\hat{\beta}$, represents a range of possible values for β such that there is a 95% probability that β falls inside the interval. Because we are now wearing our Bayesian hats, we are “allowed” to talk about β as if it were probabilistic rather than fixed. In practice, credible intervals are constructed by finding the posterior distribution of β , as in chapter 5, and then taking the middle 95%, for example.

Credible intervals are nice because they don't give rise to many of the inference fallacies surrounding confidence intervals. They actually *do* represent our beliefs about where β is likely to be, for example. Despite the technical differences between credible intervals and confidence in-

²⁵ In contrast, Bayesians think of parameters themselves as variable rather than fixed.

2883 intervals, in practice—with larger sample sizes and weaker priors—they
2884 turn out to be quite similar to one another in many cases.²⁶

2885 *6.6 Chapter summary: Inference*

2886 Inference tools help you move from characteristics of the sample to char-
2887 acteristics of the population. This move is a critical part of generaliza-
2888 tion from research data. But we hope we've convinced you that infer-
2889 ence doesn't have to mean making a binary decision about the presence
2890 or absence of an effect. A strategy that seeks to estimate an effect and
2891 its associated precision is often much more helpful as a building block
2892 for theory. As we move towards estimating causal effects in more com-
2893 plex experimental designs, the process will require more sophisticated
2894 models. Towards that goal, the next chapter provides some guidance
2895 for how to build such models.

²⁶ They can diverge sharply in cases with less data or stronger priors (Morey et al. 2016), but in our experience this is relatively rare.



DISCUSSION QUESTIONS

1. Can you write the definition of a p -value and a Bayes Factor without looking them up? Try this out—what parts of the definitions did you get wrong?
2. Take three of Goodman's (2008) "dirty dozen" in table 6.3) and write a description of why each is a misconception. (These can be checked against the original article, which gives a nice discussion of each.)



READINGS

- Many of the concepts described here are illustrated beautifully via interactive visualizations. We recommend <https://seeing-theory.brown.edu/> for a broad overview of statistical concepts and <https://rpsychologist.com/viz> for a number of interactives that specifically illustrate concepts discussed in this chapter and the previous one, including p -values, effect sizes, maximum likelihood estimation, confidence intervals, and Bayesian inference.
- A fun, polemical critique of NHST: Cohen, J. (1994). The earth is round ($p < .05$). *American Psychologist*, 49, 997–1003. <https://doi.org/10.1037/0003-066X.49.12.997>.
- A nice introduction to Bayesian data analysis: Kruschke, J. K., & Liddell, T. M. (2018). Bayesian data analysis for newcomers. *Psychonomic bulletin & review*, 25(1), 155–177. <https://doi.org/10.3758/s13423-017-1272-1>.

2897

²⁸⁹⁸ *References*

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2902

2903 7 MODELS

LEARNING GOALS

- Articulate a strategy for estimating experimental effects using statistical models
- Build intuitions about how classical statistical tests relate to linear regression models
- Explore variations of the linear model, including generalized linear models and mixed effects models
- Reason about tradeoffs and strategies for model specification, including the use of control variables

2904

2905 In the previous two chapters, we introduced concepts surrounding es-
2906 timation of an experimental effect and inference about its relationship
2907 to the effect in the population. The tools we introduced there are for
2908 fairly specific research questions, and so are limited in their applicabil-
2909 ity. Once you get beyond the world of two-condition experiments in

2910 which each participant contributes one data point from a continuous
2911 measure, the simple t -test is not sufficient.

2912 In some statistics textbooks, the next step would be to present a whole
2913 host of other statistical tests that are designed for other special cases. We

2914 could even show a decision-tree: you have repeated measures? Use Test
2915 X! Or categorical data? Use Test Y! Or three conditions? Use Test Z!

2916 But this isn't a statistics book, and even if it were, we don't advocate
2917 that approach. The idea of finding a specific narrowly-tailored test for

2918 your situation is part and parcel of the dichotomous NHST approach
2919 that we tried to talk you out of in the last chapter. If all you want is

2920 your $p < .05$, then it makes sense to look up the test that can allow you
2921 to compute a p value in your specific case. But we prefer an approach

2922 that is more focused on getting a good estimate of the magnitude of the
2923 causal effect.

2924 In this chapter, we begin to explore how to select an appropriate statis-
2925 tical model to clearly and flexibly reason about these effects. A statistical

2926 model is a way of writing down a set of assumptions about how partic-
2927 ular data are generated, the **data generating process**. Statistical models

2928 are the bread and butter tools for estimating particular **parameters** of
2929 interest from empirical data—like the magnitude of a causal effect as-

2930 sociated with an experimental manipulation. They can also quantify

2931 MEASUREMENT PRECISION.

2932 For example, suppose you watch someone tossing a coin and observe a
2933 sequence of heads and tails. A simple statistical model might assume that
2934 the observed data are generated via the flip of a weighted coin. From the
2935 perspective of the last two chapters, we could estimate a standard error
2936 for the estimated proportion of flips that are heads (e.g., for 6 heads out
2937 of 8 flips, we have $\hat{p} = 0.75 \pm 0.17$), or we could compare the observed
2938 proportion against a null hypothesis. From a model-based perspective,
2939 however, we instead begin by thinking about where the data came from:
2940 we might assume the coin being flipped has some weight (a *latent*, or
2941 unobservable, parameter of the data generating process), and our goal
2942 is to determine the most likely value of that weight given the observed
2943 data. This single unified model can then also be used to make inferences
2944 about whether the coin's weight differs from some null model (a fair
2945 coin, perhaps), or to predict future flips.

2946 This example sounds a lot like the kinds of simple inferential tests we
2947 talked about in the previous chapter; not very “model-y.” But things
2948 get more interesting when there are multiple parameters to be estimated,
2949 as in many real-world experiments. In the tea-tasting scenario we’ve
2950 belabored over the past two chapters, a real experiment might involve
2951 multiple people tasting different types of tea in different orders, all with

2952 some cups randomly assigned to be milk-first or tea-first. What we'll
2953 learn to do in this chapter is to make a model of this situation that allows
2954 us to reason about the magnitude of the milk-order effect while also
2955 estimating variation due to different people, orders, and tea types. This
2956 is the advantage of using models: once you are able to reason about
2957 estimation and inference in model-based terms, you will be set free from
2958 long decision trees and will be able to flexibly make the assumptions that
2959 make sense for your data.¹

2960 We'll begin by discussing the ubiquitous framework for building statisti-
2961 cal models, **linear regression**.² We will then build connections between
2962 regression and the *t*-test. This section will discuss how to add covariates
2963 to regression models, and when linear regression does and doesn't work.
2964 In the following section, we'll discuss the **generalized linear model**, an
2965 innovation that allows us to make models of a broader range of data
2966 types, including **logistic regression**. We'll then briefly introduce **mixed**
2967 **models**, which allow us to model clustering in our datasets (such as clus-
2968 ters of observations from a single individual or single stimulus item).
2969 We'll end with some opinionated practical advice on model building.
2970 If you're interested in building up intuitions about statistical model
2971 building, then we recommend reading this chapter all the way through.
2972 On the other hand, if you are already engaged in data analysis and

¹ We won't explore the connection to DAGs and Bayesian models here, but one way to think of this model building is as creating a causal theory of the experiment. This approach, which is advocated by McElreath (2018), creates powerful connections between the ideas about theory we presented in Chapters 1 and 2 and the ideas about models here. If this sounds intriguing, we encourage you to go down the rabbit hole!

² The name regression originally comes from Galton (1877)'s work on heredity. He was looking at the relationship between the heights of parents and children. He found that children's heights regressed, and he did so by creating a *regression model*. Now we use the term "regression" to mean any model of this form.

2973 want to see an example, we suggest that you skip to the last section,
2974 where we give some opinionated practical advice on model building
2975 and provide a worked example of fitting a mixed effects model and
2976 interpreting it in context.

2977 7.1 Regression models

2978 There are many types of statistical models, but this chapter will focus
2979 primarily on regression, a broad and extremely flexible class of mod-
2980 els. A regression model relates a dependent variable to one or more
2981 independent variables. Dependent variables are sometimes called **out-**
2982 **come variables**, and independent variables are sometimes called **predic-**
2983 **tor variables, covariates, or features**.³ We will see that many common
2984 statistical estimators (like the sample mean) and methods of inference
2985 (like the *t*-test) are actually simple regression models. Understanding
2986 this point will help you see many statistical methods as special cases of
2987 the same underlying framework, rather than as unrelated, *ad hoc* tests.

2988 7.1.1 Regression for estimating a simple treatment effect

2989 Let's start with one of these special cases, namely estimating a treatment
2990 effect, β , in a two-group design. In chapter 5, we solved this exact
2991 challenge for the tea-tasting experiment. We applied a classical model

³ The reverse is not true—not every predictor or covariate is an independent variable! One of the tricky things about relating regression models to causal hypotheses is that, just because something is on the right side of a regression equation, that doesn't mean it's a causal manipulation. And of course, just because you've got an estimate of some predictor in a regression, that doesn't mean the estimate tells you about the magnitude of the *causal* effect. It could, but it also might not!

2992 in which the milk-first ratings are assumed to be normally distributed
 2993 with mean $\theta_M = \theta_T + \beta$ and standard deviation σ .⁴

2994 Let's now write that model as a regression model, that is, as a model that
 2995 predicts each participant's tea rating, Y_i , given that participant's treat-
 2996 ment assignment, X_i . $X_i = 0$ represents the control (milk-first) group
 2997 and $X_i = 1$ represents the treatment (tea-first) group.⁵ Here, Y_i is the
 2998 dependent variable, and X_i is the independent variable. The subscripts
 2999 i index the participants. To make this concrete, you can see some sam-
 3000 ple tea-tasting data (the first three observations from each condition)
 3001 below (table 7.1), with the index i , the condition and its predictor X_i ,
 3002 and the rating Y .

3003 Let's write this model more formally as a **linear regression of Y on X**.
 3004 Conventionally, regression models are written with “ β ” symbols for all
 3005 parameters, so we'll now use $\beta_0 = \theta_M$ for the mean in the milk-first
 3006 group and $\beta_1 = \theta_T - \theta_M$ as the average difference between the tea-first
 3007 and milk-first groups. This β is a generalization of the one we're using
 3008 to denote the causal effect above and in the previous two chapters.

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$$

⁴ Here's a quick reminder that “model” here is a way of saying “set of assumptions about the data generating procedure.” So saying that some equation is a “model” is the same as saying that we think this is where the data came from. We can “turn the crank”—generate data through the process that's specified in those equations, e.g., pulling numbers from a normal distribution with mean $\theta_T + \beta$ and standard deviation σ . In essence, we're committing to the idea that this process will give us data that are substantively similar to the ones we have already.

⁵ Using 0 and 1 is known as **dummy coding**, and allows us to interpret the parameter as the difference of the treatment group (tea-first) from the baseline (milk-first). There are many other ways to code categorical variables, with other interpretations. As a practical tip, be careful to check how your variables are coded before reporting anything!

3009 The term $\beta_0 + \beta_1 X_i$ is called the **linear predictor**, and it describes the
 3010 expected value of an individual's tea rating, Y_i , given that participant's
 3011 treatment group X_i (the single independent variable in this model).
 3012 That is, for a participant in the control group ($X_i = 0$), the linear
 3013 predictor is just equal to β_0 , which is indeed the mean for the control
 3014 group that we specified above. On the other hand, for a participant in
 3015 the treatment group, the linear predictor is equal to $\beta_0 + \beta_1$, which
 3016 is the mean for the treatment group that we specified. In regression
 3017 jargon, β_0 and β_1 are **regression coefficients**, where β_1 represents the
 3018 association of the independent variable X with the outcome Y .

3019 The term ϵ_i is the **error term**, referring to random variation of partici-
 3020 pants' ratings around the group mean.⁶ Note that this is a very specific
 3021 kind of "error"; it does not include "error" due to bias, for example.
 3022 Instead, you can think of the error terms as capturing the "error" that
 3023 would be associated with predicting any given participant's rating based
 3024 on just the linear predictor. If you predicted a control group partici-
 3025 pant's rating as β_0 , that would be a good guess—but you still expect the
 3026 participant's rating to deviate somewhat from β_0 (i.e., due to variability
 3027 across participants beyond what is captured by their treatment groups).
 3028 In our regression model, the linear predictor and error terms together
 3029 say that participants' ratings scatter randomly (in fact, normally) around

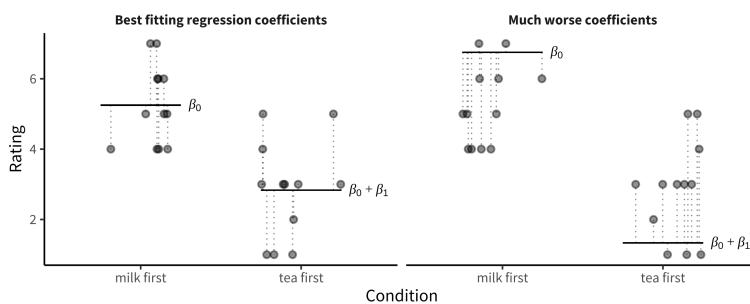
Table 7.1
Example tea tasting data.

id	condition	X	rating (Y)
1	milk first	0	6
2	milk first	0	4
3	milk first	0	5
4	tea first	1	1
5	tea first	1	3
6	tea first	1	5

⁶ Formally, we'd write $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$. The tilde means "is distributed as", and what follows is a normal distribution with mean 0 and variance σ^2 .

3030 their group means with standard deviation σ . And that is exactly the
 3031 same model we posited in chapter 5.⁷

3032 Now we have the model. But how do we estimate the regression co-
 3033 efficients β_0 and β_1 ? The usual method is called **ordinary least squares**
 3034 (**OLS**). Here's the basic idea. For any given regression coefficient es-
 3035 timates $\hat{\beta}_0$ and $\hat{\beta}_1$, we would obtain different **predicted values**, $\hat{Y}_i =$
 3036 $\hat{\beta}_0 + \hat{\beta}_1 X_i$ for each participant. Some regression coefficient estimates
 3037 will yield better predictions than others. OLS estimation is designed to
 3038 find the values of the regression coefficients that optimize these predic-
 3039 tions, meaning that the predictions are as close as possible to participants'
 3040 true outcomes, Y_i .



3041 figure 7.1 illustrates the tea tasting data for each condition (the dots)
 3042 along with the model predictions for each condition β_0 and $\beta_0 + \beta_1$
 3043 (blue lines). The gap between each data point and the corresponding
 3044 predictions (the thing that OLS wants to minimize) is shown by the dot-
 3045 ted lines.⁸ These distances are sample estimates, called **residuals**, of the
 3046 true errors (ϵ_i). The left-hand plot shows the OLS coefficient values—

⁷ You may be wondering why so much effort was put into building boutique solutions for these special cases when a unified framework was available the whole time. A partial answer is that the classical infrastructure of statistics was developed before computers were widespread, and these special cases were chosen because they were easy to work with “analytically” (meaning to work out all the math by hand, using values from big numerical tables). Now that we have computers with more flexible algorithms, the model-based perspective is more practi-

Figure 7.1 is accessible than it used to be.
 (left) Best-fitting regression coefficients for the tea-tasting experiment. (right) Much worse coefficients for the same data. Dotted lines: residuals. Circles: data points for individual participants.

3047 the ones that move the model’s predictions as close as possible to the
 3048 data points, in the sense of minimizing the total squared length of the
 3049 dashed lines. The right-hand plot shows a substantially worse set of
 3050 coefficient values.

3051 You’ll notice that we aren’t talking much about p -values in this chapter.
 3052 Regression models can be used to produce p -values for specific coef-
 3053 ficients, representing inferences about the likelihood of the observed
 3054 data under some null hypothesis regarding the coefficients. You can
 3055 also compute Bayes Factors for specific regression coefficients, or use
 3056 Bayesian inference to fit these coefficients under some prior expecta-
 3057 tion about their distribution. We won’t talk much about this, or more
 3058 generally how to fit the models we describe. As we said, we’re not going
 3059 to give a full treatment of all the relevant statistical topics. Instead we
 3060 want to help you begin thinking about making models of your data.

⁸ OLS minimizes squared error loss, in the sense that it will choose the regression coefficient estimates whose predictions minimize $\sum_{i=1}^n (Y_i - \hat{Y}_i)^2$, where n is the sample size. A wonderful thing about OLS is that those optimal regression coefficients (generically termed $\hat{\gamma}$) turn out to have a very simple closed form solution: $\hat{\gamma} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$. We are using more general notation here that supports multiple independent variables: $\hat{\gamma}$ is a vector, \mathbf{X} is a matrix of independent variables for each subject, and \mathbf{y} is a vector of participants’ outcomes. As more good news, the standard error for $\hat{\gamma}$ has a similarly simple closed form!

CODE

As it turns out, fitting an OLS regression model in R is extremely easy. The underlying function is `lm()`, which stands for linear model. You can fit the model with a single call to this function with a “formula” as its argument. Here’s the call:

```
mod <- lm(rating ~ condition, data = tea_data)
```

Formulas in R are a special kind of terse notation for regression equations where you write the outcome, \sim (distributed as), and the predictors. R assumes that you want an intercept by default, and there are also a number of other handy defaults that make R formulas a nice easy way to specify relatively complex regression models, as we'll see below.

Once you've fit the model and assigned it to a variable, you can call `summary()` to see a summary of the parameters of the model:

```
summary(mod)
```

You can also extract the coefficient values using `coef(mod)`, and put them in a handy dataframe using `tidy(mod)` from the `broom` package.

3062

3063 7.1.2 Adding predictors

3064 The regression model we just wrote down is the same model that un-
3065 derlies the t -test from chapter 6. But the beauty of regression modeling
3066 is that much more complex estimation problems can also be written as
3067 regression models that extend the model we made above. For example,
3068 we might want to add another predictor variable, such as the age of the
3069 participant.⁹

3070 Let's add this new independent variable and a corresponding regression

3071 coefficient to our model:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \epsilon_i$$

3072 Now that we have multiple independent variables, we've labeled them

3073 X_1 (treatment group) and X_2 (age) for clarity.

3074 To illustrate how to interpret the regression coefficients in this model,

3075 let's use the linear predictor to compare the model's predicted tea ratings

3076 for two hypothetical participants who are both in the treatment group:

3077 20-year-old Alice and 21-year old Bob. Alice's linear predictor tells us

3078 that her expected rating is $\beta_0 + \beta_1 + \beta_2 \cdot 20$. In contrast, Bob's linear

3079 predictor is $\beta_0 + \beta_1 + \beta_2 \cdot 21$. We could therefore calculate the expected

3080 difference in ratings for 21-year-olds versus 20-year olds by subtracting

3081 Alice's linear predictor from Bob's, yielding just β_2 .

3082 We would get the same result if Alice and Bob were instead 50 and 51

3083 years old, respectively. This equivalence illustrates a key point about

3084 linear regression models in general:

3085 The regression coefficient represents the expected differ-

3086 ence in outcome when comparing any two participants

3087 who differ by 1 unit of the relevant independent variable,

3088 and who do not differ on any other independent variables

3089 in the model.

3090 Here, the coefficient compares participants who differ by 1 year of age.
3091 In “Practical modeling considerations” below, we discuss whether and
3092 when to “control for” additional variables (i.e., when to add them to
3093 your model).

3094 *7.1.3 Interactions*

3095 In our running example, we now have two predictors: condition and
3096 age. But what if the effect of condition varies depending on the age
3097 of the participant? This situation would correspond to a case where
3098 (say) older people were more sensitive to tea ordering, perhaps because
3099 of their greater tea experience. We call this an **interaction** effect: the
3100 effect of one predictor depends on the state of another.

3101 Interaction effects are easily accommodated in our modeling framework.
3102 We simply add a term to our model that is the product of condition (X_1)
3103 and age (X_2), and weight this product by another beta, which represents
3104 the strength of this interaction:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i1}X_{i2} + \epsilon_i$$

3105 Statistical interactions are a very powerful modeling tool that can help
3106 us understand the relationship between different experimental manip-
3107 ulations or between manipulationes and covariates (such as age). We

3108 discuss their role in experimental design—as well as some of the inter-
3109 pretive challenges that they pose—in much more detail in chapter 9.¹⁰

3110 *7.1.4 When does linear regression work?*

3111 Linear regression modeling with OLS is an incredibly powerful tech-
3112 nique for creating models to estimate the influence of multiple predic-
3113 tors on a single dependent variable. In fact, OLS is in a mathematical
3114 sense the *best* way to fit a linear model!¹¹ But OLS only “works”—in
3115 the sense of yielding good estimates—if three big conditions are met.

3116 1. **The relationship between the predictor and outcome must be lin-**
3117 **ear.** In our comparison of Alice’s and Bob’s expected outcomes
3118 based on their 1-year age difference, we were able to interpret
3119 the coefficient β_2 as the average difference in Y_i when compar-
3120 ing participants who differ by 1 year of age, *regardless* of whether
3121 those ages are 20 vs. 21 or 50 vs. 51. If we believed this relation-
3122 ship was **non-linear**, then we could transform our predictor—for
3123 example, including a **quadratic** effect of age by adding a $\beta_3 * X_2^2$
3124 term. The *relationship* between this new predictor and the out-
3125 come would still be linear, however. It is always a good idea to
3126 use visualizations like scatter plots to look for possible problems

¹⁰ We won’t go into this topic here, but we do want to provide a pointer to one of the most persistent challenges that come up when you specify regression models with categorical predictors—and especially their interactions: how you “code” these categorical predictors. Above we created a “dummy” variable X that encoded milk-first tea as 0 and tea-first tea as 1. Dummy variables are very easy to think about, but in models with interactions, they can cause some problems. Because the interaction in our example model is a product of the dummy-coded condition variable and age, the interaction term β_3 is interpreted as the effect of age *for the tea-first condition* ($X = 1$) and hence the effect of age β_2 is actually the effect of age *for the milk-first condition*. The way to deal with this issue is to use a different coding system, such as **contrast coding**. Davis (2010) gives a good tutorial on this tricky topic.

3127 with assuming a linear relationship between a predictor and your
3128 outcome.

3129 **2. Errors must be independent.** In our example, observations in the
3130 regression model (i.e., rows in the dataset) were sampled inde-
3131 pendently: each participant was recruited independently to the
3132 study and each performed a single trial. On the other hand, sup-
3133 pose we have repeated-measures data in which we sample partic-
3134 ipants, and then obtained multiple measurements for each partici-
3135 pant. Within each participant, measurements would likely be cor-
3136 related (perhaps because participants differ on their general level
3137 of tea enjoyment). This correlation can invalidate inferences from
3138 a model that does not accommodate the correlation. We'll discuss
3139 this problem in detail below.

3140 **3. Errors must be normally distributed and unrelated to the predic-**
3141 **tor.** Imagine older people have very consistent tea-ordering pref-
3142 erences while younger people do not. In that case, the models' er-
3143 ror term would be less variable for older participants than younger
3144 ones. This issue is called **heteroskedasticity**. It is a good idea to
3145 plot each independent variable versus the residuals to see if the
3146 residuals are more variable for certain values of the independent
3147 variable than for others.

¹¹ There is a precise sense in which OLS gives the *very best* predictions we could ever get from any model that posits linear relationships between the independent variables and the outcome. That is, you can come up with any other linear, unbiased model you want, and yet if the assumptions of OLS are fulfilled, predictions from OLS will always be less noisy than those of your model. This is because of an elegant mathematical result called the Gauss-Markov Theorem.

³¹⁴⁸ If any of these three conditions are violated, it can undermine the esti-
³¹⁴⁹ mates and inferences you draw from your model.

³¹⁵⁰ 7.2 *Generalized linear models*

³¹⁵¹ So far we have considered continuous outcome measures, like tea rat-
³¹⁵² ings. What if we instead had a binary outcome, such as whether a partic-
³¹⁵³ ipant liked or didn't like the tea, or a count outcome, such as the number
³¹⁵⁴ of cups a participant chose to drink? These and other non-continuous
³¹⁵⁵ outcomes often violate the assumptions of OLS, in particular because
³¹⁵⁶ they often induce heteroskedastic errors.

³¹⁵⁷ Binary outcomes inherently produce heteroskedastic errors because the
³¹⁵⁸ variance of a binary variable depends directly on the outcome probabil-
³¹⁵⁹ ity. Errors will be more variable when the outcome probability is closer
³¹⁶⁰ to 0.50, and much less variable for when the probability is closer to 0
³¹⁶¹ or 1.¹² This heteroskedasticity in turn means that inferences from the
³¹⁶² model (e.g., p -values) can be incorrect; sometimes just a little bit off but
³¹⁶³ sometimes dramatically incorrect.¹³

³¹⁶⁴ Happily, generalized linear models (GLMs) are regression models
³¹⁶⁵ closely related to OLS that can handle non-continuous outcomes.
³¹⁶⁶ These models are called “generalized” because OLS is one of many

¹² Specifically, the variance of a bi-
nary variable with probability p is sim-
ply $p(1 - p)$, which is largest when $p =$
0.50.

¹³ OLS can also be used with binary
outcomes, in which case the coeffi-
cients represent differences in probabili-
ties. However, the usual model-based
standard errors will be incorrect.

³¹⁶⁷ members of this large class of models. To see the connection, let's first
³¹⁶⁸ write an OLS model more generally in terms of what it says about the
³¹⁶⁹ expected value of the outcome, which we notate as $E[Y_i]$:

$$E[Y_i] = \beta_0 + \sum_{j=1}^p \beta_j X_{ij}$$

³¹⁷⁰ where p is the number of independent variables, β_0 is the intercept, and
³¹⁷¹ β_j is the regression coefficient for the j^{th} independent variable. This
³¹⁷² equation is just a math-y way of saying that you predict from a regres-
³¹⁷³ sion model by adding up each of the predictors' contributions to the
³¹⁷⁴ expected outcome ($\beta_j X_{ij}$).

³¹⁷⁵ The linear predictor of a GLM (i.e., $\beta_0 + \sum_{j=1}^p \beta_j X_{ij}$) looks exactly the
³¹⁷⁶ same as for OLS, but instead of modeling $E[Y_i]$, a GLM models some
³¹⁷⁷ **transformation**, $g(\cdot)$, of the expectation:

$$g(E[Y_i]) = \beta_0 + \sum_{j=1}^p \beta_j X_{ij}$$

³¹⁷⁸ GLMs involve transforming the *expectation* of the outcome, not the out-
³¹⁷⁹ come itself! That is, in GLMs, we are not just taking the outcome vari-
³¹⁸⁰ able in our dataset and transforming it before fitting an OLS model, but
³¹⁸¹ rather we are fitting a different model entirely, one that posits a fun-
³¹⁸² damentally different relationship between the predictors and the ex-
³¹⁸³ pected outcomes. This transformation is called the **link function**. In
³¹⁸⁴ other words, to fit different kinds of outcomes, all we need to do is con-

3185 struct a standard linear model and then just transform its output via the
 3186 appropriate link function.

3187 Perhaps the most common link function is the **logit** link, which is suit-
 3188 able for binary data. This link function looks like this, where w is any
 3189 probability that is strictly between 0 and 1:

$$g(w) = \log\left(\frac{w}{1-w}\right)$$

3190 The term $w/(1-w)$ is called the **odds** and represents the probability of
 3191 an event occurring divided by the probability of its not occurring. The
 3192 resulting model is called **logistic regression** and looks like:

$$\text{logit}(E[Y_{it}]) = \log\left(\frac{E[Y_i]}{1 - E[Y_i]}\right) = \beta_0 + \sum_{j=1}^p \beta_j X_{ij}$$

3193 Exponentiating the coefficients (i.e., e^β) would yield **odds ratios**, which
 3194 are the *multiplicative* increase in the odds of $Y_i = 1$ that is associated
 3195 with a one-unit increase in the relevant predictor variable.

3196 figure 7.2 shows the way that a logistic regression model transforms a
 3197 predictor (X) into an outcome probability that is bounded at 0 and 1.
 3198 Critically, although the predictor is still linear, the logit link means that
 3199 the same change in X can result in a different change in the absolute
 3200 probability of Y depending on where you are on the X scale. In this
 3201 example, if you are in the middle of the predictor range, a one-unit

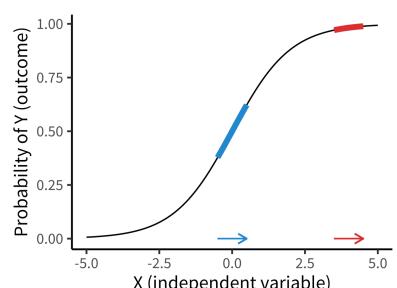


Figure 7.2

An example of how logistic regression transforms a change in the mean-centered predictor X into a change in the expected outcome Y . The same absolute change in X is associated in a large difference in the probability of the outcome when X is near its mean (blue) vs. a small change in the outcome when X is large (red) or small.

3202 change in X results in a 0.24 change in probability (blue). At a higher
3203 value, the change is much smaller (0.02). Notice how this is different
3204 from the linear regression model above, where the same change in age
3205 always resulted in the same change in preference!

CODE

GLMs are as easy to fit in R as standard LMs. You simply need to call the `glm()` function—and to specify the link function. For our example above of a binary “liking” judgment, the call would be:

```
glm(liked_tea ~ condition, data = tea_data, family = "binomial")
```

The `family` argument specifies the type of distribution being used, where `binomial` is the logistic link function.

3206

3207 We have only scratched the surface of GLMs here. First, there are many
3208 different link functions that are suitable for different outcome types.
3209 And second, GLMs differ from OLS not only in their link functions,
3210 but also in how they handle the error terms. Our broader goal in this
3211 chapter is to show you how regression models are *models of data*. In that
3212 context, GLMs use link functions as a way to make models that generate
3213 many different types of outcome data.¹⁴

¹⁴ We sometimes think of linear models as a set of tinker toys you can snap together to stack up a set of predictors. In that context, link functions are an extra “attachment” that you can snap onto your linear model to make it generate a different response type.

3214 7.3 Linear mixed effects models

3215 Experimental data often contain multiple measurements for each par-
3216 ticipant (so-called **repeated measures**). In addition, these measurements
3217 are often based on a sample of stimulus items (which then each have mul-
3218 tiple measures as well). This clustering is problematic for OLS models,
3219 because the error terms for each datapoint are not independent.

3220 Non-independence of datapoints may seem at first glance like a small
3221 issue, but it can present a deep problem for making inferences. Take the
3222 tea-tasting data we looked at above, where we had 24 observations in
3223 each condition. If we fit an OLS model, we observe a highly significant
3224 tea-first effect. Here is the estimate and confidence interval for that
3225 coefficient: $b = -2.42$, 95% CI $[-3.50, -1.33]$. Based on what we
3226 talked about in the previous chapter, it seems like we'd be licensed in
3227 rejecting the null hypothesis that this effect is due to sampling variation
3228 and interpret this instead as evidence for a generalizable difference in
3229 tea preference in our sampled population.

3230 But suppose we told you that all of those 48 total observations (24 in
3231 each condition) were from one individual named George. That would
3232 change the picture considerably. Now we'd have no idea whether the
3233 big effect we observed reflected a difference in the population, but we
3234 would have a very good sense of what George's preference is!¹⁵ The

¹⁵ We discuss the strengths and weaknesses of repeated-measures designs like this in chapter 9 and the statistical trade-offs of having many people with a small number of observations per person vs. a small number of people with many observations per person in chapter 10.

3235 confidence intervals and p-values from our OLS model would be wrong
3236 now because all of the error terms would be highly correlated—they
3237 would all reflect George’s preferences.

3238 How can we make models that deal with clustered data? There are a
3239 number of widely-used approaches for solving this problem including
3240 **linear mixed effects models, generalized estimating equations, and clus-**
3241 **tered standard errors** (often used in economics). Here we will illustrate
3242 how the problem gets solved in linear mixed models, which are an ex-
3243 tension of OLS models that are fast becoming a standard in many areas
3244 of psychology (Bates et al. 2014).

3245 *7.3.1 Modeling random variation in clusters*

3246 In linear mixed effects models, we modify the linear predictor itself to
3247 model differences across clusters. Instead of just measuring George’s
3248 preferences, suppose we modified the original tea-tasting experiment
3249 (without the age covariate) to collect ten ratings from each participant:
3250 five milk-first and five tea-first. We define the model the same way as
3251 we did before, with some minor differences:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \gamma_i + \epsilon_{it}$$

³²⁵² where Y_{it} is participant i 's rating in trial t and X_{it} is the participant's
³²⁵³ assigned treatment in trial t (i.e., milk-first or tea-first).

³²⁵⁴ If you compare this equation to the OLS equation above, you will notice
³²⁵⁵ that we added two things. First, we've added subscripts that distinguish
³²⁵⁶ trials from participants. But the big one is that we added γ_i , a separate
³²⁵⁷ intercept value for each participant. We call this a **random intercept**
³²⁵⁸ because it varies across participants (who are randomly selected from
³²⁵⁹ the population).¹⁶

³²⁶⁰ The random intercept means that we have assumed that each participant
³²⁶¹ has their own typical "baseline" tea rating—some participants overall
³²⁶² just like tea more than others—and these baseline ratings are normally
³²⁶³ distributed across participants. Thus, ratings are correlated within par-
³²⁶⁴ ticipants because ratings cluster around each participant's *distinct* base-
³²⁶⁵ line tea rating. This model is better able to block misleading inferences.

³²⁶⁶ For example, suppose we only had one participant in each condition
³²⁶⁷ (say, George provided 24 milk-first ratings and Alice provided 24 tea-
³²⁶⁸ first ratings). If we found higher ratings in one condition, we would be
³²⁶⁹ able to attribute this difference to participant-level variation rather than
³²⁷⁰ to the treatment.¹⁷

³²⁷¹ Following the same logic, we could fit random intercepts for different
³²⁷² stimulus items (for example, if we used different types of tea for dif-

¹⁶ Formally, we'd note this random variation by saying that $\gamma_i \sim N(0, \tau^2)$ —in other words, that participants' random intercepts are sampled from a normal distribution around the shared intercept β_0 with standard deviation τ .

¹⁷ Of course, this would be a terrible experiment! Ideally, we would address this problem upstream in our experiment design; see chapter 9.

3273 ferent trials). We modeled participants as having normally distributed
3274 variation, and we can model stimulus variation the same way. Each stim-
3275 ulus item is assumed to produce a particular average outcome (i.e. some
3276 teas are tastier than others), with these average outcomes sampled from
3277 a normally distributed population.

CODE

Remarkably, GLMMs are not much harder to specify in R than standard
LMs. One very popular package is `lme4` (Bates et al. 2014), which pro-
vides the `lmer()` and `glmer()` functions (the latter for generalized linear
mixed effect models). For our example here, we'd write:

```
library(lme4)  
  
lmer(rating ~ condition + (1 | id), data = tea_data)
```

In this model, the syntax `(1 | id)` specifies that we want a random in-
tercept for each level of `id`.

3278
3279 7.3.2 *Random slopes and the challenges of mixed effects models*
3280 Linear mixed effects models can be further extended to model cluster-
3281 ing of the independent variables' *effects* within subjects, not just clus-
3282 tering of average *outcomes* within subjects. To do so, we can introduce
3283 **random slopes** (δ_i) to the model, which are multiplied by the condition
3284 variable X and represent differences across participants in the effect of

3285 tea-tasting:

$$Y_i = \beta_0 + \beta_1 X_{it} + \gamma_i + \delta_i X_{it} + \epsilon_{it}$$

3286 Just like the random intercepts, these random slopes will be assumed to

3287 vary across participants, following a normal distribution.¹⁸

3288 This model now describes random variation in both overall how much

3289 someone likes tea *and* how strong their ordering preference is. Both of

3290 these likely do vary in the population and so it seems like a good thing

3291 to put these in your model. Indeed under some circumstances, adding

3292 random slopes is argued to be very important for making appropriate

3293 inferences.¹⁹

¹⁸ These random slopes and intercepts can be assumed to be independent or correlated with one another, depending on the modeler's preference.

CODE

Specifying random slopes in the `lme4` package is also relatively straightforward:

```
lmer(rating ~ condition + (condition | id), data = tea_data)
```

Here, `(condition | id)` means “a separate random slope for `condition` should be fit for each level of `id`.” Of course, specifying such a model is easier than fitting it correctly.

¹⁹ There's lots of debate in the literature about the best random effect structure for mixed effects models. This is a very tricky and technical subject. In brief, some folks argue for so-called **maximal** models, in which you include every random effect that is justified by the design (Barr et al. 2013). Here that would mean including random slopes for each participant. The problem is that these models can get very complex, and can be very hard to fit using standard software. We won't weigh in on this topic, but as you start to use these models on more complex experimental designs, it might be worth reading up.

3294

3295 On the other hand, the model is much more complicated. When we

3296 had a simple OLS model above, we had only two parameters to fit (β_0

3297 and β_1) but now we have those two plus two more, representing the

3298 standard deviations of the individual participant intercepts and slopes,
3299 plus parameters for each participant and for the condition effect for each
3300 participant. So we went from two parameters to $24!$ ²⁰ This complexity
3301 can lead to problems in fitting the models, especially with very small
3302 datasets (where these parameters are not very well-constrained by the
3303 data) or very large datasets (where computing all these parameters can
3304 be tricky).²¹

3305 More generally, linear mixed effects models are very flexible, and they
3306 have become quite common in psychology. But they do have signifi-
3307 cant limitations. As we discussed, they can be tricky to fit in standard
3308 software packages. Further, the accuracy of these models relies on our
3309 ability to specify the structure of the random effects correctly.²² If we
3310 specify an incorrect model, our inferences will be wrong! But it is some-
3311 times difficult to know how to check whether your model is reasonable,
3312 especially with a small number of clusters or observations.

3313 7.4 How do you use models to analyze data?

3314 In the prior parts of this chapter, we've described a suite of regression-
3315 based techniques—standard OLS, the generalized linear model, and lin-
3316 ear mixed effects models—that can be used to model the data result-
3317 ing from randomized experiments (as well as many other kinds of data).

²⁰ Though we should note that these pa-
rameters aren't technically all indepen-
dent from one another due to the struc-
ture of the mixed effect model.

²¹ Many R users may be familiar with
the widely-used `lme4` package for fit-
ting mixed effects models using frequen-
tist tools related to maximum likeli-
hood. Such models can also be fit us-
ing Bayesian inference with the `brms`
package, which provides many powerful
methods for specifying complex models.

²² One particularly problematic situa-
tion is when the correlation structure
of the errors is mis-specified, for exam-
ple if observations within a participant
are more correlated for participants in
the treatment group than in the control
group; in such cases, mixed model esti-
mates can be substantially biased (Bie et
al. 2021).

3318 The advantage of regression models over the simpler estimation and in-
3319 ference methods we described in the prior two chapters is that these
3320 models can more effectively take into account a range of different kinds
3321 of variation including covariates, multiple manipulations, and clustered
3322 structure. Further, when used appropriately to analyze a well-designed
3323 randomized experiment, regression models can give an unbiased esti-
3324 mate of a causal effect of interest, our main goal in doing experiments.

3325 But—practically speaking—how should you about building a model
3326 for your experiment? What covariates should you include and what
3327 should you leave out? There are many ways to use models to explore
3328 datasets, but in this section we will try to sketch a default approach for
3329 the use of models to estimate causal effects in experiments in the most
3330 straightforward way. Think of this as a starting point. We'll begin this
3331 section by giving a set of rules of thumb, then discuss a worked example.
3332 Our final subsections will deal with the issues of when you should in-
3333 clude covariates in your model and how to check if your result is robust
3334 across multiple different model specifications.

 DEPTH

An alternative approach: Generalized estimating equations

A second class of methods that helps resolve issues of clustering is **generalized estimating equations** (GEE). In this approach, we leave the linear predictor alone. We do not add random intercepts or slopes, nor do we assume anything about the distribution of the errors (i.e., we no longer assume that they are normal, independent, and homoskedastic).

In GEE, we instead provide the model with an initial “guess” about how we think the errors might be related to one another; for example, in a repeated-measures experiment, we might guess that the errors are exchangeable, meaning that they are correlated to the same degree within each participant but are uncorrelated across participants. Instead of *assuming* that our guess is correct, as do linear mixed models (LMM), GEE estimates the correlation structure of the errors empirically, using our guess as a starting point, and it uses this correlation structure to arrive at point estimates and inference for the regression coefficients. Remarkably, as the number of clusters and observations become very large, GEE will *always* provide unbiased point estimates and valid inference, *even if* our guess about the correlation structure was bad. Additionally, with simple finite-sample corrections (Mancl and DeRouen 2001), GEE seems to provide valid inference at smaller numbers of clusters than does LMM.

The price paid for these nice safeguards against model misspecification

is that, in principle, GEE will typically have less statistical power than LMM *if* the LMM is in fact correctly specified, but the difference may be surprisingly slight in practice (Bie et al. 2021). For these reasons, some of this book’s authors actually favor GEE with finite-sample corrections over LMM as the default model for clustered data, though they are much less common in psychology.

3336

3337 7.4.1 Modeling rules of thumb

3338 Our approach to statistical modeling is to start with a “default model”
3339 that is known in the literature as a **saturated model**. The saturated model
3340 of an experiment includes the full design of the experiment—all main
3341 effects and interactions—and nothing else. If you are manipulating a
3342 variable, include it in your model. If you are manipulating two, in-
3343 clude them both and their interaction. If your design includes repeated
3344 measurements for participants, include a random effect of participant;
3345 if it includes experimental items for which repeated measurements are
3346 made, include random effect of stimulus.²³

3347 Don’t include lots of other stuff in your default model. You are doing
3348 a randomized experiment, and the strength of randomized experiments
3349 is that you don’t have to worry about confounding based on the popu-
3350 lation (see chapter 1). So don’t put a lot of covariates in your default

Barr et al. 2013

3351 model—usually don’t put in any!²⁴

3352 This default saturated model then represents a simple summary of your
3353 experimental results. Its coefficients can be interpreted as estimates of
3354 the effects of interest, and it can be used as the basis for inferences about
3355 the relation of the experimental effect to the population using either
3356 frequentist or Bayesian tools.

3357 Here’s a bit more guidance about this modeling strategy.

3358 1. **Preregister your model.** If you change your analysis approach af-
3359 ter you see your data, you risk *p*-hacking—choosing an analysis
3360 that biases the estimate of your effect of interest. As we discussed
3361 in chapter 3 and as we will discuss in more detail in chapter 11,
3362 one important strategy for minimizing this problem is to prereg-
3363 ister your analysis.²⁵

3364 2. **Visualize the model predictions against the observed data.** As
3365 we’ll discuss in chapter 15, the “default model” for an experi-
3366 ment should go alongside a “default visualization” known as the
3367 **design plot** that similarly reflects the full design structure of the
3368 experiment and any primary clusters. One way to check whether
3369 a model fits your data is then to plot it on top of those data. Some-
3370 times this combination of model and data can be as simple as a

²⁴ One corollary to having this kind of default perspective on data analysis: When you see an analysis that deviates substantially from the default, these deviations should provoke some questions. If someone drops a manipulation from their analysis, adds a covariate or two, or fails to control for some clustering in the data, did they deviate because of different norms in their sub-field, or was there some other rationale? This line of reasoning sometimes leads to questions about the extent to which particular analytic decisions are post-hoc and driven by the data (in other words, *p*-hacked). For an example, see the case study in chapter 11.

²⁵ A side benefit of preregistration is it makes you think through whether your experimental design is appropriate—that is, is there actually an analysis capable of estimating the effect you want from the data you intend to collect?

3371 scatter plot with a regression line. But seeing the model plotted
3372 alongside the data can often reveal a mismatch between the two.
3373 A model that does not describe the data very well is not a good
3374 source of generalizable inferences!

3375 **3. Interpret the model predictions.** Once you have a model, don't
3376 just read off the *p*-values for your coefficients of interest. Walk
3377 through each coefficient, considering how it relates to your
3378 outcome variable. For a simple two group design like we've been
3379 considering, the condition coefficient is the estimate of the causal
3380 effect that you intended to measure! Consider its sign, its magni-
3381 tude, and its precision (standard error or confidence interval).

3382 That said, there are some contexts in which it does make sense to de-
3383 part from the default saturated model. For example, there may be in-
3384 sufficient statistical power to estimate multiple interaction terms, or co-
3385 variates might be included in the model to help handle certain forms of
3386 missing data. The default model simply represents a very good starting
3387 point.



Figure 7.3
Example stimulus materials analogous
to those used in Stiller, Goodman, and
Frank (2015).

3388 7.4.2 *A worked example*

3389 All this advice may seem abstract, so let's put it into practice on a simple
3390 example. For a change, let's look at an experiment that's not about tea
3391 tasting. Here we'll consider data from an experiment testing preschool
3392 children's language comprehension (Stiller, Goodman, and Frank 2015).

3393 In this experiment, 2–5 year old children saw displays like the one in
3394 figure 7.3. In the experimental condition, a puppet might say, for exam-
3395 ple, “My friend has glasses! Which one is my friend?” The goal was to
3396 measure how many children made the “pragmatic inference” that the
3397 puppet’s friend was the face with glasses and *no* hat.

3398 To estimate the effect, participants were randomly assigned to either the
3399 experimental condition or to a control condition in which the puppet
3400 had eaten too much peanut butter and couldn't talk, but they still had
3401 to guess which face was his friend. There were also three other types
3402 of experimental stimuli (houses, beds, and plates of pasta). Data from
3403 this experiment consisted of 588 total observations from 147 children,
3404 with all four stimuli presented to each child. The primary hypothesis of
3405 this experiment was that that preschool children could make pragmatic
3406 inferences by correctly inferring which of the three faces (for example)
3407 the puppet was describing.

CODE

If you want to follow along with this example, you'll have to load the example data and do a little bit of preprocessing (also covered in appendix D):

```
repo <- "https://raw.githubusercontent.com/langcog/experimentology/main/"

sgf <- read_csv(file.path(repo, "data/tidyverse/stiller_scales_data.csv")) |>

  mutate(age_group = cut(age, 2:5, include.lowest = TRUE),
         condition = condition |>

    fct_recode("Experimental" = "Label", "Control" = "No Label"))
```

3408

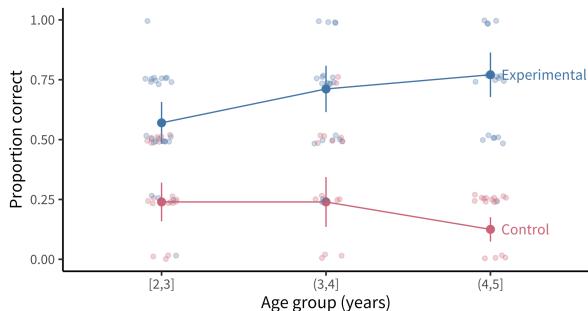


Figure 7.4

Data for Stiller, Goodman, and Frank (2015). Each point shows a single participant's proportion correct trials (out of 4 experimental stimuli) plotted by age group, jittered slightly to avoid overplotting. Larger points and associated confidence intervals show mean and 95% confidence intervals for each condition.

3409 This experimental design looks a lot like some versions of our
 3410 tea-tasting experiment. We have one primary condition manipula-
 3411 tion (the puppet provides information versus does not), presented
 3412 between-participants so that some participants are in the experimental
 3413 condition and others are in the control condition. Our measurements
 3414 are repeated within participants across different experimental stimuli.
 3415 Finally, we have one important, pre-planned covariate: children's age.
 3416 Experimental data are plotted in figure 7.4.²⁶

²⁶ Our sampling plan for this experiment was actually **stratified** across age, meaning that we intentionally recruited the same number of participants for each one-year age group—because we anticipated that age was highly correlated with children's ability to succeed in this task. We'll describe this kind of sampling in more detail in chapter 10.

3417 How should we go about making our default model for this dataset?²⁷

3418 We simply include each of these design factors in a mixed effects model;

3419 we use a logistic link function for our mixed effects model (a **general-**

3420 **ized linear mixed effects model**) because we would like to predict cor-

3421 rect performance on each trial, which is a binary variable. So that gives

3422 us an effect of condition and age as a covariate. We further add an in-

3423 teraction between condition and age in case the condition effect varies

3424 meaningfully across groups. Finally, we add random effects of partici-

3425 pant, γ_i , and experimental item, γ_t .²⁸

3426 The resulting model looks like this:

$$\text{logit}(E[Y_{it}]) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i1}X_{i2} + \gamma_i + \delta_t$$

3427 Let's break this complex equation down left to right:

- 3428 – $\text{logit}(E[Y_{it}])$ says that we are predicting a logistic function of
- 3429 $E[Y_{it}]$ (where Y_{it} indicates whether child i was correct on trial
- 3430 t).
- 3431 – β_0 is the **intercept**, our estimate of the average log-odds (i.e., the
- 3432 log of the odds ratio) of correct responses for participants in the
- 3433 control condition.
- 3434 – $\beta_1 X_{i1}$ is the condition predictor. β_1 represents the change in log-
- 3435 odds associated with being in the experimental condition (the

²⁷ This experiment was not preregistered, but the paper includes a separate replication dataset with the same analysis.

²⁸ As discussed above, this is a tricky decision-point; we could very reasonably have added random slopes as well.

causal effect of interest!), and X_{i1} is an indicator variable that is 1 if child i is in the experimental condition and 0 for the control condition. Multiplying β_1 by this indicator means that the predictor has the value 0 for participants in the control condition and β_1 for those in the experimental condition.

- $\beta_2 X_{i2}$ is the age predictor. β_2 represents the difference in log odds associated with one additional year of age for participants in the control condition[The age coefficient is a **simple effect**, meaning it is the effect of age in the control condition only. That's because we have dummy coded the condition predictor. If we wanted the average age effect (the **main effect**) then we would need to use contrast coding, per the note in the Interactions section above.], and X_{i2} is the age for each participant.²⁹
- $\beta_3 X_{i1} * X_{i2}$ is the interaction between experimental condition and age. β_3 represents the difference in log odds (i.e., the log of the odds ratio) that is associated with being one year older *and* in the experimental condition versus the control condition. This term is multiplied by both each child's age *and* the condition indicator X_i .
- γ_i is the random intercept for participant i , capturing individual variation in the odds of success across trials.
- γ_t is the random intercept for stimulus t , capturing variation in

²⁹ We have centered our age predictor in this example so that all estimates from our model are for the average age of our participants. Centering is a good practice for modeling continuous predictors because it increases the interpretability of other parts of the model. For example, because age is centered in this model, the intercept β_0 can be interpreted as the predicted odds of a correct trial for a participant in the control condition at the average age.

3458 the odds of success across the four different stimuli.

Table 7.2

Estimated effects for our generalized linear mixed effects model on data from Stiller, Goodman, and Frank (2015).

term	estimate	conf.int	statistic	p.value
Control condition	0.80	[0.42, 1.18]	4.16	< .001
Age (years)	0.55	[0.21, 0.88]	3.19	.001
Expt condition	-2.26	[-2.70, -1.82]	-10.07	< .001
Age (years) * Expt condition	-0.92	[-1.43, -0.42]	-3.60	< .001

CODE

To fit the model described above, the first step is to prepare your predictors. In this case, we center the age predictor.

```
sgf$age_centered <- scale(sgf$age, center = TRUE, scale = FALSE)
```

Again we use the `lme4` package, this time with the `glmer()` function.

Again we have to specify our link function, just like in a standard GLM, by choosing the distribution family.

```
mod <- glmer(correct ~ age_centered * condition + (1|subid) + (1|item),
               family = "binomial", data = sgf)
```

You can see a summary of the fitted model using `summary(mod)` as before.

The only big difference from `lm()` is that here you can extract both fixed and random effects (with `fixef(mod)` and `ranef(mod)` respectively).

3459

3460 Let's estimate this model and see how it looks. We'll focus here on

3461 interpretation of the so-called **fixed effects** (the main predictors), as op-
 3462 posed to the participant and item random effects.³⁰ table 7.2 shows the
 3463 coefficients. Again, let's walk through each.

3464 – The **intercept** (control condition estimate) is $\hat{\beta} = 0.80$, 95% CI
 3465 $[0.42, 1.18]$, $z = 4.16$, $p < .001$. This estimate reflects that the

3466 log-odds of a correct response for an average-age participant in
 3467 the control condition is 0.8, which corresponds to a probability
 3468 of 0.69. If we look at figure 7.4, that estimate makes sense: 0.69
 3469 seems close to the average for the control condition.

3470 – The **age effect** estimate is $\hat{\beta} = 0.55$, 95% CI $[0.21, 0.88]$, $z = 3.19$,
 3471 $p = .001$. This means there is a slight decrease in the log-odds
 3472 of a correct response for older children in the control condition.

3473 Again, looking at figure 7.4, this estimate is interpretable: we see a
 3474 small decline in the probability of a correct response for the oldest
 3475 age group.

3476 – The key experimental condition estimate then is $\hat{\beta} = -2.26$, 95%
 3477 CI $[-2.70, -1.82]$, $z = -10.07$, $p < .001$. This estimate means
 3478 that the log-odds of a correct response for an average-age partic-
 3479 ipant in the experimental condition is the sum of the estimates
 3480 for the control (intercept) and the experimental conditions: 0.8
 3481 + -2.26, which corresponds to a probability of 0.19. Grounding

³⁰ Participant means are estimated to have a standard deviation of 0.23 (in log-odds) while items have a standard deviation of 0.27. These indicate that both of our random effects capture meaningful variation.

3482 our interpretation in figure 7.4, this estimate corresponds to the
3483 average value for the experimental condition.

3484 – Finally, the interaction of age and condition is $\hat{\beta} = -0.92$, 95% CI
3485 $[-1.43, -0.42]$, $z = -3.60$, $p < .001$. This positive coefficient
3486 reflects that with every year of age, the difference between control
3487 and experimental conditions grows.

3488 In sum, this model suggests that there was a substantial difference in
3489 performance between experimental and control conditions, in turn sup-
3490 porting the hypothesis that children in the sampled age group can per-
3491 form pragmatic inferences above chance.

3492 This example illustrates the “default saturated model” framework that
3493 we recommend—the idea that a single regression model corresponding
3494 to the design of the experiment can yield an interpretable estimate of
3495 the causal effect of interest, even in the presence of other sources of
3496 variation.

 DEPTH

When does it makes sense to include covariates in a model?

Let's come back to one piece of advice that we gave above about making a "default" model of an experiment: not including covariates. This advice can seem surprising. Many demographic factors are of interest to psychologists and other behavioral scientists, and in observational studies these factors will almost always be related to important life outcomes. So why not put them into our experimental models? After all, we did include age in our worked example above!

Well, if you have one or at most a small handful of covariates that you believe are meaningfully related to the outcome, you *can* plan in advance to put them in your model. If you think that your effect is likely to be moderated by a specific demographic characteristic—as we did with age in our developmental example above—then this inclusion can be quite useful.

Further, including covariates can increase the precision of your estimates by reducing "noise" in your outcome, if you hypothesize that they interact. What's surprising though is how *little* this adjustment does to increase your overall precision unless the correlation between covariate and outcome is very strong.

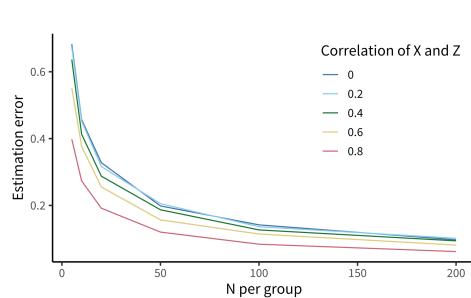


Figure 7.5

Decreases in estimation error due to adjusting for covariates, plotted by the N participants in each group and the correlation between the outcome (X) and the covariate (Z).

figure 7.5 shows the results of a simple simulation investigating the relationship between estimation error and the inclusion of covariates. Only when the correlation between covariate and outcome (e.g., age and tea rating) is greater than $r = 0.6$ to $r = 0.8$ does this adjustment really help.

That said, there are quite a few reasons not to include covariates. These motivate our recommendation to skip them in your default model unless you have very strong theory-based expectations for either (A) a correlation with the outcome or (B) a strong moderation relationship.

The first reason not to include covariates is simply because we don't need to. Because randomization cuts causal links, our experimental estimate is an unbiased estimate of the causal effect of interest (at least for large samples). We are guaranteed that, in the limit of many different experiments, even though people with different ages will be in the different tea tasting conditions, this source of variation will be averaged out. Actually, including unnecessary covariates into models (slightly) decreases the probability that the model can detect a true effect (that is, it decreases statistical pre-

cision and power). Just by chance, covariates can “soak up” variation in the outcome, leaving less to be accounted for by the true effect!

The second reason is that you can actually compromise your causal inference by including some covariates, particularly those that are collected *after* randomization. The logic of randomization is that you cut all causal links between features of the sample and the condition manipulation. But you can “uncut” these links by accident by adding variables into your model that are related to group status. This problem is generically called **conditioning on post-treatment variables** and a full discussion of is out of the scope of this book, but it’s something to avoid (and read up on if you’re worried about it, see [Montgomery, Nyhan, and Torres 2018](#)).

Finally, one of the standard justifications for adding covariates—because your groups are unbalanced—is actually ill-founded as well. People often talk about “unhappy randomization”: you randomize to the different tea-tasting groups, for example, but then it turns out the mean age is a bit different between groups. Then you do a *t*-test or some other statistical test and find out that you actually have a significant age difference. This practice makes no sense! Because you randomized, you know that the difference in ages occurred by chance. Further, incidental demographic differences between groups are unlikely to be important unless that characteristic is highly correlated with the outcome (see above). Instead, if the sample size is small enough that meaningfully large incidental differences could arise in important confounders, then it is preferable to **stratify** on that confounder at the outset—we’ll have lot more to say about this issue

in chapter 10.

So these are our options: if a covariate is known to be very strongly related to our outcome, we can include it in our default model. Otherwise, we avoid a lot of trouble by leaving covariates out.

3500

3501 7.4.1 Robustness checks and the multiverse

3502 Using the NHST statistical testing approach that has been common in
3503 the psychology literature, even a simple two factor experimental de-
3504 sign affords a host of different t -tests and ANOVAs,³¹ offering many op-
3505 portunities for p -hacking and selective reporting. We've been advocat-
3506 ing here instead for a "default model" approach in which you pre-plan
3507 and pre-register a single regression model that captures the planned fea-
3508 tures of your experimental design including manipulations and sources
3509 of clustering. This approach can help you to navigate some of the com-
3510 plexity of data analysis by having a standard approach that you take in
3511 almost every case.

3512 Not every dataset will be amenable to this approach, however. For
3513 complex experimental designs or unusual measures, sometimes it can
3514 be hard to figure out how to specify or fit the default saturated model.
3515 And especially in these cases, the choice of model can make a big differ-
3516 ence to the magnitude of the reported effect. To quantify variability in

3517 effect size due to model choice, “Many Analysts” projects have asked a
3518 set of teams to approach a dataset using different analysis methods. The
3519 result from these projects has been that there is substantial variability in
3520 outcomes depending on what approach is taken (Silberzahn et al. 2018;
3521 Botvinik-Nezer et al. 2020).³²

3522 **Robustness analysis** (also sometimes called “sensitivity analysis” or
3523 “multiverse analysis”, which sounds cooler) is a technique for address-
3524 ing the possibility that an individual analysis over- or under-estimates
3525 a particular effect by chance (Steegen et al. 2016). The general idea
3526 is that analysts explore a space of different possible analyses. In its
3527 simplest form, alternative model specifications can be reported in a
3528 supplement; more sophisticated versions of the idea call for averaging
3529 estimates across a range of possible specifications and reporting this
3530 average as the primary effect estimate.

3531 The details of this kind of analysis will vary depending on what you
3532 are worried about your model being sensitive to. One analyst might
3533 be concerned about the effects of adding different covariates; another
3534 might be using a Bayesian framework and be concerned about sensitivity
3535 to particular prior values. If you get similar results across many different
3536 specifications, you can sleep better at night. The primary principle to
3537 take home is a bit of humility about our models. Any given model is

³² To be fair, often the analytic questions being investigated in “Many Analysts” projects are more complex than the simple experiments we recommend doing, and there is debate about how much true variability these investigations reveal (Breznau et al. 2022; Mathur, Covington, and VanderWeele 2023).

3538 likely wrong in some of its details. Investigating the sensitivity of your
3539 estimates to the details of your model specification is a good idea.

3540 *7.5 Chapter summary: Models*

3541 In the last three chapters, we have spelled out a framework for data
3542 analysis that focuses on our key experimental goal: a measurement of a
3543 particular causal effect. We began with basic techniques for estimat-
3544 ing effects and making inferences about how these effects estimated
3545 from a sample can be generalized to a population. This chapter showed
3546 how these ideas naturally give rise to the idea of making models of
3547 data, which allow estimation of effects in more complex designs. Sim-
3548 ple regression models, which are formally identical to other inference
3549 methods in the most basic case, can be extended with the generalized
3550 linear model as well as with mixed effects models. Finally, we ended
3551 with some guidance on how to build a “default model”—an (often pre-
3552 registered) regression model that maps onto your experimental design
3553 and provides the primary estimate of your key causal effect.



DISCUSSION QUESTIONS

1. Choose a paper that you have read for your research and take a look at the statistical analysis. Does the reporting focus more on hypothesis

testing or on estimating effect sizes?

2. We focused here on the linear model as a tool for building models, contrasting this perspective with the common “statistical testing” mindset. But—here’s the mind-blowing thing—most of those statistical tests are special cases of the linear model anyway. Take a look at this extended meditation on the equivalences between tests and models: https://lindeloev.github.io/tests-as-linear/#9_teaching_materials_and_a_course_outline. If the paper you chose for question 1 used tests, could their tests be easily translated to models? How would the use of a model-based perspective change the results section of the paper?
3. Take a look at this cool visualization of hierarchical (mixed effect) models: <http://mfviz.com/hierarchical-models/>. In your own research, what are the most common units that group together your observations?

3555

READINGS

- An opinionated practical guide to regression modeling and data description: Gelman, A., Hill, J., & Vehtari, A. (2020). *Regression and other stories*. Cambridge University Press. Free online at <https://avehtari.github.io/ROS-Examples/>.
- A more in-depth introduction to the process of developing Bayesian models of data that allow for estimation and inference in complex

3556

datasets: McElreath, R. (2020). *Statistical rethinking: A Bayesian course with examples in R and Stan*. Chapman and Hall/CRC. Free materials available at <https://xcelab.net/rm/statistical-rethinking/>.

III

3558

PLANNING

3559

³⁵⁶⁰ *References*

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8 MEASUREMENT

3563

LEARNING GOALS

- Discuss the reliability and validity of psychological measures
- Reason about tradeoffs between different measures and measure types
- Identify the characteristics of well-constructed survey questions
- Articulate risks of measurement flexibility and the costs and benefits of multiple measures

3564

3565 In the previous section of the book, we described a set of measurement-focused statistical techniques for quantifying (and maximizing) our pre-cision. In this next set of three chapters focusing on planning experiments, we will develop our toolkit for designing the measures (this chapter), design manipulations (chapter 9), and sampling (chapter 10) strategies that will allow us to create and evaluate experiments. These chapters form a core part of our approach to “experimentology”: a set of decisions to REDUCE BIAS, maximize MEASUREMENT PRECISION, and assess GENERALIZABILITY. Let’s begin with measurement.

Throughout the history of science, advances in measurement have gone hand in hand with advances in knowledge.¹ Telescopes revolutionized astronomy, microscopes revolutionized biology, and patch clamping revolutionized physiology. But measurement isn't easy. Even the humble thermometer, allowing reliable measurement of temperature, required centuries of painstaking effort to perfect (Chang 2004). Psychology and the behavioral sciences are no different—we need reliable instruments to measure the things we care about. In this next section of the book, we're going to discuss the challenges of measurement in psychology, and the properties that distinguish good instruments from bad.

What does it mean to measure something? Intuitively, we know that a ruler measures the quantity of length, and a scale measures the quantity of mass (Kisch 1965). As we discussed in chapter 2, those quantities are latent (unobserved). Individual measurements, in contrast, are manifest: they are observable to us. What does it mean to measure a psychological construct—a hypothesized theoretical quantity inside the head?

We first have to keep in mind that not every measure is equally precise. This point is obvious when you think about physical measurement instruments: a caliper will give you a much more precise estimate of thickness than a ruler will. One way to see that the measurement is more

¹ As such, measurement is a perennially controversial topic in philosophy of science. For an overview of competing frameworks, see Tal (2020) or Maul, Irribarra, and Wilson (2016), which focuses specifically on measurement in psychology.

3595 precise is by repeating it a bunch of times. The measurements from the
3596 caliper will likely be more similar to one another, reflecting the fact that
3597 the amount of error in each individual measurement is smaller. We can
3598 do the same thing with a psychological measurement—repeat and assess
3599 variation—though as we’ll see below it’s a little trickier. Measurement
3600 instruments that have less error are called more **reliable** instruments.²

3601 Second, psychological measurements do not directly reflect latent the-
3602 oretical constructs of interest, quantities like happiness, intelligence, or
3603 language processing ability. And unlike quantities like length and mass,
3604 there is often disagreement in psychology about what the right theore-
3605 tical quantities are. Thus, we have to measure an observable behavior—
3606 our operationalization of the construct—and then make an argument
3607 about how the measure relates to a proposed construct of interest (and
3608 sometimes whether the construct really exists at all!). This argument is
3609 about the **validity** of our measurements.³

3610 These two concepts, reliability and validity, provide a conceptual toolkit
3611 for assessing a psychological measurement and how well it serves the
3612 researcher’s goal.

² Is reliability the same as **precision**? Yes, more or less. Confusingly, different fields call these concepts different things (there’s a helpful table of these names in [Brandmaier et al. 2018](#)). Here we’ll talk about reliability as a property of instruments specifically while using the term precision to talk about the measurements themselves.

³ We are also going to talk in chapter 9 about the validity of manipulations. The way you identify a causal effect on some measure is by operationalizing some construct as well. To identify causal effects, we must link a particular construct of interest to something we can concretely manipulate in an experiment, like the stimuli or instructions.

3613 **8.1 Reliability**

3614 Reliability is a way of describing the extent to which a measure yields
3615 signal relative to noise. Intuitively, if there's less noise, then there will be
3616 more similarity between different measurements of the same quantity,
3617 illustrated in figure 8.1 as a tighter grouping of points on the bulls-eye.

3618 But how do we measure signal and noise?

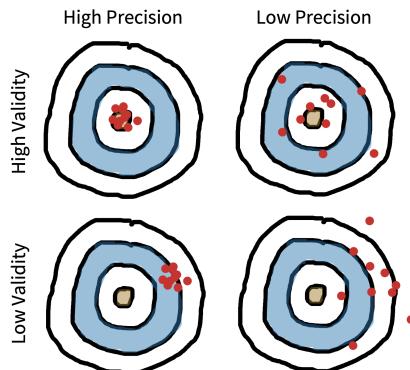


Figure 8.1
 Reliability and validity visualized. The reliability of an instrument is its expected precision. The bias of measurements from an instrument also provide a metaphor for its validity.

 **CASE STUDY**

A reliable and valid measure of children's vocabulary

Anyone who has worked with little children, or had children of their own, can attest to how variable their early language is. Some children speak clearly and produce long sentences from an early age, while others struggle; this variation appears to be linked to later school outcomes (Marchman and Fernald 2008). Thus, there are many reasons why you'd want to make precise measurements of children's early language ability as a latent construct of interest.

Because bringing children into a lab can be expensive, one popular alter-

native option for measuring child language is the MacArthur Bates Communicative Development Inventory (CDI for short), a form which asks parents to mark words that their child says or understands. CDI forms are basically long checklists of words. But is parent report a reliable or valid measure of children's early language?

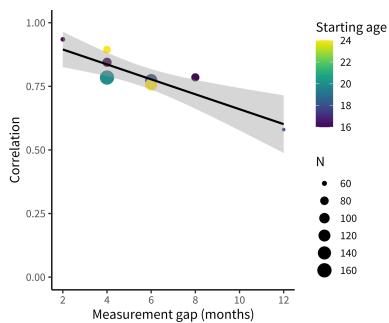


Figure 8.2
Longitudinal (test-retest) correlations between a child's score on one administration of the CDI and another one several months later. Based on Frank et al. (2021).

As we'll see below, one way to measure the reliability of the CDI to compute the correlation between two different administrations of the form for the same child. Unfortunately, this analysis has one issue: the longer you wait between observations the more the child has changed! figure 8.2 displays these correlations for two CDIs, showing how correlations start off high and drop off as the gap between observations increases (Frank et al. 2021).

Given that CDI forms are relatively reliable instruments, are they valid? That is, do they really measure the construct of interest, namely children's early language ability? Bornstein and Haynes (1998) collected many different measures of children's language—including the ELI (an early CDI

form) and other “gold standard” measures like transcribed samples of children’s speech. CDI scores were highly correlated with all the different measures, suggesting that the CDI was a valid measure of the construct.

The combination of reliability and validity evidence suggests that CDIs are a useful (and relatively inexpensive source) of data about children’s early language, and indeed they have become one of the most common assessments for this age group!

3622 8.1.1 Measurement scales

3623 In the physical sciences, it's common to measure the precision of an
 3624 instrument using its coefficient of variation (Brandmaier et al. 2018):

$$CV = \frac{\sigma_w}{\mu_w}$$

3625 where σ_w is the standard deviation of the measurements within an in-
 3626 dividual and μ_w is the mean of those measurements (figure 8.3).

3627 Imagine we measure the height of a person five times, resulting in mea-
 3628 surements of 171cm, 172cm, 171cm, 173cm, and 172cm. These are the
 3629 combination of the person's true height (we assume they have one!) and
 3630 some **measurement error**. Now we can use these measurements to com-
 3631 pute the coefficient of variation, which is 0.005, suggesting very limited
 3632 variability relative to the overall quantity being measured. Why can't
 3633 we just do this same thing with psychological measurements?

3634 Thinking about this question takes us on a detour through the differ-
 3635 ent kinds of measurement scales used in psychological research (Stevens
 3636 1946). The height measurements in our example are on what is known
 3637 as a **ratio scale**: a scale in which numerical measurements are equally
 3638 spaced and on which there is a true zero point. These scales are com-
 3639 mon for physical quantities but somewhat less frequent in psychology
 3640 (with reaction times as a notable exception). More common are **interval**

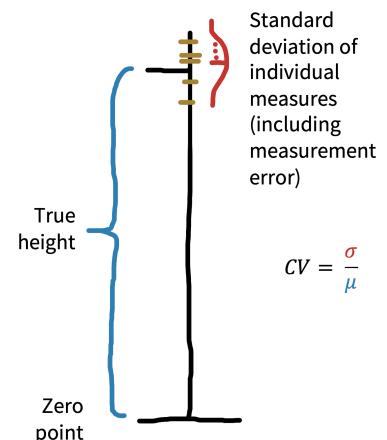
Measuring reliability with a true zero

Figure 8.3
 Computing the coefficient of variation (CV).

3641 scales, in which there is no true zero point. For example, IQ (and other
 3642 standardized scores) are intended to capture interval variation on some
 3643 dimension but 0 is meaningless—an IQ of 0 does not correspond to any
 3644 particular interpretation.

3645 **Ordinal** scales are also often used. These are scales that are ordered but
 3646 are not necessarily spaced equally. For example, levels of educational
 3647 achievement (“Elementary”, “High school”, “Some college”, “Col-
 3648 lege”, “Graduate school”) are ordered, but there is no sense in which
 3649 “High school” is as far from “Elementary” as “Graduate school” is
 3650 from “College.” The last type in Stevens’ hierarchy is **nominal** scales, in
 3651 which no ordering is possible either. For example, race is an unordered
 3652 scale in which multiple categories are present but there is no inherent
 3653 ordering of these categories. The hierarchy is shown in table 8.1.

Table 8.1
 Scale types and their associated operations and statistics (Stevens 1946).

Scale	Definition	Operations	Statistics
Nominal	Unordered list	Equality	Mode
Ordinal	Ordered list	Greater than or less than	Median
Interval	Numerical	Equality of intervals	Mean, SD
Ratio	Numerical & zero.	Equality of ratios	Coefficient of variation

3654 Critically, different summary measures work for each scale type. If you
 3655 have an unordered list like a list of options for a question about race on

It can actually be shown in a suitably
 rigorous sense that ratio and interval
 scales (and another lying in between)
 are the *only* scales possible for the real

3656 a survey, you can present the modal response (the most likely one). It
3657 doesn't even make sense to think about what the median was—there's
3658 no ordering! For ordered levels of education, a median is possible but
3659 you can't compute a mean. And for interval variables like “number of
3660 correct answers on a math test” you can compute a mean and a standard
3661 deviation.⁴

3662 Now we're ready to answer our initial question about why we can't
3663 quantify reliability using the coefficient of variation. Unless you have a
3664 ratio scale with a true zero, you can't compute a coefficient of variation.
3665 Think about it for IQ scores: currently, by convention, standardized IQ
3666 scores are set to have a mean of 100. If we tested someone multiple
3667 times and found the standard deviation of their test scores was 4 points,
3668 then we could estimate the precision of their measurements as “CV” of
3669 $4/100 = .04$. But since IQ of 0 isn't meaningful, we could just set the
3670 mean IQ for the population to 200. Our test would be the same, and
3671 so the CV would be $4/200 = .02$. On that logic we just doubled the
3672 precision of our measurements by rescaling the test! That doesn't make
3673 any sense.

⁴ You might be tempted to think that “number of correct answers” is a ratio variable—but is zero really meaningful? Does it truly correspond to “no math knowledge” or is it just a stand-in for “less math knowledge than this test requires”?

 DEPTH

Early controversies over psychological measurement

“Psychology cannot attain the certainty and exactness of the physical sciences, unless it rests on a foundation of [...] measurement” ([Cattell 1890](#)).

It is no coincidence that the founders of experimental psychology were obsessed with measurement ([Heidelberger 2004](#)). It was viewed as the primary obstacle facing psychology on its road to becoming a legitimate quantitative science. For example, one of the final pieces written by Hermann von Helmholtz (Wilhelm Wundt’s doctoral advisor), was a 1887 philosophical treatise entitled “Zahlen und Messen” (“Counting and Measuring,” see [Darrigol 2003](#)). In the same year, Fechner ([1987](#)) explicitly grappled with the foundations of measurement in “Über die psychischen Massprincipien” (“On Psychic Measurement Principles”).

Many of the early debates over measurement revolved around the emerging area of *psychophysics*, the problem of relating objective, physical stimuli (e.g. light, sound, pressure) to the subjective sensations they produce in the mind. For example, Fechner ([1860](#)) was interested in a quantity called the “just noticeable difference”, the smallest change in a stimulus that can be discriminated by our senses. He argued for a lawful (logarithmic) relationship: a logarithmic change in the intensity of, say, brightness corresponded to a linear change in the intensity people reported (up to some constant). In other words, sensation was *measurable* via instruments

like just noticeable difference.

It may be surprising to modern ears that the basic claim of measurability was controversial, even if the precise form of the psychophysical function would continue to be debated. But this claim led to a deeply rancorous debate, culminating with the so-called Ferguson Committee, formed by the British Association for the Advancement of Science in 1932 to investigate whether such psychophysical procedures could count as quantitative ‘measurements’ of anything at all (Moscati 2018). It was unable to reach a conclusion, with physicists and psychologists deadlocked:

Having found that individual sensations have an order, they [some psychologists] assume that they are *measurable*. Having travestied physical measurement in order to justify that assumption, they assume that their sensation intensities will be related to stimuli by numerical laws [...] which, if they mean anything, are certainly false. (Ferguson et al. 1940)

The heart of the disagreement was rooted in the classical definition of quantity requiring strictly *additive* structure. An attribute was only considered measurable in light of a meaningful concatenation operation. For example, weight was a measurable attribute because putting a bag of three rocks on a scale yields the same number as putting each of the three rocks on separate scales and then summing up those numbers (in philosophy of science, attributes with this concatenation property are known as “extensive” attributes, as opposed to “intensive” ones). Norman Campbell,

one of the most prominent members of the Ferguson Committee, had recently defined *fundamental measurement* in this way (e.g., Campbell 1928), contrasting it with *derived measurement*, which involved computing some function based on one or more fundamental measures. According to the physicists on the Ferguson Committee, measuring mental sensations was impossible because they could never be grounded in any *fundamental scale* with this kind of additive operation. It just didn't make sense to break up people's sensations into parts the way we would weights or lengths: they didn't come in "amounts" or "quantities" that could be combined (Catell 1962). Even the intuitive additive logic of Donders (1868/1969)'s "method of subtraction" for measuring the speed of mental processes was viewed skeptically on the same grounds by the time of the committee (e.g., in an early textbook, Woodworth (1938) claimed "we cannot break up the reaction into successive acts and obtain the time for each act.")

The primary target of the Ferguson Committee's investigation was the psychologist S. S. Stevens, who had claimed to measure the sensation of loudness using psychophysical instruments. Exiled from classical frameworks of measurement, he went about developing an alternative "operational" framework (Stevens 1946), where the classical ratio scale recognized by physicists was only one of several ways of assigning numbers to things (see table 8.1 above). Stevens' framework quickly spread, leading to an explosion of proposed measures. However, operationalism remains controversial outside psychology (Michell 1999). The most extreme version of Steven's stance ("measurement is the assignment of numerals to

objects or events according to rule") permits researchers to *define* constructs operationally in terms of a measure (Hardcastle 1995). For example, one may say that the construct of intelligence is simply *whatever it is* that IQ measures. It is then left up to the researcher to decide which scale type their proposed measure should belong to.

In chapter 2, we outlined a somewhat different view, closer to a kind of constructive realism (Giere 2004; Putnam 2000). Psychological constructs like happiness are taken to exist independent of any given operationalization, putting us on firmer ground to debate the pros and cons associated with different ways of measuring the same construct. In other words, we are not free to assign numbers however we like. Whether a particular construct or quantity *is measurable* on a particular scale should be treated as an empirical question.

The next major breakthrough in measurement theory emerged with the birth of mathematical psychology in the 1960s, which aimed to put psychological measurement on more rigorous foundations. This effort culminated in the three-volume Foundations of Measurement series (Krantz et al. 1971; Suppes et al. 1989; Robert Duncan Luce et al. 1990), which has become the canonical text for every psychology student seeking to understand measurement in the non-physical sciences. One of the key breakthroughs was to shift the burden from measuring (additive) constructs themselves to measuring (additive) *effects* of constructs in conjunction with one another:

When no natural concatenation operation exists, one should try to discover a way to measure factors and responses such that the ‘effects’ of different factors are additive. (R. Duncan Luce and Tukey 1964).

This modern viewpoint broadly informs the view we describe here.

3678

3679 8.1.1 *Measuring reliability*

3680 So then how do we measure signal and noise when we don’t have a true
3681 zero? We can still look at the variation between repeated measurement,
3682 but rather than comparing that variation between measurements to the
3683 mean, we can compare it to some other kind of variation, for exam-
3684 ple, variation between people. In what follows, we’ll discuss reliability
3685 on interval scales, but many of the same tools have been developed for
3686 ordinal and nominal scales.

3687 Imagine that you are developing an instrument to measure some cogni-
3688 tive ability. We assume that every participant has a true ability, t , just
3689 the same way that they have a true height in the example above. Ev-
3690 ery time we measure this true ability with our instrument, however, it
3691 gets messed up by some measurement error. Let’s specify that error is
3692 normally distributed with a mean of zero—so it doesn’t bias the mea-
3693 surements, it just adds noise. The result is our observed score, o .⁵

3694 Taking this approach, we could define a relative version of the coefficient
3695 of variation. The idea is that the reliability of a measurement is
3696 the amount of variance attributable to the true score variance (signal),
3697 rather than the observed score variance (which includes noise). If σ_t^2 is
3698 the variance of the true scores and σ_o^2 is the variance of the observed
3699 scores, then this ratio is:

$$R = \frac{\sigma_t^2}{\sigma_o^2}.$$

3700 When noise is high, then the denominator is going to be big and R will
3701 go down to 0; when noise is low, the numerator and the denominator
3702 will be almost the same and R will approach 1.

3703 This all sounds great, except for one problem: we can't compute re-
3704 liability using this formula without knowing the true scores and their
3705 variance. But if we did, we wouldn't need to measure anything at all!

3706 There are two main approaches to computing reliability from data.
3707 Each of them makes an assumption that lets you circumvent the
3708 fundamental issue that we only have access to observed scores and not
3709 true scores. Let's think these through in the context of a math test.

3710 **Test-retest reliability.** Imagine you have two parallel versions of your
3711 math test that are the same difficulty. Hence, you think a student's score
3712 on either one will reflect the same true score, modulo some noise. In

3713 that case, you can use these two sets of observed scores (o_1 and o_2) to
 3714 compute the reliability of the instrument by simply computing the cor-
 3715 relation between them (ρ_{o_1, o_2}). The logic is that, if both variants reflect
 3716 the same true score, then the shared variance (covariance in the sense of
 3717 chapter 5) between them is just σ_t^2 , the true score variance, which is the
 3718 variable that we wanted but didn't have. Test-retest reliability is thus a
 3719 very convenient way to measure reliability (figure 8.4).

3720 **Internal reliability.** If you don't have two parallel versions of the test, or
 3721 you can't give the test twice for whatever reason, then you have another
 3722 option. Assuming you have multiple questions on your math test (which
 3723 is a good idea!), then you can split the test in pieces and treat the scores
 3724 from each of these sub-parts as parallel versions. The simplest way to
 3725 do this is to split the instrument in half and compute the correlation
 3726 between participants' scores on the two halves—this quantity is called
 3727 **split half reliability**.⁶

3728 Another method for computing the internal reliability (the **consistency**
 3729 of a test) is to treat each test item as a sub-instrument and compute
 3730 the average split-half correlation over all splits. This method yields the
 3731 statistic **Cronbach's α** ("alpha"). α is a widely reported statistic, but it
 3732 is also widely misinterpreted (Sijtsma 2009). First, it is actually a lower
 3733 bound on reliability rather than a good estimate of reliability itself. And

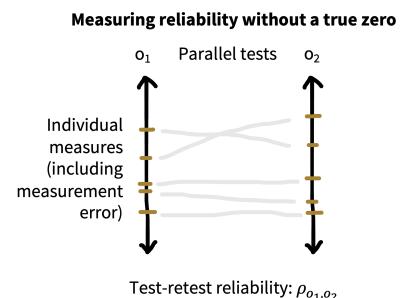


Figure 8.4
Computing test-retest reliability.

⁶ The problem is that each half is... half as long as the original instrument. To get around this, there is a correction called the Spearman-Brown correction that can be applied to estimate the expected correlation for the full-length instrument. You also want to make sure that the test doesn't get harder from the beginning to the end. If it does, you may want to use the even-numbered and odd-numbered questions as the two parallel versions.

3734 second, it is often misinterpreted as evidence that an instrument yields
3735 scores that are “internally consistent,” which it does not; it’s not an ac-
3736 curate summary of dimensionality. α is a standard statistic, but it should
3737 be used with caution.

3738 One final note: these tools often get used for observers’ ratings of the
3739 same stimulus (**inter-rater or inter-annotator reliability**), say for exam-
3740 ple when you have two coders rate how aggressive a person seems in a
3741 video. The most common measure of inter-annotator agreement is a
3742 categorical measure called **Cohen’s κ** (“kappa”), for categorical agree-
3743 ment, but you can use **intra-class correlation coefficients** (see Depth box
3744 below) for continuous data as well as many other measures.

⊕ DEPTH

Reliability paradoxes!

There’s a major issue with calculating reliabilities using the approaches we described here: because reliability is defined as a ratio of two measures of variation, it will always be relative to the variation in the sample. So if a sample has less variability, reliability will decrease!

One way to define reliability formally is by using the intra-class correlation coefficient (ICC):

$$ICC = \frac{\sigma_b^2}{\sigma_w^2 + \sigma_b^2}$$

where σ_w^2 is the within-subject variance in measurements and σ_b^2 is the

between-subject variance in the measurements. (The denominator of the ICC comes from partitioning the total observed variance σ_o^2 in the reliability formula above).

So now instead of comparing variation to the mean, we're comparing variation on one dimension (between person) to total variation (within and between person). ICCs are tricky and there are several different flavors available depending on the structure of your data and what you're trying to do with them. McGraw and Wong (1996) and Gwet (2014) provide extensive guidance on how to compute and interpret this statistic in different situations.

Let's think about the CDI data in our case study, which showed high reliability. Now imagine we restricted our sample to only change scores between 16–18-month-olds (our prior sample had 16–30-month-olds). Within this more restricted subset, overall vocabularies would be lower and more similar to one another, and so the average amount of change *within* a child (σ_w) would be larger relative to the differences *between* children (σ_b). That would make our reliability go *down*, even though we would be computing it on a subset of the exact same data.

That doesn't sound so bad. But we can construct a much more worrisome version of the same problem. Say we are very sloppy in our administration of the CDI and create lots of between-participants variability, perhaps by giving different instructions to different families. This practice will actually *increase* our estimate of split-half reliability (by increasing

σ_b). While the within-participant variability will remain the same, the between-participant variability will go up! You could call this a “reliability paradox”—sloppier data collection can actually lead to higher reliabilities.

We need to be sensitive to the sources of variability we’re quantifying reliability over—both the numerator and the denominator. If we’re computing split-half reliabilities, typically we’re looking at variability across test questions (from some question bank) vs. across individuals (from some population). Both of these sampling decisions affect reliability—if the population is more variable *or* the questions are less variable, we’ll get higher reliability. In sum, *reliability is relative*: reliability measures depend on the circumstances in which they are computed.

3747

3748 8.1.1 Practical advice for computing reliability

3749 If you don’t know the reliability of your measures for an experiment,

3750 you risk wasting your and your participants’ time. Ignorance is not bliss.

3751 A higher reliability measure will lead to more precise measurements of

3752 a causal effect of interest and hence smaller required sample sizes.

3753 Test-retest reliability is generally the most conservative practical mea-

3754 sure of reliability. Test-retest estimates include not only measurement

3755 error but also participants’ state variation across different testing sessions

3756 and variance due to differences between versions of your instrument.

3757 These real-world quantities are absent from internal reliability estimates,
3758 which may make you erroneously think that there is more signal present
3759 in your instrument than there is.⁷ It's hard work to measure test-retest
3760 reliability estimates, in part because you need two different versions of a
3761 test (to avoid memory effects). If you plan on using an instrument more
3762 than once or twice, though, it will likely be worthwhile!

3763 Finally, if you have multiple measurement items as part of your instru-
3764 ment, make sure you evaluate how they contribute to the reliability
3765 of the instrument. Perhaps you have several questions in a survey that
3766 you'd like to use to measure the same construct; perhaps multiple exper-
3767 imental vignettes that vary in content or difficulty. Some of these items
3768 may not contribute to your instrument's reliability—and some may even
3769 detract. At a bare minimum, you should always visualize the distribu-
3770 tion of responses across items to scan for **floor and ceiling effects**—when
3771 items always yield responses bunched at the bottom or top of the scale,
3772 limiting their usefulness—and take a look at whether there are particu-
3773 lar items on which items do not relate to the others.

3774 If you are thinking about developing an instrument that you use repeat-
3775 edly, it may be useful to use more sophisticated psychometric models
3776 to estimate the dimensionality of responses on your instrument as well
3777 as the properties of the individual items. If your items have binary an-

⁷ Even though α is a theoretical lower bound on reliability, in practice, test-retest accuracy often ends up lower than α because it incorporates all these other sources of variation.

3778 swers, like test questions, then item response theory is a good place to
3779 start (Embreton and Reise 2013). If your items are more like ratings
3780 on a continuous (interval or ratio) scale, then you may want to look at
3781 factor analysis and related methods (Furr 2021).

⚠ ACCIDENT REPORT

Wasted effort

Low-reliability measures limit your ability to detect correlations between measurements. Mike spent several fruitless months in graduate school running dozens of participants through batteries of language processing tasks and correlating the results across tasks. Every time data collection finished, one or the other (spurious) correlation would show up in the data analysis. Something was always correlated with something else. Thankfully, he would always attempt to replicate the correlation in a new sample—and in that next dataset, the correlation we were trying to replicate would be null but another (again likely spurious) correlation would show up.

This exercise was a waste of time because most of the tasks were of such low reliability that, even had they been highly correlated with one another, relationship would have been almost impossible to detect without a huge sample size. (It also would have been helpful if someone had mentioned multiplicity corrections (chapter 6) to him.)

One rule of thumb that's helpful for individual difference designs of this sort is that the maximal correlation that can be observed between two

variables x and y is the square root of the product of their reliabilities:

$\sqrt{r_x r_y}$. So if you have two measures that are reliable at .25, the maximal measured correlation between them is .25 as well! This kind of method is now frequently used in cognitive neuroscience (and other fields as well) to compute the so-called **noise ceiling** for a measure: the maximum amount of signal that in principle *could* be predicted (Lage-Castellanos et al. 2019).

If your sample size is too small to detect correlations at the noise ceiling (see chapter 10), then the study is not worth doing.

3783

3784 8.2 Validity

3785 In chapter 2, we talked about the process of theory building as a process

3786 of describing the relationships between constructs. But for the theory

3787 to be tested, the constructs must be measured so that you can test the

3788 relationships between them! Measurement and measure construction

3789 is therefore intimately related to theory construction, and the notion of

3790 validity is central.⁸

3791 A valid instrument measures the construct of interest. In figure 8.1, in-

3792 validity is pictured as bias—the holes in the target are tightly grouped

3793 but in the wrong place.⁹ How can you tell if a measure is valid, given

3794 that the construct of interest is unobserved? There is no single test of the

3795 validity of a measure (Cronbach and Meehl 1955). Rather, the measure

Shadish,

Cook, and Campbell 2002

3796 is valid if there is evidence that fits into the broader theory as it relates
3797 to the specific construct it is supposed to be measuring. For example, it
3798 should be strongly related to other measures of the construct, but not as
3799 related to measures of different constructs.

3800 How do you establish that a measure fits into the broader theory? Va-
3801 lidity of a measure is typically established via an argument that calls on
3802 different sources of support (Kane 1992). Here are some of the ways
3803 that you might support the relationship between a measure and a con-
3804 struct:

3805 – **Face validity:** The measure looks like the construct, such that in-
3806 tuitively it is reasonable that it measures the construct. Face valid-
3807 ity is a relatively weak source of evidence for validity, since it re-
3808 lies primarily on pre-theoretic intuitions rather than any quantita-
3809 tive assessment. For example, reaction time is typically correlated
3810 with intelligence test results (e.g., Jensen and Munro 1979), but
3811 does not appear to be a face-valid measure of intelligence in that
3812 simply being fast doesn't accord with our intuition about what it
3813 means to be intelligent!

3814 – **Ecological validity:** The measure relates to the context of
3815 people's lives. For example, a rating of a child's behavioral
3816 self-control in the classroom is a more ecologically valid measure

of executive function than a reaction-time task administered in a lab context. Ecological validity arguments can be made on the basis of the experimental task, the stimuli, and the general setting of the experiment (Schmuckler 2001). Researchers differ in how much weight they assign to ecological validity based on their goals and their theoretical orientation.

- **Internal validity:** Usually used negatively. A “challenge to internal validity” is a description of a case where the measure is administered in such a way as to weaken the relationship between measure and construct. For example, if later items on a math test showed lower performance due to test-taker’s fatigue rather than lower knowledge of the concepts, the test might have an internal validity issue.¹⁰
- **Convergent validity:** The classic strategy for showing validity is to show that a measure relates (usually, correlates) with other putative measures of the same construct. When these relationships are measured concurrently, this is sometimes called **concurrent validity**. As we mentioned in chapter 2, self-reports of happiness relate to independent ratings by friends and family, suggesting that both measure the same underlying construct (Sandvik, Diener, and Seidlitz 1993).¹¹
- **Predictive validity.** If the measure predicts other later measures

¹⁰ Often this concept is described as being relevant to the validity of a *manipulation* also, e.g. when the manipulation of the construct is confounded and some other psychological variable is manipulated as well. We discuss internal validity further in chapter 9.

¹¹ This idea of convergent validity relates to the idea of holism we described in chapter 2. A measure is valid if it relates to other valid measures, which themselves are only valid if the first one is! The measures are valid because the theory works, and the theory works because the measures are valid. This circularity is a difficult but perhaps unavoidable part of constructing psychological theories (see the above Depth Box on the history of measurement). We don’t ever have an objective starting point for the study of the human mind.

of the construct, or related outcomes that might be of broader significance. Predictive validity is often used in lifespan and developmental studies where it is particularly prized for a measure to be able to predict meaningful life outcomes such as educational success in the future. For example, classroom self-control ratings (among other measures) appear strongly predictive of later life health and wealth outcomes (Moffitt et al. 2011).

- **Divergent validity.** If the measure can be shown to be distinct from measure(s) of a different construct, this evidence can help establish that the measure is specifically linked to the target construct. For example, measures of happiness (specifically, life satisfaction) can be distinguished from measures of optimism as well as both positive and negative affect, suggesting that these are distinct constructs (Lucas, Diener, and Suh 1996).

8.2.1 Validity arguments in practice

Let's take a look at how we might make an argument about the validity of the CDI, the vocabulary instrument from our case study.

First, the CDI is face valid—it is clearly about early language ability. In contrast, even though a child's height would likely be correlated with their early language ability, we should be skeptical of this measure due

3859 to its lack of face validity. In addition, the CDI shows good convergent
3860 and predictive validity. Concurrently, the CDI correlates well with evi-
3861 dence from transcripts of children's actual speech and from standardized
3862 language assessments (as discussed in the case study above). And predic-
3863 tively, CDI scores at age 2 relate to reading scores during elementary
3864 school (Marchman and Fernald 2008).

3865 On the other hand, users of the CDI must avoid challenges to the in-
3866 ternal validity of the data they collect. For example, some CDI data
3867 are compromised by confusing instructions or poor data collection pro-
3868 cesses (Frank et al. 2021). Further, advocates and critics of the CDI
3869 argue about its ecological validity. There is something quite ecologi-
3870 cally valid about asking parents and caregivers—who are experts on their
3871 own child—to report on their child's abilities. On the other hand, the
3872 actual experience of filling out a structured form estimating language
3873 ability might be more familiar to some families from high education
3874 backgrounds than for others from lower education backgrounds. Thus,
3875 a critic could reasonably say that comparisons of CDI scores across so-
3876 cioeconomic strata would be an invalid usage (Feldman et al. 2000).

3877 8.2.2 *Avoid questionable measurement practices!*

3878 Experimentalists sometimes have a tendency to make up ad hoc mea-
3879 sures on the fly. It's fine to invent new measures, but the next step is
3880 to think about what evidence there is that it's valid! table 8.2 gives a
3881 set of questions to guide thoughtful reporting of measurement practices
3882 (adapted from [Flake and Fried 2020](#)).

Table 8.2
Questions about measurement that every researcher should answer in their paper.
Adapted from Flake and Fried (2020).

Question	Information to Report
What is your construct?	Define construct, describe theory and research.
What measure did you use to operationalize your construct?	Describe measure and justify operationalization.
Did you select your measure from the literature or create it from scratch?	Justify measure selection and review evidence on reliability and validity (or disclose the lack of such evidence).
Did you modify your measure during the process?	Describe and justify any modifications; note whether they occurred before or after data collection.

Question	Information to Report
How did you quantify your measure?	Describe decisions underlying the calculation of scores on the measure; note whether these were established before or after data collection and whether they are based on standards from previous literature.

3883 One big issue to be careful about is that researchers have been known to
3884 modify their scales and their scale scoring practices (say, omitting items
3885 from a survey or rescaling responses) after data collection. This kind of
3886 post-hoc alteration of the measurement instrument can sometimes be
3887 justified by features of the data, but it can also look a lot like *p*-hacking!
3888 If researchers modify their measurement strategy after seeing their data,
3889 this decision needs to be disclosed, and it may undermine their statistical
3890 inferences.

⚠ ACCIDENT REPORT

Talk about flexible measurement!

The Competitive Reaction Time Task (CRTT) is a lab-based measure of aggression. Participants are told that they are playing a reaction-time game against another player and are asked to set the parameters of a noise blast that will be played to their opponent. Unfortunately, in an analysis

of the literature using CRTT, Elson et al. (2014) found that different papers using the CRTT use dramatically different methods for scoring the task. Sometimes the analysis focused on the volume of the noise blast and sometimes it focused on the duration. Sometimes these scores were transformed (via logarithms) or thresholded. Sometimes they were combined into a single score. Elson was so worried by this flexibility, he created a website, <https://flexiblemeasures.com>, to document the variation he observed.

As of 2016, Elson had found 130 papers using the CRTT. And across these papers, he documented an astonishing 157 quantification strategies. One paper reported ten different strategies for extracting numbers from this measure! More worrisome still, Elson and colleagues found that when they tried out some of these strategies on their own data, different strategies led to very different effect sizes and levels of statistical significance. They could effectively make a finding appear bigger or smaller depending on which scoring they chose.

Triangulating a construct through multiple pre-specified measurements can be a good thing. But the issue with the CRTT analysis was that changes in the measurement strategy appeared to be made in a *post hoc*, data-driven way so as to maximize the significance of the experimental manipulation (just like the *p*-hacking we discussed in Chapters 3 and 6).

This examination of the use of the CRTT measure has several implications. First, and most troublingly, there may have been undisclosed flex-

ability in the analysis of CRTT data across the literature, with investigators taking advantage of the lack of standardization to try many different analysis variants and report the one most favorable to their own hypothesis. Second, it is unknown which quantification of CRTT behavior is in fact most reliable and valid. Since some of these variants are presumably better than others, researchers are effectively “leaving money on the table” by using suboptimal quantifications. As a consequence, if researchers adopt the CRTT, they find much less guidance from the literature on what quantification to adopt.

3893

3894 8.3 How to select a good measure?

3895 Ideally you want a measure that is reliable and valid. How do you get
3896 one? An important first principle is to use a pre-existing measure. Per-
3897 haps someone else has done the hard work of compiling evidence on
3898 reliability and validity, and in that case you will most likely want to pig-
3899 gyback on that work. Standardized measures are typically broad in their
3900 application and so the tendency can be to discard these because they are
3901 not tailored for our studies specifically. But the benefits of a standar-
3902 ized measure are substantial. Not only can you justify the measure us-
3903 ing the prior literature, you also have an important index of population
3904 variability by comparing absolute scores to other reports.¹²

3905 If you don't use someone else's measure, you'll need to make one up
3906 yourself. Most experimenters go down this route at some point, but if
3907 you do, remember that you will need to figure out how to estimate its
3908 reliability and also how to make an argument for its validity!

3909 We can assign numbers to almost anything people do. We could run
3910 an experiment on children's exploratory play and count the number of
3911 times they interact with another child (Ross and Lollis 1989), or run an
3912 experiment on aggression where we quantify the amount of hot sauce
3913 participants serve (Lieberman et al. 1999). Yet most of the time we
3914 choose from a relatively small set of operational variables: asking survey
3915 questions, collecting choices and reaction times, and measuring physio-
3916 logical variables like eye-movements. Besides following these conven-
3917 tions, how do we choose the right measurement type for a particular
3918 experiment?

3919 There's no hard and fast rule about what aspect of behavior to measure,
3920 but here we will focus on two dimensions that can help us organize the
3921 broad space of possible measure targets.¹³ The first of these is the contin-
3922 uum between simple and complex behaviors. The second is the focus
3923 on explicit, voluntary behaviors vs. implicit or involuntary behaviors.

¹³ Some authors differentiate between "self-report" and "observational" measures. This distinction seems simple on its face, but actually gets kind of complicated. Is a facial expression a "self-report"? Language is not the only way that people communicate with one another—many actions are intended to be communicative (Shafto, Goodman, and Frank 2012).

3924 8.3.1 *Simple vs. complex behaviors*

3925 figure 8.5 shows a continuum between simple and complex behaviors.

3926 The simplest measurable behaviors tend to be button presses, e.g.:

- 3927 – pressing a key to advance to the next word in a word-by-word
- 3928 self-paced reading study,
- 3929 – selecting “yes” or “no” in a lexical decision task, and
- 3930 – making a forced choice between different alternatives to indicate which has been seen before.

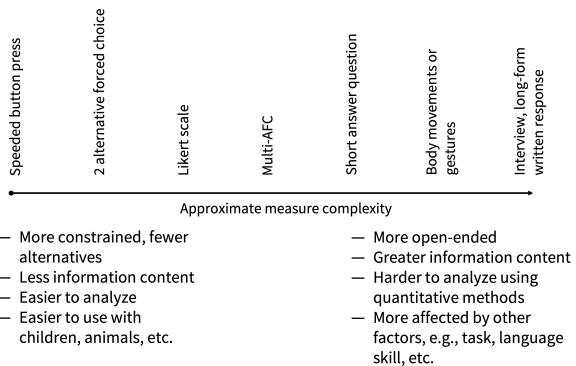


Figure 8.5

Often choosing a measure can be consolidated into a choice along a continuum from simple measures that provide a small amount of information but are quick and easy to repeat and those that provide much richer information but require more time.

3932 These specific measures—and many more like them—are the bread and

3933 butter of many cognitive psychology studies. Because they are quick

3934 and easy to explain, these tasks can be repeated over many trials. They

3935 can also be executed with a wider variety of populations including with

3936 young children and sometimes even with non-human animals with ap-

3937 propriate adaptation. (A further benefit of these paradigms is that they

3938 can yield useful reaction time data, which we discuss further below).

3939 In contrast, a huge range of complex behaviors have been studied by
3940 psychologists, including:

- 3941 – open-ended verbal interviews;
3942 – written expression, e.g. via handwriting or writing style;
3943 – body movements, including gestures, walking, or dance; and
3944 – drawing or artifact building.

3945 There are many reasons to study these kinds of behaviors. First, the
3946 behaviors themselves may be examples of tasks of interest (e.g., studies
3947 of drawing that seek to understand the origins of artistic expression).
3948 Or, the behavior may stand in for other even more complex behaviors
3949 of interest, as in studies of typing that use this behavior as a proxy for
3950 lexical knowledge (Rumelhart and Norman 1982).

3951 Complex behaviors typically afford a huge variety of different measure-
3952 ment strategies. So any experiment that uses a particular measurement
3953 of a complex behavior will typically need to do significant work up front
3954 to justify the choice of that measurement strategy—e.g., how to quantify
3955 dances or gestures or typing errors—and provide some assurance about
3956 its reliability. Further, it is often much more difficult to have a partici-
3957 pant repeat a complex behavior many times under the same conditions.
3958 Imagine asking someone to draw hundreds of sketches as opposed to

3959 pressing a key hundreds of times! Thus, the choice of a complex behav-
3960 ior is often a choice to forego a large number of simple trials for a small
3961 number of more complex trials.

3962 Complex behaviors can be especially useful to study either at the be-
3963 ginning or the end of a set of experiments. At the beginning of a set of
3964 experiments, they can provide inspiration about the richness of the tar-
3965 get behavior and insight into the many factors that influence it. And at
3966 the end, they can provide an ecologically valid measure to complement
3967 a reliable but more artificial, lab-based behavior.

3968 The more complex the behavior, however, the more it will vary across
3969 individuals and the more environmental and situational factors will af-
3970 fect it. These can be important parts of the phenomenon, but they can
3971 also be nuisances that are difficult to get under experimental control.¹⁴
3972 Simple measures are typically easier to use and hence easier to deploy
3973 repeatedly in a set of experiments where you iterate your manipulation
3974 to test a causal theory.

3975 8.3.2 *Implicit vs. explicit behaviors*

3976 A second important dimension of organization for measures is the dif-
3977 ference between implicit and explicit measures. An explicit measure
3978 provides a measurement of a behavior that a participant has conscious

¹⁴ When they are not designed with care, complex, open-ended behaviors such as verbal interviews can be especially affected by the experimental biases that we will describe in chapter 9, including for example demand characteristics, in which participants say what they think experimenters want to hear. Qualitative interview methods can be incredibly powerful as a method in their own right, but they should be deployed with care as measures for an experimental intervention.

3979 awareness of—e.g., the answer to a question. In contrast, implicit mea-
3980 sures provide measurements of psychological processes that participants
3981 are unable to report (or occasionally, unwilling to).¹⁵ Implicit measures,
3982 especially reaction time, have long been argued to reflect internal psy-
3983 chological processes (Donders 1868/1969). They also have been pro-
3984 posed as measures of qualities such as racial bias that participants may
3985 have motivation not to disclose (Greenwald, McGhee, and Schwartz
3986 1998). There are also of course a host of physiological measurements
3987 available. Some of these measure eye-movements, heart rate, or skin
3988 conductance, which can be linked to aspects of cognitive process. Oth-
3989 ers reflect underlying brain activity via the signals associated with MRI,
3990 MEG, NIRS, and EEG measurements. These methods are outside the
3991 scope of this book, though we note that the measurement concerns we
3992 discuss here definitely apply (e.g., Zuo, Xu, and Milham 2019).

3993 Many tasks produce both accuracy and reaction time data. Often these
3994 trade off with one another in a classic speed-accuracy tradeoff: the
3995 faster participants respond, the less accurate they are. For example, to
3996 investigate racial bias in policing, Payne (2001) showed US college stu-
3997 dents a series of pictures of tools and guns, proceeded by a prime of
3998 either a White face or a Black face. In a first study, participants were
3999 faster to identify weapons when primed by a Black face but had similar
4000 accuracies. A second study added a response deadline to speed up judg-

¹⁵ Implicit/explicit is likely more of a continuum, but one cut-point is whether the participants' behavior is considered intentional: that is, participants *intend* to press a key to register a decision, but they likely do not intend to react in 300 as opposed to 350 milliseconds due to having seen a prime.

4001 ments: this manipulation resulted in equal reaction times across condi-
4002 tions but greater errors in weapon identification after Black faces. These
4003 studies likely revealed the same phenomenon—some sort of bias to as-
4004 sociate Black faces with weapons—but the design of the task moved
4005 participants along a speed accuracy tradeoff, yielding effects on differ-
4006 ent measures.¹⁶

4007 Simple, explicit behaviors are often a good starting point. Work us-
4008 ing these measures—often the least ecologically valid—can be enriched
4009 with implicit measures or measurements of more complex behaviors.

4010 *8.4 The temptation to measure lots of things*

4011 If one measure is good, shouldn't two be better? Many experimenters
4012 add multiple measurements to their experiments, reasoning that more
4013 data is better than less. But that's not always true!

4014 Deciding whether to include multiple measures is an aesthetic and prac-
4015 tical issue as well as a scientific one. Throughout this book we have been
4016 advocating for a viewpoint in which experiments should be as simple
4017 as possible. For us, the best experiment is one that shows that a simple
4018 and valid manipulation affects a single, reliable and valid measure.¹⁷ If

¹⁶ One way of describing the information processing underlying this tradeoff is given by drift diffusion models, which allow joint analysis of accuracy and reaction time (Voss, Nagler, and Lerche 2013). Used appropriately, drift diffusion models can provide a way to remove speed-accuracy tradeoffs and extract more reliable signals from tasks where accuracy and reaction time are both measured (see Johnson et al. 2017 for an example of DDM on a weapon-decision task).

¹⁷ In an entertaining article called “things I have learned (so far)”, Cohen (1990) quips that he leans so far in the direction of large numbers of observations and small numbers of measures that some students think his perfect study has 10,000 participants and *no* measures.

4019 you are tempted to include more than one measure, see if we can talk
4020 you out of it.¹⁸

4021 First, make sure that including more measures doesn't compromise each
4022 individual measure. This can happen via fatigue or carryover effects.
4023 For example, if a brief attitude manipulation is followed by multiple
4024 questionnaire measures, it is a good bet that there is likely to be "fade-
4025 out" of the effect over time, so it won't have the same effect on the
4026 first questionnaire as the last one. Further, even if a manipulation has
4027 a long duration effect on participants, survey fatigue may lead to less
4028 meaningful responses to later questions (Herzog and Bachman 1981).

4029 Second, consider whether you have a strong prediction for each measure,
4030 or whether you're just looking for more ways to see an effect of your
4031 manipulation. As discussed in chapter 2, we think of an experiment as
4032 a "bet." The more measures you add, the more bets you are making
4033 but the less value you are putting on each. In essence, you are "hedging
4034 your bets" and so the success of any one bet is less convincing.

4035 Third, if you include multiple measures in your experiment, you need
4036 to think about how you will interpret inconsistent results. Imagine you
4037 have experimental participants engage in a brief written reflection that
4038 is hypothesized to affect a construct (vs a control writing exercise, say

¹⁸ As usual, we want to qualify that we are only talking about randomized experiments here! In observational studies, often the point is to measure the associations between multiple measures so you typically *have* to include more than one. Additionally, some of the authors of this book have advocated for measuring multiple outcomes in longitudinal observational studies, which could reduce investigator bias, encourage reporting null effects, enable comparison of effect sizes, and improve research efficiency (VanderWeele, Mathur, and Chen 2020). We've also done plenty of descriptive studies—these can be very valuable. In a descriptive context, often the goal is to include as many measures as possible so as to have a holistic picture of the phenomenon of interest.

4039 listing meals). If you include two measures of the construct of inter-
4040 est and one shows a larger effect, what will you conclude? It may be
4041 tempting to assume that the one that shows a larger effect is the “better
4042 measure” but the logic is circular—it’s only better if the manipulation
4043 affected the construct of interest, which is what you were testing in the
4044 first place! Including multiple measures because you’re uncertain which
4045 one is more related to the construct indulges in this circular logic, since
4046 the experiment often can’t resolve the situation. A much better move
4047 in this case is to do a preliminary study of the reliability and validity
4048 of the two measures so as to be able to select one as the experiment’s
4049 primary endpoint.¹⁹

4050 Finally, if you do include multiple measures, selective reporting of sig-
4051 nificant or hypothesis-aligned measures becomes a real risk. For this rea-
4052 son, preregistration and transparent reporting of all measures becomes
4053 even more important.

4054 There are some cases where more measures are better. The more expen-
4055 sive the experiment, the less likely it is to be repeated to gather a new
4056 measurement of the effects of the same manipulation. Thus, larger stud-
4057 ies present a stronger rationale for including multiple measures. Clinical
4058 trials often involve interventions that can have effects on many differ-
4059 ent measures; imagine a cancer treatment that might affect mortality

¹⁹ One caveat to this argument is that it can sometimes be useful to examine the effects of a manipulation on different measures because the measures are important. For example, you might be interested in whether an educational intervention increased grades *and* decreased dropout rates. Both outcome measures are important and so it is useful to include both in your study.

4060 rates, quality of life, tumor growth rates, etc. Further, such trials are ex-
4061 tremely expensive and difficult to repeat. Thus, there is a good reason
4062 for including more measures in such studies.

🔍 DEPTH

Survey measures

Sometimes the easiest way to elicit information from participants is simply to ask. Surveys are an important part of experimental measurement, so we'll share a few best practices, primarily derived from Krosnick and Presser (2010).

Treat survey questions as a conversation. The easier your items are to understand, the better. Don't repeat variations on the same question unless you want different answers! Try to make the order reasonable, for example by grouping together questions about the same topic and moving from more general to more specific questions. The more you include "tricky" items the more you invite tricky answers to straightforward questions. One specific kind of tricky questions are "check" questions that evaluate participant compliance. We'll talk more in chapter 12 about various ways of evaluating compliance and their strengths and weaknesses.

Open-ended survey questions can be quite rich and informative, especially when an appropriate coding (classification) scheme is developed in advance and responses are categorized into a relatively small number of types. On the other hand, they present practical obstacles because they require coding (often by multiple coders to ensure reliability of the cod-

ing). Further, they tend to yield nominal data, which are often less useful for quantitative theorizing. Open-ended questions are a useful tool to add nuance and color to the interpretation of an experiment.

One common mistake that survey developers make is trying to put too much into one question. Imagine asking a restaurant-goer for a numerical ranking on the question, “How do you like our food and service?” What if they loved the food but hated the service, or vice versa—would they choose an intermediate option? Items that ask about more than one thing at once are known as **double-barreled** questions. They can confuse and frustrate participants as well as leading to uninterpretable data.

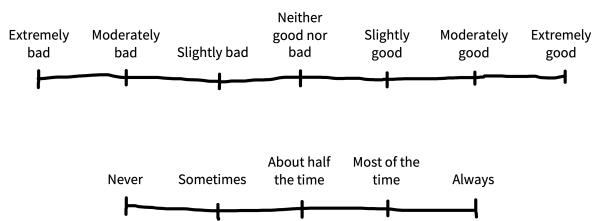


Figure 8.6
Likert scales based on survey best practices: a bipolar opinion scale with seven points and a unipolar frequency scale with five points. Both have all points labeled.

Especially given their ubiquity in commercial survey research, **Likert scales**—scales with a fixed number of ordered, numerical response options—are a simple and conventional way of gathering data on attitude and judgment questions (figure 8.6). Bipolar scales are those in which the endpoints represent opposites, for example the continuum between “strongly dislike” and “strongly like.” Unipolar scales have one neutral endpoint, like the continuum between “no pain” and “very intense pain.” Survey methods research suggests that reliability is maximized when bipo-

lar scales have seven points and unipolar scales have five. Labeling every point on the scale with verbal labels is preferable to labeling only the end-points.

One important question is whether to treat data from Likert scales as ordinal or interval. It's extremely common (and convenient) to make the assumption that Likert ratings are interval, allowing the use of standard statistical tools like means, standard deviations, linear regression, etc. The risk in this practice comes from the possibility that scale items are not evenly spaced—for example, on a scale labeled “never”, “seldom”, “occasionally”, “often”, “always,” the distance from “often” to “always” may be larger than the distance from “seldom” to “occasionally.”

In practice, you can choose to use regression variants that are appropriate, e.g. ordinal logistic regression and its variants, or they can attempt to assess and mitigate the risks of treating the data as interval. If you choose the second option, it's definitely a good idea to look carefully at the raw distributions for individual items to see if their distribution appears approximately normal (see chapter 15).

Recently some researchers have begun to use “visual analog scales” (or sliders) as a solution. We don't recommend these—the distribution of the resulting data is often anchored at the starting point or endpoints (Matejka et al. 2016), and a meta-analysis shows they're a lot lower than Likert scales in reliability (Krosnick and Presser 2010).

It rarely helps matters to add a “don't know” or “other” option to survey

questions. These are some of a variety of practices that encourage **satisficing**, where survey takers give answers that are good enough but don't reflect substantial thought about the question. Another behavior that results from satisficing is "straight-lining"—that is, picking the same option for every question. In general, the best way to prevent straight-lining is to make surveys relatively short, engaging, and well-compensated. The practice of "reverse coding" to make the expected answers to some questions more negative can block straight-lining, but at the cost of making items more confusing. Some obvious formatting options can reduce straight-lining as well, for example placing scales further apart or on subsequent (web) pages.

In sum, survey questions can be a helpful tool for eliciting graded judgments about explicit questions. The best way to execute them well is to try and make them as clear and easy to answer as possible.

4066

8.5 Chapter summary: Measurement

4068 In olden times, all the psychologists went to the same conferences and
4069 worried about the same things. But then a split formed between differ-
4070 ent groups. Educational psychologists and psychometricians thought
4071 a lot about how different problems on tests had different measurement
4072 properties. They began exploring how to select good and bad items, and
4073 how to figure out people's ability abstracted away from specific items.

4074 This research led to a profusion of interesting ideas about measurement,
4075 but these ideas rarely percolated into day-to-day practice in other areas
4076 of psychology. For example, cognitive psychologists collected lots of
4077 trials and measured quantities of interest with high precision, but wor-
4078 ried less about measurement validity. Social psychologists spent more
4079 time worrying about issues of ecological validity in their experiments,
4080 but often used *ad hoc* scales with poor psychometric properties.

4081 These sociological differences between fields has led to an unfortunate
4082 divergence, where experimentalists often don't recognize the value of
4083 the conceptual tools developed to aid measurement, and so fail to reason
4084 about the reliability and validity of their measures in ways that can help
4085 them make better inferences. As we said in our discussion of reliability,
4086 ignorance is not bliss. Much better to think these choices through!



DISCUSSION QUESTIONS

1. Let's go back to our example on the relationship between money and happiness from chapter 1. How many different kinds of measures of happiness can you come up with? Make a list with at least five.
2. Choose one of your measures of happiness and come up with a validation strategy for it, making reference to at least three different types of validity. What data collection would this validation effort require?



READINGS

- A classic textbook on psychometrics that introduces the concepts of reliability and validity in a simple and readable way: Furr, R. M. (2021). *Psychometrics: an introduction*. SAGE publications.
- A great primer on questionnaire design: Krosnick, J.A. (2018). Improving Question Design to Maximize Reliability and Validity. In: Vannette, D., Krosnick, J. (eds) The Palgrave Handbook of Survey Research. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-319-54395-6_13.
- Introduction to general issues in measurement and why they shouldn't be ignored: Flake, J. K., & Fried, E. I. (2020). Measurement schmeasurement: Questionable measurement practices and how to avoid them. *Advances in Methods and Practices in Psychological Science*, 3(4), 456–465. <https://doi.org/10.1177/2515245920952393>.
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9 DESIGN

4098



LEARNING GOALS

- Describe key elements of experimental design
- Define randomization and counterbalancing strategies for removing confounds
- Discuss strategies to design experiments that are appropriate to the populations of interest

4099

4100 The key thesis of our book is that experiments should be designed to
4101 yield precise and unbiased measurements of a causal effect. But the
4102 causal effect of what? The manipulation! In an experiment we manipu-
4103 late (intervene on) some aspect of the world and measure the effects of
4104 that manipulation. We then compare that measurement to a situation
4105 where the intervention has not occurred.

4106 We refer to different intervention states as **conditions** of the experiment.
4107 The most common experimental design is the comparison between a

4108 control condition, in which the intervention is not performed, and an
4109 **experimental** (sometimes called **treatment**) condition in which the in-
4110 tervention is performed.

4111 But many other experimental designs are possible. In more complex ex-
4112 periments, manipulations along different dimensions (sometimes called
4113 **factors** in this context) can be combined. In the first part of the chapter,
4114 we'll introduce some common experimental designs and the vocabu-
4115 lary for describing them. Our focus here is in identifying designs that
4116 maximize MEASUREMENT PRECISION.

4117 A good experimental measure must be a valid measure of the construct
4118 of interest. The same is true for a manipulation—it must validly relate to
4119 the causal effect of interest. In the second part of the chapter, we'll dis-
4120 cuss issues of **manipulation validity**, including both issues of ecological
4121 validity and **confounding**. We'll talk about how practices like **random-**
4122 **ization** and **counterbalancing** can help remove nuisance confounds, an
4123 important part of **BIAS REDUCTION** for experimental designs.¹

4124 To preview our general take-home points from this chapter: we think
4125 that your default experiment should manipulate one or two factors—
4126 usually not more—and should manipulate those factors continuously
4127 and within-participants. Although such designs are not always possible,

¹ This section will draw on our introduction to causal inference in chapter 1, so if you haven't read that, now's the time.

⁴¹²⁸ they are typically the most likely to yield precise estimates of a particu-
⁴¹²⁹ lar effect that can be used to constrain future theorizing. We'll start by
⁴¹³⁰ considering a case study in which a subtle confound led to difficulties
⁴¹³¹ interpreting an experimental result.



CASE STUDY

Automatic theory of mind?

In an early version of our course, student Desmond Ong set out to replicate a thought-provoking finding: both infants and adults seemed to show evidence of tracking other agents' belief state, even when it was irrelevant to the task at hand (Kovács, Téglás, and Endress 2010). In the paradigm, an animated Smurf character would watch as a self-propelled ball came in and out from behind a screen. At the end of the video, the screen would swing down and the participant had to respond whether the ball was present or absent. Reaction time for this decision was the key dependent variable.

The experimental design investigated two factors: whether the participant believed the ball was present or absent ($P+/P-$) and whether the animated agent *would have believed* the ball was present or absent ($A+/A-$) based on what it saw. The result was four conditions: $P+/A+$, $P+/A-$, $P-/A+$, and $P-/A-$. (We could call this a **fully crossed** design because each level of one factor was presented with each level of the other).

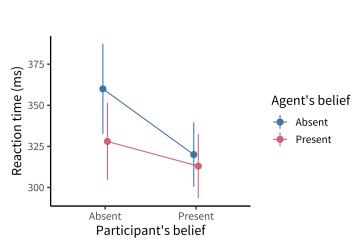


Figure 9.1

Original data from Kovács, Téglás, and Endress (2010). Error bars show 95% confidence intervals. Based on Phillips et al. (2015).

Both the original experiments and the replication that Desmond ran showed a significant effect of the agent's beliefs on participants' reaction times, suggesting that what the—totally irrelevant—agent thought about the ball was leading them to react more or less quickly to the presence of the ball. Figure 9.1 shows the original data ($N=24$). But although both studies showed an effect of agent belief, the replication and several variations also showed a crossover interaction of participant and agent belief. The participants were slower when the agents *and* the participants believed that the ball was behind the screen (figure 9.2). That finding wasn't consistent with the theory that tracking inconsistent beliefs slowed down reaction times. If participants were tracking their own beliefs about the ball *and* the agent's, they should have been fastest in the P+/A+ condition, not slower.

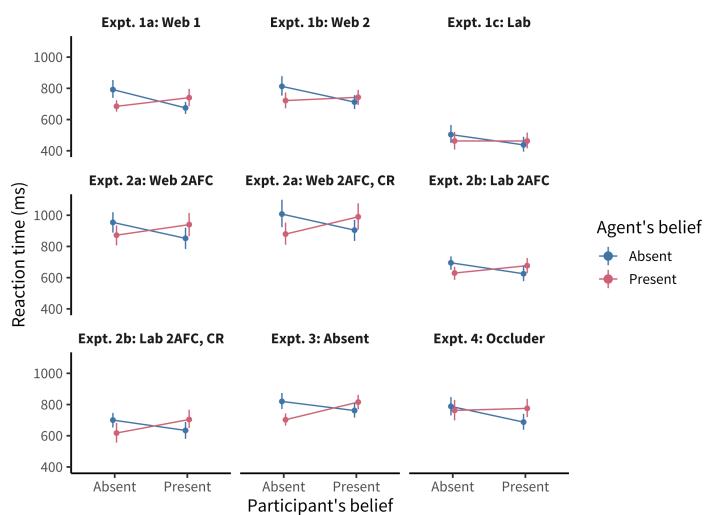


Figure 9.2

Data from a series of replications of Kovács, Téglás, and Endress (2010), including versions on the web (Experiments 1a and 1b) and in lab (Experiment 1c), as well as several variations on the format of responding (Experiments 2 and 3; 2AFC = two alternative forced choice) and an experiment where a large wall kept the agent from seeing the ball at all (Experiment 4). “Hits” and “CRs” panels refer to different subsets of trials where participants responded “present” when the ball was present and “absent” when the ball was absent. Error bars are 95% confidence intervals. Based on Phillips et al. (2015).

A collaborative team working on this paradigm identified a key issue (Phillips et al. 2015). There was a **confound** in the experimental design—another factor that varied across conditions besides the target factors. In other words, something was changing between conditions other than the agent’s and participant’s belief states. The confound was an attention check (discussed further in chapter 12): participants had to press a key when the agent left the scene to show that they were paying attention. This attention check appeared a few seconds later in the videos for the P+/A+ and P-/A- trials—the ones that yielded the slow reaction times—than it did for the other two. When the attention check was removed or when its timing was equalized across conditions, reaction time effects

were eliminated, suggesting that the original pattern of findings may have been due to the confound.

If the standard for replication is significance of particular statistical tests at $p < .05$, then this experiment replicated successfully. But the effect estimates were inconsistent with the proposed theoretical explanation. A finding can be replicable without providing support for the underlying theory!

There's an important caveat to this story. The followup work *only* revealed that there was a confound in one particular experimental operationalization, and did not provide evidence against automatic theory of mind in general. Indeed, others have suggested that different versions of this paradigm *do* reveal evidence for theory of mind processing once the confound is eliminated (El Kaddouri et al. 2020).

4135

4136 9.1 Experimental designs

4137 Experimental designs are fundamental to many fields; unfortunately the
4138 terminology used to describe them can vary, which can get quite con-
4139 fusing! Here we will mostly describe an experiment as a relationship
4140 between some manipulation(s), in which participants are randomly as-
4141 signed to experimental conditions to estimate effects on some measure.
4142 Factors are the dimensions along which manipulations vary. For exam-
4143 ple, in our case study above, the two factors were participant belief and

4144 agent belief. Another terminology it's good to be familiar with is the
4145 terms used in Chapters 5–7, which are often used in econometrics and
4146 statistics: **treatment** (manipulation) and **outcome** (measure).²

4147 In this section, we'll discuss key dimensions on which experiments vary:
4148 1) how many factors they incorporate and how these factors are crossed,
4149 2) how many conditions and measures are given to each participant, and
4150 3) if manipulations have discrete levels or fall on a continuous scale.

4151 9.1.1 *A two-factor experiment*

4152 The classical “design of experiments” framework has as its goal to sep-
4153 arate observed variability in the dependent measure into 1) variability
4154 due to the manipulation(s) and (2) other variability, including measure-
4155 ment error and participant-level variation. This framework maps nicely
4156 onto the statistical framework described in Chapters 5–7. In essence,
4157 this framework models the distribution of the measure using the condi-
4158 tion structure of our experiment as the predictor.

4159 Different experimental designs will allow us to estimate specific effects
4160 more and less effectively. Recall in chapter 5, we estimated the effect of
4161 our tea/milk order manipulation by a simple subtraction: $\beta = \theta_T - \theta_C$
4162 (where β is the effect estimate, and θ s indicate the estimates for each
4163 condition, treatment T and control C ; we called them θ_T and θ_M in

² Terminology here is hard. In psychology people sometimes say there's an **independent variable** (the manipulation, which is causally prior and hence “independent” of other causal influences) and a **dependent variable** (the measure, which causally depends on the manipulation, or so we hypothesize). We find this terminology to be hard to remember because the terms are so different from the actual concepts being described.

that chapter to denote tea- and milk-first conditions). This logic works just fine also if there are two distinct treatments in a three condition experiment: each treatment can be compared to control separately. For treatment 1, $\beta_{T_1} = \theta_{T_1} - \theta_C$ and $\beta_{T_2} = \theta_{T_2} - \theta_C$.

This logic is going to get more complicated if we have more than one distinct factor of interest, though. Let's look at an example.

Young et al. (2007) were interested in how moral judgments depend on both the beliefs of actors and the outcomes of their actions. They presented participants with vignettes in which they learned, for example, that Grace visits a chemical factory with her friend and goes to the coffee break room, where she sees a white powder that she puts in her friend's coffee. They then manipulated both Grace's *beliefs* and the *outcomes* of her action following the schema in figure 9.3. Participants (N=10) used a four-point Likert scale to rate whether the actions were morally forbidden (1) or permissible (4). Figure 9.4 shows the data.

		Outcome	
		Negative	Neutral
Belief	Negative	Grace thinks the powder is toxic . It is toxic . Her friend dies .	Grace thinks the powder is toxic . It is sugar . Her friend is fine .
	Neutral	Grace thinks the powder is sugar . It is toxic . Her friend dies .	Grace thinks the powder is sugar . It is sugar . Her friend is fine .

Figure 9.3
The 2x2 crossed design used in Young et al. (2007)

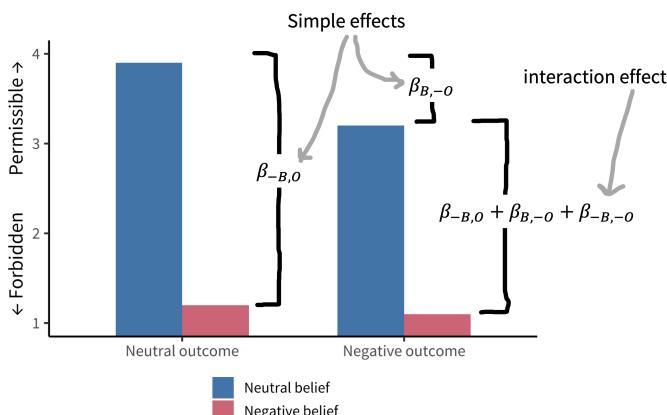


Figure 9.4
Moral permissibility as a function of belief and outcome. Results from Young et al. (2007), annotated with the estimated effects. Simple effects measure differences between the individual conditions and the neutral belief, neutral outcome condition. The interaction measures the difference between the predicted sum of the two simple effects and the actual observed data for the negative belief, negative outcome condition.

4179 Young et al.'s design has two factors—belief and outcome—each with
 4180 two levels (neutral and negative, noted as B and $-B$ for belief and O
 4181 and $-O$ for outcome).³ These factors are **fully crossed**: each level of
 4182 each factor is combined with each level of each other.

4183 This fully-crossed design makes it easy for us to estimate quantities of
 4184 interest. Let's say that our **reference group** (equivalent to the control
 4185 group for now) is neutral belief, neutral outcome. Now it's easy to use
 4186 the same kind of subtraction we did before to estimate particular effects
 4187 we care about. For example, we can look at the effect of negative belief
 4188 in the case of a neutral outcome: $\beta_{-B,O} = \theta_{-B,O} - \theta_{B,O}$. This effect is
 4189 shown on the left side of figure 9.4.

4190 But now there is a complexity: these two **simple effects** (effects of one
 4191 variable at a particular level of another variable) together suggest that the
 4192 combined effect $\beta_{-B,-O}$ in the negative belief, negative outcome con-
 4193 dition should be equal to the sum of $\beta_{-B,O}$ and $\beta_{B,-O}$.⁴ As we can see
 4194 from figure 9.4, that's not right. If it were, the negative belief, negative
 4195 outcome condition would be below the minimum possible rating!

4196 Instead, we observe an **interaction effect** (sometimes called a **two-way**
 4197 **interaction** when there are two factors): The effect when both factors
 4198 are present is different than the sum of the two simple effects. To cap-
 4199 ture this effect, we need an interaction term: $\beta_{-B,-O}$.⁵ In other words,

³ Neither of these is necessarily a “control” condition: the goal is simply to compare these two levels of the factor—negative and neutral—to estimate the effect due to the factor.

⁴ If you're interested, you can also compute the **average** or **main effect** of a particular factor via the same subtractive logic. For example, the average effect of negative belief ($-B$) vs. a neutral belief (B) can be computed as $\beta_{-B} = \frac{(\theta_{-O,-B} + \theta_{O,-B}) - (\theta_{-O,B} + \theta_{O,B})}{2}$.

⁵ If you're reading carefully, you might be thinking that this all sounds like we're talking about the analysis of variance (ANOVA), not about experimental design per se. These two topics are actually the same topic! The question is how to design an experiment so that these statistical models can be used to estimate particular effects—and combinations of effects—that we care about. In case you missed it, we discuss modeling interactions in a regression framework in chapter 7.

4200 the effect of negative beliefs (intent) on subjective moral permissibil-
 4201 ity depends on whether the action caused harm. Critically, without a
 4202 fully-crossed design, we can't estimate this interaction and we would
 4203 have made an incorrect prediction about one condition.

4204 *9.1.2 Generalized factorial designs*

4205 Young et al.'s design, in which there are two factors with two levels
 4206 each, is called a **2x2 design** (pronounced "two by two"). 2x2 designs
 4207 are incredibly common and useful, but they are only one of an infinite
 4208 variety of such designs that can be constructed.

4209 Say we added a third factor to Young et al.'s design such that Grace ei-
 4210 ther feels neutral towards her friend or is angry on that day. If we fully
 4211 crossed this third affective factor with the other two (belief and out-
 4212 come), we'd have a 2x2x2 design. This design would have eight con-
 4213 ditions: (A, B, O) , $(A, B, -O)$, $(A, -B, O)$, $(A, -B, -O)$, $(-A, B, O)$,
 4214 $(-A, B, -O)$, $(-A, -B, O)$, $(-A, -B, -O)$. These conditions would
 4215 in turn allow us to estimate both two-way and three-way interactions,
 4216 enumerated in table 9.1.

Table 9.1
 Effects in a 2x2x2 design with affect, belief, and outcome as factors.

Effect	Term Type
Affect	Main effect

Effect	Term Type
Belief	Main effect
Outcome	Main effect
Affect X Belief	2-way interaction
Affect X Outcome	2-way interaction
Belief X Outcome	2-way interaction
Affect X Belief X Outcome	3-way interaction

⁴²¹⁷ Three-way interactions are hard to think about! The affect X belief X outcome interaction tells you about the difference in moral permissibility that's due to all three factors being present as opposed to what you'd predict on the basis of your estimates of the two-way interactions. In addition to being hard to think about, higher order interactions tend to be hard to estimate, because estimating them accurately requires you to have a stable estimate of all of the lower-order interactions (McClelland and Judd 1993). For this reason, we recommend against experimental designs that rely on higher-order interactions unless you are in a situation where you both have strong predictions about these interactions and are confident in your ability to estimate them appropriately.

⁴²²⁸ Things can get even more complicated. If you have three factors with two levels each, as in the example above (table 9.1), you can estimate 7 total effects of interest. But if you have *four* factors with two levels each,

4231 you get 15. Four factors with *three* levels each gets you a horrifying 80
4232 different effects!⁶ This way lies madness, at least from the perspective of
4233 estimating and interpreting individual effects in a reasonable sample size.

4234 Again, we suggest starting with one- and two-factor designs. There is
4235 a lot to be learned from simple designs that follow good measurement
4236 and sampling practices.

⁶ The general formula for N factors with M levels each is $M^N - 1$.

DEPTH

Estimation strategies for generalized factorial designs

So what should you do if you really do care about four or more factors—in the sense that you want to estimate their effects and include them in your theory? The simplest strategy is to start your research off by measuring them independently in a series of single-factor experiments. This kind of setup is natural when there is a single reference level for each factor of interest, and such experiments can provide a basis for judging which factors are most important for your outcome and hence which should be prioritized for experiments to estimate interactions.

On the other hand, sometimes there is no reference level for a factor. For example, in the Kovács, Téglás, and Endress (2010) paradigm, it's not clear whether a positive or negative belief is the reference level. That's not a problem in a fully-crossed design like theirs, but this situation can pose a problem if you have more than two such factors. Ideally you would want to run independent experiments, but you have to choose some level for all

of the other variables—you can't just assume that one level is “neutral.”

One solution that lets you compute main effects but not interactions is called a **Latin square**. Latin squares are a good solution for three-factor designs, which is the level at which a fully-crossed design typically gets overwhelming. A Latin square is an $n \times n$ matrix in which each number occurs exactly once in each row and column, e.g.

$$\begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix}$$

This Latin square for $n = 3$ gives the solution for how to balance factors across a $3 \times 3 \times 3$ experiment. The row number is one factor, the column number is the second factor, and the number in the cell is the third factor. So one condition would be (1,1,1), the first level of all factors, shown in the upper left cell. Another would be (3,3,2), the lower right cell. Although a fully-crossed design would require 27 cells to be run, the Latin square has only nine. Critically, the combinations of factors are balanced across the nine cells so that the average effect of each level of the three factors can be estimated.

There are also fancier methods available. For example, the literature on **optimal experiment design** contains methods for choosing the most informative sequence of experiments to run in order to estimate the parameters in a model that can include many factors and their interactions ([Myung and Pitt 2009](#)). Going down this road typically means having

an implemented computational theory of your domain, but it can be a very productive strategy for exploring a complex experimental space with many factors.

4239

4240 9.1.1 *Between- vs. within-participant designs*

4241 Once you know what factor(s) you would like to manipulate in your
 4242 experiment, the next step is to consider how these will be presented
 4243 to participants, and how that presentation will interact with your mea-
 4244 surements. The biggest decision to be made is whether each participant
 4245 will experience one level of a factor—a **between-participants design**—or
 4246 whether they will experience multiple levels—a **within-participants de-
 4247 sign**. Figure 9.5 shows a simple example of between-participants design
 4248 with four participants (two assigned to each condition), while figure 9.6
 4249 shows a within-participants version of the same design.

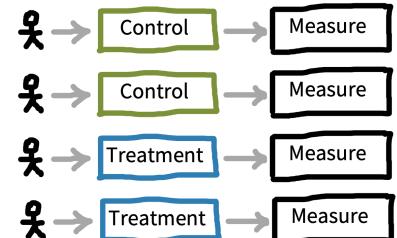


Figure 9.5
 A between-participants design.

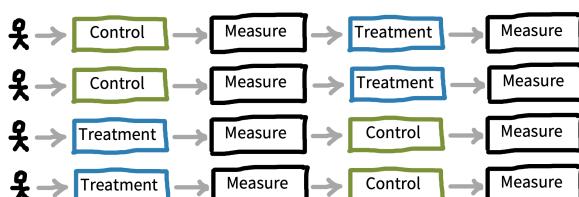


Figure 9.6
 A within-participants design, counter-
 balanced for order (discussion of coun-
 terbalancing below).

4250 Because people are very variable, the decision whether to measure a par-
 4251 ticular factor between- or within-participants is consequential. Imag-
 4252 ine we’re estimating our treatment effect as before, simply by comput-
 4253 ing $\hat{\beta} = \hat{\theta}_T - \hat{\theta}_C$ with each of these estimates from different populations

4254 of participants. In this scenario, our estimate $\hat{\beta}$ contains three compo-
4255 nents: 1) the true differences between θ_T and θ_C , 2) sampling-related
4256 variation in which participants from the population ended up in the
4257 samples for the two conditions, and 3) measurement error. Component
4258 #2 is present because any two samples of participants from a population
4259 will differ in their average on a measure—this is precisely the kind of
4260 sampling variation we saw in the null distributions in chapter 6.

4261 When our experimental design is within-participants, component #2
4262 is not present, because participants in both conditions are sampled from
4263 the *same* population. If we get unlucky and all of our participants are
4264 lower than the population mean on our measure, then that unluckiness
4265 affects our conditions equally. The consequences for choosing an ap-
4266 propriate sample size are fairly extreme: Between-participants designs
4267 typically require between two and eight times as many participants as
4268 within-participants designs!⁷

4269 Given these advantages, why would you consider using a between-
4270 participants design? A within-participants design is simply not possible
4271 for all experiments. For example, consider a medical intervention—say,
4272 a new surgical procedure that is being compared to an established
4273 one. Patients cannot receive two different procedures, and so no
4274 within-participant comparison is possible.

⁷ If you want to estimate how big an advantage you get from within-participants data collection, you need to know how correlated (reliable) your observations are. One analysis of this issue (Lakens 2016) suggests that the key relationship is that $N_{within} = N_{between}(1 - \rho)/2$ where ρ is the correlation between the measurement of the two conditions within individuals. The more correlated they are, the smaller your within-participants N .

4275 Most manipulations in the behavioral sciences are not so extreme, but
4276 it still may be impractical or inadvisable to deliver multiple conditions.

4277 Greenwald (1976) distinguishes three types of undesirable effects:⁸

- 4278 – **Practice effects** occur when administering the measure or the treatment will lead to change. Imagine a curriculum intervention for teaching a math concept –it would be hard to convince a school to teach the same topic to students twice, and the effect of the second round of teaching would likely be quite different than the first!
- 4284 – **Sensitization effects** occur when seeing two versions of an intervention mean that you might respond differently to the second than the first because you have compared them and noticed the contrast. Consider a study on room lighting—if the experimenters are constantly changing the lighting, participants may become aware that lighting is the focus of the study!
- 4290 – **Carry-over effects** refer to the case where one treatment might have a longer-lasting effect than the measurement period. For example, imagine a study in which one treatment was to make participants frustrated with an impossible puzzle; if a second condition were given after this first one, participants might still be frustrated, leading to spill-over of effects between conditions.

⁸ We tend to think of all of these as being forms of carry-over effect, and sometimes use this label as a catch-all description. Some people also use the picturesque description “poisoning the well” (Gelman 2017)—earlier conditions “ruin” the data for later conditions.

4296 All of these issues can lead to real concerns with respect to within-
4297 participant designs. But the desire for effect estimates that are
4298 completely unbiased by these concerns may lead to the overuse of
4299 between-participant designs (Gelman 2017). As we mentioned above,
4300 between-participant designs come at a major cost in terms of power
4301 and precision.

4302 An alternative approach is to acknowledge the possibility of carry-over
4303 type effects and seek to mitigate them. First, you can make sure that the
4304 order of condition is randomized or balanced (see below); and second,
4305 you can analyze carryover effects these within your statistical model (for
4306 example by estimating the interaction of condition and order).⁹

4307 We summarize the state of affairs from our perspective in figure 9.7. We
4308 think that within-participant designs should be preferred whenever pos-
4309 sible. This conclusion is also consistent with meta-research we've done
4310 on replications from our course: across 176 student replications, the use
4311 of a within-subjects design was the strongest correlate of a successful
4312 replication (Boyce, Mathur, and Frank 2023).¹⁰

4313 9.1.2 Repeated measurements and experimental items

4314 We just discussed decision-making about whether to administer mul-
4315 tiple *manipulations* to a single participant. An exactly analogous deci-

⁹ Even when one factor must be varied between participants, it is often still possible to vary others within subjects, leading to a **mixed design** in which some factors are between and others within.

¹⁰ Caveat: this study used an observational design, so no causal inference is possible.

- | Between | Within |
|---|--|
| <ul style="list-style-type: none"> • Main advantage <ul style="list-style-type: none"> • No contamination by other exposure to experimental materials • Disadvantages <ul style="list-style-type: none"> • Requires many participants • Individual differences create a lot of variability in groups • Potential for assignment bias: need to control for differences between groups • Other environmental group differences | <ul style="list-style-type: none"> • Main advantage <ul style="list-style-type: none"> • Eliminates subject variability • Relatively few participants needed, because of this lack of variability • Disadvantages <ul style="list-style-type: none"> • Carryover effects mean that ordering of conditions can be problematic • Not always possible • General contention: preferable when possible |

Figure 9.7

Pros and cons of between- vs. within-participant designs. We recommend within-participant designs when possible.

4316 sion comes up for *measures*! And our take-home will be similar: unless
 4317 there are specific difficulties that come up, it's usually a very good idea
 4318 to make multiple measurements (via multiple experimental trials) for
 4319 each participant in each condition.

4320 You can create a between-participants design where you administer
 4321 your manipulation and then measure multiple times. This scenario is
 4322 pictured in figure 9.8). Sometimes this works quite well. For example,
 4323 imagine a transcranial magnetic stimulation (TMS) experiment: partic-
 4324 ipants receive neural stimulation for a period of time, targeted at a par-
 4325 ticular region. Then they perform some measurement task repeatedly
 4326 until it wears off. The more times they perform the measurement task,
 4327 the better the estimate of whatever effect (when compared to a control
 4328 of TMS to another region, say).

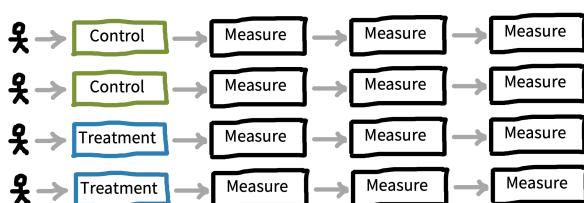


Figure 9.8

A between-participants, repeated-measures design.

4329 Sometimes this design is called a **repeated measures** design, but termino-
4330 nology here is tricky again. The term “repeated measures” refers to any
4331 experiment where each participant is measured more than once, includ-
4332 ing both between-participants *and* within-participants designs.¹¹ Our
4333 advice is *both* to use within-participants designs *and* to get multiple mea-
4334 surements from each participant.

4335 Why? In the last subsection, we described how variability in our esti-
4336 mates in a between-participants design depend on three components:

- 4337 1. true condition differences,
- 4338 2. sampling variation between conditions, and
- 4339 3. measurement error.

4340 Within-participants designs are good because they don’t include (2).

4341 Repeated measurements reduce (3): the more times you measure, the
4342 lower your measurement error, leading to greater measure reliability!

4343 There are problems with repeating the same measure many times, how-
4344 ever. Some measures can’t be repeated without altering the response.

4345 To take an obvious example, we can’t give the exact same math prob-
4346 lem twice and get two useful measurements of mathematical ability!

4347 The typical solution to this problem is to create multiple items. In the
4348 case of a math assessment, you create multiple problems that you believe

¹¹ We’re talking about multiple trials with the same measure, not multiple distinct measures. As we discussed in chapter 8, we tend to be against measuring lots of different things in a single experiment—in part because of the concerns that we’re articulating in this chapter: if you have time, it’s better to make more precise measures of what you care about most. Measuring one thing well is hard enough. Much better to measure one thing well than many things badly.

4349 test the same concept but have different numbers or other superficial
4350 characteristics.

4351 Using multiple items for measurement is good for two reasons. First, it
4352 reduces measurement error by allowing responses to be combined across
4353 items. But second, it increases the generalizability of the measurement.
4354 An effect that is consistent across many different items is more likely
4355 to be an effect that can be generalized to a whole class of stimuli—in
4356 precisely the same way that the use of multiple participants can license
4357 generalizations across a population of people (Clark 1973).

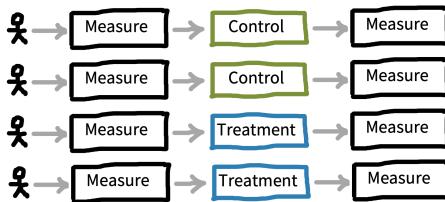


Figure 9.9
A between-participants, pre-post design.

4358 One variation on the repeated measures, between-participants design is
4359 a specific version where the measure is administered both before (pre-)
4360 and after (post-) intervention, as in figure 9.9. This design is sometimes
4361 known as a **pre-post** design. It is extremely common in cases where
4362 the intervention is larger-scale and harder to give within-participants,
4363 such as in a field experiment where a policy or curriculum is given to
4364 one sample and not to another. The pre measurements can be used
4365 to subtract out participant-level variability and recover a more precise
4366 estimate of the treatment effect. Recall that our treatment effect in a

⁴³⁶⁷ pure between participants design is $\beta = \theta_T - \theta_C$. In a pre-post design,

⁴³⁶⁸ we can do better by computing $\beta = (\theta_{T_{post}} - \theta_{T_{pre}}) - (\theta_{C_{post}} - \theta_{C_{pre}})$.

⁴³⁶⁹ This equation says “how much more did the treatment group go up than

⁴³⁷⁰ the control group?¹²

⁴³⁷¹ In sum, within-participants, repeated measurement designs are the

⁴³⁷² bread and butter of most research in perception, psychophysics, and

⁴³⁷³ cognitive psychology. When both manipulations and measures can be

⁴³⁷⁴ repeated, these designs afford high measurement precision even with

⁴³⁷⁵ small sample sizes; they are recommended whenever possible.

¹² This estimate is sometimes called a “difference in differences.” The basic idea is widely used in the field of econometrics, both in experimental and quasi-experimental cases (Cunningham 2021). In practice, though, we recommend using the pre-treatment measurements as a covariate in a model-based analysis, not just doing the simple subtraction.



ACCIDENT REPORT

Stimulus-specific effects

Imagine you’re a psycholinguist who has the hypothesis that nouns are processed faster than verbs. You run an experiment where you pick out ten verbs and ten nouns, then measure a large sample of participants’ reading time for each of these. You find strong evidence for the predicted effect and publish a paper on your claim. The only problem is that, at the same time, someone else has done exactly the same study—with different nouns and verbs—and published a paper making the opposite claim. When this happens, it is possible that each effect is driven by the specific experimental items that were chosen, rather than a generalization that is true of nouns and verbs in general (Clark 1973).

The problem of generalization from sample to population is not new—as we discussed in chapter 6, we are constantly making this kind of inference with the samples of people that participate in our experiments. Our classic statistical techniques are designed to quantify our ability to generalize from a sample of participants to a population, so we recognize that a very small sample size leads to a weak generalization. The exact same issue comes up with *items*: a very small sample of experimental items leads to a weak generalization to the population of items.

Item effects are kind of like accidentally finding a group of ten people whose left toes are longer than their right ones. If you continued to measure the same group’s toes, you could continue to replicate the difference in length. But that doesn’t mean it’s true of the population as a whole.

This kind of **stimulus generalizability** problem comes up across many different areas of psychology. In one example, hundreds of papers were written about a phenomenon called the “risky shift”—in which groups deliberating about a decision would produce riskier decisions than individuals. Unfortunately, this phenomenon appeared to be completely driven by the specific choice of vignettes that groups deliberated about, with some stories producing a risky shift and others producing a more conservative shift (Westfall, Judd, and Kenny 2015).

Another example comes from the memory literature, where a classic paper by Baddeley, Thomson, and Buchanan (1975) suggested that words that take longer to pronounce (“tycoon” or “morphine”) would be re-

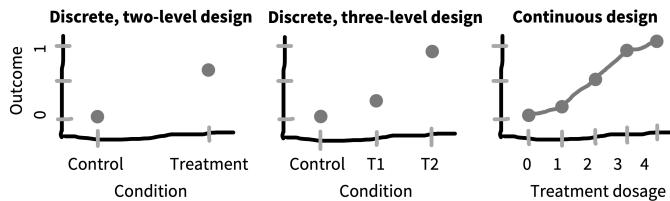
membered worse than words that took a shorter amount of time (“ember” or “wicket”) even when they had the same number of syllables. This effect also appears to be driven by the specific sets of words chosen in the original paper. It’s very replicable with that particular stimulus set but not generalizable across other sets (Lovatt, Avons, and Masterson 2000).

The implication of these examples is clear: experimenters need to take care in both their experimental design and analysis to avoid overgeneralizing from their stimuli to a broader construct. Three primary steps can help experimenters avoid this pitfall:

1. To maximize generality, use samples of experimental items—words, pictures, or vignettes—that are comparable in size to your samples of participants.
2. When replicating an experiment, consider taking a new sample of items as well as a new sample of participants. It’s more work to draft new items, but it will lead to more robust conclusions.
3. When experimental items are sampled at random from a broader population, use a statistical model that includes this sampling process (e.g., mixed effects models with random intercepts for items from chapter 7).

⁴³⁷⁹ 9.1.1 Discrete and continuous experimental manipulations

⁴³⁸⁰ Most experimental designs in psychology use discrete condition manipulations: treatment vs. control. In our view, this decision often leads
⁴³⁸¹ to a lost opportunity relative to a more continuous manipulation of the
⁴³⁸² strength of the treatment. The goal of an experiment is to estimate a
⁴³⁸³ causal effect; ideally, this estimate can be generalized to other contexts
⁴³⁸⁴ and used as a basis for theory. Measuring not just one effect but instead
⁴³⁸⁵ a **dose–response** relationship—how the measure changes as the strength
⁴³⁸⁶ of the manipulation is changed—has a number of benefits in helping to
⁴³⁸⁷ achieve this goal.



⁴³⁸⁸ Many manipulations can be **titrated**—that is, their strength can be varied
⁴³⁸⁹ continuously—with a little creativity on the part of an experimenter. A
⁴³⁹⁰ curriculum intervention can be applied at different levels of intensity,
⁴³⁹¹ perhaps by changing the number of sessions in which it is taught. For a
⁴³⁹² priming manipulation, the frequency or duration of prime stimuli can
⁴³⁹³ be varied. Two stimuli can be morphed continuously so that categorization boundaries can be examined.¹³

⁴³⁹⁴ Dose–response designs are useful because they provide insight into

Figure 9.10

Three schematic designs. (left) Control and treatment are two levels of a nominal variable. (middle) Control is compared to ordered levels of a treatment. (right) Treatment level is an interval or ratio variable such that points can be connected and a parametric curve can be extrapolated.

¹³ These methods are extremely common in perception and psychophysics research, in part because the dimensions being studied are often continuous in nature. It would be basically impossible to estimate a participant's visual contrast sensitivity *without* continuously manipulating the contrast of the stimulus!

4397 the shape of the function mapping your manipulation to your mea-
4398 sure. Knowing this shape can inform your theoretical understanding!
4399 Consider the examples given in figure 9.10. If you only have two
4400 conditions in your experiment, then the most you can say about the
4401 relationship between your manipulation and your measure is that
4402 it produces an effect of a particular magnitude; in essence, you are
4403 assuming that condition is a nominal variable. If you have multiple
4404 ordered levels of treatment, you can start to speculate about the nature
4405 of the relationship between treatment and effect magnitude. But if
4406 you can measure the strength of your treatment, then you can begin
4407 to describe the nature of the relationship between the strength of
4408 treatment and strength of effect via a parametric function (e.g., a linear
4409 regression, a sigmoid, or other function.¹⁴ These parametric functions
4410 can in turn allow you to generalize from your experiment, making
4411 predictions about what would happen under intervention conditions
4412 that you didn't measure directly!

DEPTH

Tradeoffs associated with titrated designs

Like adults, babies like to look at more interesting, complex stimuli. But do they uniformly prefer complex stimuli, or do they search for stimuli at an appropriate level of complexity for their processing abilities? To

¹⁴ These assumptions are theory-laden, of course—the choice of a linear function or a sigmoid is not necessary: nothing guarantees that simple, smooth, or monotonic functions are the right ones. The important point is that choosing a function makes explicit your assumptions about the nature of the treatment-effect relationship.

test this hypothesis, Brennan, Ames, and Moore (1966) exposed infants in three different age groups (3, 8, and 14 weeks, N=30) to black and white checkerboard stimuli with three different levels of complexity (2x2, 8x8, and 24x24).

Their findings are plotted in figure 9.11: the youngest infants preferred the simplest stimuli, while infants at an intermediate age preferred stimuli of intermediate complexity, and the oldest infants preferred the most complex stimuli. These findings help to motivate the theory that infants attend preferentially to stimuli that provide appropriate learning input for their processing ability (Kidd, Piantadosi, and Aslin 2012).

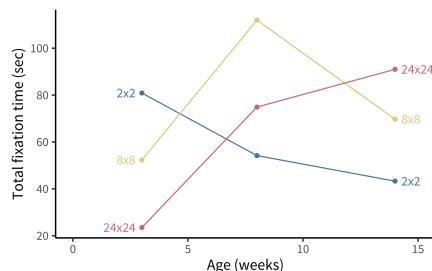


Figure 9.11
Infants' looking time, plotted by stimulus complexity and infant age. Data from Brennan, Ames, and Moore (1966).

If your goal is simply to detect whether an effect is zero or non-zero, then dose-response designs do not achieve the maximum statistical power. For example, if Brennan, Ames, and Moore (1966) simply wanted to achieve maximal statistical power, they probably should have only tested two age groups and two levels of complexity (say, 3 and 14 week infants and 2x2 and 24x24 checkerboards). That would have been enough to show an interaction of complexity and age, and their greater resources devoted

to these four (as opposed to nine) conditions would mean more precise estimates of each. But their findings would be less clearly supportive of the view that infants prefer stimuli that are appropriate to their processing ability, because no group would have preferred an intermediate level of complexity (as the 9-week-olds apparently did). By seeking to measure intermediate conditions, they provided a stronger test of their theory.

4415

4416 9.2 Choosing your manipulation

4417 In the previous section, we reviewed a host of common experimental
4418 designs. These designs provide a palette of common options for combin-
4419 ing manipulations and measures. But your choice must be predicated on
4420 the specific manipulation you are interested in! In this section, we dis-
4421 cuss considerations for experimenters as they design manipulations.

4422 In chapter 8, we talked about *measurement* validity, but the idea of va-
4423 lidity concept can be applied to manipulations as well as measures. In
4424 particular, a manipulation is valid if it corresponds to the construct that
4425 the experimenter intends to intervene on. In this context, *internal* va-
4426 lidity threats to manipulations tend to refer to cases where factors in
4427 the experimental design keep the intended manipulation from actually
4428 intervening on the construct of interest. In contrast, *external* validity

4429 threats to manipulations tend to be cases where the manipulation sim-
4430 ply doesn't line up well with the construct of interest.

4431 *9.2.1 Internal validity threats: Confounding*

4432 First and foremost, manipulations must actually manipulate the con-
4433 struct whose causal effect is being estimated. If they *actually* manipulate
4434 something else instead, they are **confounded**. This term is used widely
4435 in psychology, but it's worth revisiting what it means. An **experimental**
4436 **confound** is a variable that is created in the course of the experimental
4437 design that is both causally related to the predictor and potentially also
4438 related to the outcome. As such, it is a threat to **internal validity**.

4439 Let's go back to our discussion of causal inference in chapter 1. Our
4440 goal was to use a randomized experiment to estimate the causal effect of
4441 money on happiness. But just giving people money is a big intervention
4442 that involves contact with researchers—contact alone can lead to an ex-
4443 perimental effect even if your manipulation fails. For that reason, many
4444 studies that provide money to participants either give a small amount
4445 of money or a large amount of money. This design keeps researcher
4446 contact consistent in both conditions, implying that the difference in
4447 outcomes between these two conditions should be due to the amount
4448 of money received (unless there are other confounds!).

4449 Suppose you were designing an experiment of this sort and you wanted
 4450 to follow our advice and use a within-participants design. You could
 4451 measure happiness, give participants \$100, wait a month and measure
 4452 happiness again, give participants \$1000, wait a month, and then mea-
 4453 sure happiness for the third time. The trouble is, this design has an
 4454 obvious experimental confound (figure 9.12): the order of the mone-
 4455 tary gifts. Maybe happiness just went up more over time, irrespective
 4456 of getting the second gift.

4457 If you think your experimental design might have a confound, you
 4458 should think about ways to remove it. A first option is **elimination**,
 4459 which we described above: basically, matching a particular variable
 4460 across different conditions. This should be our first option for most con-
 4461 founds. Unfortunately, in our within-participants money-happiness
 4462 study, order is confounded with condition so if we match orders we
 4463 have eliminated our condition manipulation entirely.

4464 A second option is **counterbalancing**, in which we vary a confounding
 4465 factor systematically across participants so its average effect is zero across
 4466 the whole experiment. In the case of our example, counterbalancing
 4467 order across participants is a very safe choice. Some participants get
 4468 \$100 first and others get \$1000 first. That way, you are guaranteed that
 4469 the order of conditions will have no effect of the confound on your

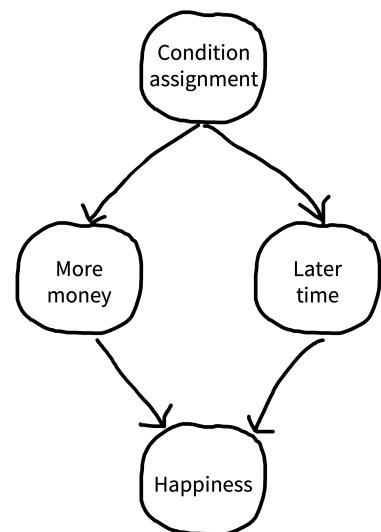


Figure 9.12
 Confounding order and condition as-
 signment means that you can't make an
 inference about the link between money
 and happiness.

average effect. The effect of this counterbalancing is that it “snips” the causal dependency between condition assignment and later time. We notate this on our causal diagram with a scissors icon (figure 9.13).¹⁵

Time can still have an effect on happiness, but the effect is independent from the effect of condition and hence your experiment can still yield an unbiased estimate of the condition effect.

Counterbalancing gets trickier when you have too many levels on a variable or multiple confounding variables. In that case, it may not be possible to do a full counterbalance so that all combinations of these factors are seen by equal numbers of participants. You may have to rely on partial counterbalancing schemes or Latin square designs (see Depth box above; in this case, the Latin squares are used to create orderings of stimuli such that the position of each treatment in the order is controlled across two other confounding variables).

A final option, especially useful for such tricky cases is **randomization**, that is, choosing which level of a nuisance variable to administer to the participant via a random choice. Randomization is increasingly common now that many experimental interventions are delivered by software. If you *can* randomize experimental confounds, you probably should. The only time you really get in trouble with randomization is when you have a large number of options, a small number of partic-

¹⁵ In practice, counterbalancing is like adding an additional factor to your factorial design! But because the factor is a **nuisance factor**—basically, one we don’t care about—we don’t discuss it as a true condition manipulation. Despite that, it’s a good practice to check for effects of these sorts of nuisance factors in your preliminary analysis. Even though your average effect won’t be biased by it, it introduces variation that you might want to understand to interpret other effects and plan new studies.

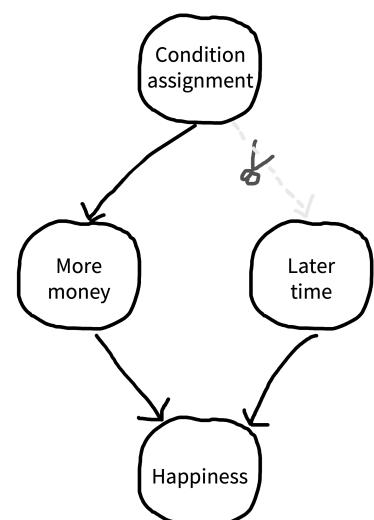


Figure 9.13
Confounding between a specific condition and the time at which it's administered can be removed by counterbalancing or randomization of order.

4491 ipants, or some combination of the two. Then you can end up with
4492 unbalanced levels of the randomized factors. Averaging across many ex-
4493 periments, a lack of balance will come out in the wash, but in a single
4494 experiment, it can lead to unfortunate bias in numbers.

4495 A good approach to thinking through your experimental design is to
4496 walk through the experiment step by step and think about potential
4497 confounds. For each of these confounds, consider how it might be
4498 removed via counterbalancing or randomization. As our case study
4499 shows, confounds are not always obvious, especially in complex
4500 paradigms. There is no sure-fire way to ensure that you have spotted
4501 every one—sometimes the best way to avoid them is simply to present
4502 your candidate design to a skeptical friend.

4503 9.2.2 Internal validity threats: Placebo, demand, and expectancy

4504 A second class of important threats to internal validity comes from cases
4505 where the research design is confounded by factors related to how the
4506 manipulation is administered, or even *that* a manipulation is adminis-
4507 tered. In some cases, these create confounds that can be controlled; in
4508 others they must simply be understood and guarded against. Rosnow
4509 and Rosenthal (1997) called these “artifacts”: systematic errors related
4510 to research *on* people, conducted *by* people.

4511 A placebo effect is a positive effect on the measure that comes as a re-
4512 sult of participants' expectations about a treatment in the context of
4513 research study. The classic example of a placebo is medical: giving an
4514 inactive sugar pill as a "treatment" leads some patients to report a reduc-
4515 tion in whatever symptom they are being treated for. Placebo effects are
4516 a major concern in medical research as well as a fixture in experimental
4517 designs in medicine (Benedetti 2020). The key insight is that treatments
4518 must not simply be compared to a baseline of no treatment but rather
4519 to a baseline in which the psychological aspects of treatment are present
4520 but the "active ingredient" is not. In the terms we have been using, the
4521 experience of receiving a treatment (independent of the content of the
4522 treatment) is a confounding factor when you simply compare treatment
4523 to no treatment conditions.

⚠️ ACCIDENT REPORT

Brain training?

Can doing challenging cognitive tasks make you smarter? In the late 2000s and early 2010s, a large industry for "brain training" emerged. Companies like Lumos Labs, CogMed, BrainHQ, and CogniFit offered games, often modeled on cognitive psychology tasks, that claimed to lead to gains in memory, attention, and problem solving.

These companies were basing their claims in part on a scientific literature reporting that concerted training on difficult cognitive tasks could lead

to benefits that transferred to other cognitive domains. Among the most influential of these was a study by Jaeggi et al. (2008). They conducted four experiments in which participants ($N=70$ across the studies) were assigned to either working memory training via a difficult working memory task (the “dual N-back”) or a no-training control, with training varying from 8 days all the way to 19 days.

The finding from this study excited a tremendous amount of interest because they reported not only gains in performance on the specific training task but also on a general intelligence task that the participants had trained on. While the control group’s scores on these tasks improved, presumably just from being tested twice, there was a condition by time (pre- vs. post) interaction such that the scores of the trained groups (consolidated across all four training experiments) grew significantly more over the training period (figure 9.14). These results were interpreted as supporting transfer—whereby training on one task leads to broader gains—a key goal for “brain training.”

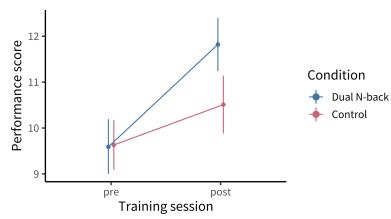


Figure 9.14
The primary outcome graph for data from Jaeggi et al. (2008).

Careful readers of the original paper noticed signs of analytic flexibility (as discussed in Chapters 3 and 6), however. For example, the key statistical model was fit to dataset created by post-hoc consolidation of experi-

ments, which yielded $p = .025$ on the key interaction (Redick et al. 2013).

When data were disaggregated, it was clear that the measures and effects had differed in each of the different sub-experiments (figure 9.15).

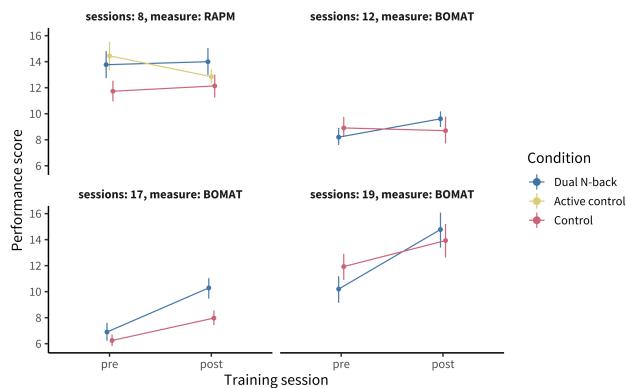


Figure 9.15

The four sub-experiments of Jaeggi et al. (2008), now disaggregated. Panels show 8-, 12-, 17-, and 19-session studies. Note the different measures: RAPM = Raven's Advanced Progressive Matrices; BOMAT = Bochumer Matrizentest. Based on Redick et al. (2013).

Several replications by the same group addressed some of these issues, but still failed to show convincing evidence of transfer. In particular, there was no comparison to an **active control group** in which participants did some kind of alternative activity for the same amount of time (Simons et al. 2016). Such a comparison is critical because a comparison to a **passive control group** (a group that does no intervention) confounds participants' general effort and involvement in the study with the specific training being used. Successful transfer compared to passive control could be the result of participants' involvement, expectations, or motivation rather than brain training per se.

A careful replication of the training study ($N=74$) with an active control

group and a wide range of outcome measures failed to find any transfer effects from working-memory training (Redick et al. 2013). A meta-analysis of 23 studies concluded that their findings cast doubt on working memory training for increasing cognitive functioning (Melby-Lervåg and Hulme 2013). In one convincing test of the cognitive transfer theory, a BBC show (“Bang Goes The Theory”) encouraged its listeners to participate in a six week online brain training study. More than 11,000 listeners completed the pre- and post-tests and at least two training sessions. Neither focused training of planning and reasoning nor broader training on memory, attention and mathematics led to transfer to untrained tasks.

Placebo effects are one plausible explanation for some positive findings in the brain training literature. Foroughi et al. (2016) recruited participants to participate via two different advertisements. The first advertised that “numerous studies have shown working memory training can increase fluid intelligence” (“placebo treatment” group) while the second simply offered experimental credits (control group). After a single training session, the placebo treatment group showed significant improvements to their matrix reasoning abilities. Participants in the placebo treatment group realized gains from training out of proportion with any they could have realized through training. Further, those participants who responded to the placebo treatment ad tended to endorse statements about the malleability of intelligence, suggesting that they might have been especially likely to self-select into the intervention.

Summarizing the voluminous literature on brain training, Simons et al.

(2016) wrote: “Despite marketing claims from brain-training companies of ‘proven benefits’... we find the evidence of benefits from cognitive brain training to be ‘inadequate.’”

4528

4529 If placebo effects reflect what participants expect from a treatment then

4530 **demand characteristics** reflect what participants think *experimenters*

4531 want and their desire to help the experimenters achieve that goal

4532 (Orne 1962). Demand characteristics are often raised as a reason for

4533 avoiding within-participants designs—if participants become alert to

4534 the presence of an intervention, they may then respond in a way that

4535 they believe is helpful to the experimenter. Typical tools for control-

4536 ling or identifying demand characteristics include using a cover story

4537 to mask the purpose of an experiment, using a debriefing procedure

4538 to probe whether participants typically guessed the purpose of an

4539 experiment, and (perhaps most effectively) creating a control condition

4540 with similar demand characteristics but missing a key component of

4541 the experimental intervention. Note that if you use a cover story

4542 to mask the purpose of your experiment, it’s worth thinking about

4543 whether you are using deception, which can raise ethical issues (see

4544 chapter 4). Certainly you should be sure to debrief participants about

4545 the true function of the experiment!

4546 The final entry into this list of internal validity threats is **experimenter**

4547 expectancy effects, where the experimenter's behavior biases partici-
4548 pants in a way that results in the appearance of condition differences
4549 where no true difference exists. The classic example of such effects is
4550 from the animal learning literature and the story of Clever Hans. Clever
4551 Hans was a horse who appeared able to do arithmetic by tapping out so-
4552 lutions with his hoof. On deeper investigation, it became apparent he
4553 was being cued by his trainer's posture (apparently without the trainer's
4554 knowledge) to stop tapping when the desired answer was reached. The
4555 horse knew nothing about math, but the experimenter's expectations
4556 were altering the horse's behavior across different conditions.

4557 In any experiment delivered by human experimenters who know what
4558 condition they are delivering, condition differences can result from ex-
4559 perimenters imparting their expectations. Table 9.2 shows the results
4560 of a meta-analysis estimating sizes of expectancy effects in a range of
4561 domains—the magnitudes are shocking. There's no question that ex-
4562 perimenter expectancy is sufficient to “create” many interesting phe-
4563 nomena artifactually. The mechanisms of expectancy are an interesting
4564 research topic in their own right; in many cases expectancies appear to
4565 be communicated non-verbally in much the same way that Clever Hans
4566 learned (Rosnow and Rosenthal 1997).

Table 9.2
Magnitudes of expectancy effects. Based on Rosenthal (1994).

Domain	d	r	Example of type of study
Laboratory interviews	0.14	.07	Effects of sensory restriction on reports of hallucinatory experiences
Reaction time	0.17	.08	Latency of word associations to certain stimulus words
Learning and ability	0.54	.26	IQ test scores, verbal conditioning (learning)
Person perception	0.55	.27	Perception of other people's success
Inkblot tests	0.84	.39	Ratio of animal to human Rorschach responses
Everyday situations	0.88	.40	Symbol learning, athletic performance
Psychophysical judgments	1.05	.46	Ability to discriminate tones
Animal learning	1.73	.65	Learning in mazes and Skinner boxes
<i>Weighted mean</i>	0.70	.33	
<i>Unweighted mean</i>	0.74	.35	
<i>Median</i>	0.70	.33	

⁴⁵⁶⁷ In medical research, the gold standard is an experimental design where

4568 neither patients nor experimenters know which condition the patients
4569 are in.¹⁶ Results from other designs are treated with suspicion because
4570 of their vulnerability to demand and expectancy effects. In psychology,
4571 the most common modern protection against experimenter expectancy
4572 is the delivery of interventions by a computer platform that can give
4573 instructions in a coherent and uniform way across conditions.

4574 In the case of interventions that must be delivered by experimenters,
4575 ideally experimenters should be unaware of which condition they are
4576 delivering. On the other hand, the logistics of maintaining experi-
4577 menter ignorance can be quite complicated in psychology. For this
4578 reason, many researchers opt for lesser degrees of control, for example,
4579 choosing to standardize delivery of an intervention via a script. These
4580 designs are sometimes necessary for practical reasons but should be
4581 scrutinized closely. “How can you rule out experimenter expectancy
4582 effects?” is an uncomfortable question that should be asked more
4583 frequently in seminars and paper reviews.

4584 9.2.1 *External validity of manipulations*

4585 The goal of a specific experimental manipulation is to operationalize
4586 a particular causal relationship of interest. Just as the relationship be-
4587 tween measure and construct can be more or less valid, so too can the

¹⁶ These are commonly referred to as double blind designs (though the term masked is now often preferred).

4588 relationship between manipulation and construct. How can you tell?

4589 Just like in the case of measures, there's no one royal road to validity.

4590 You need to make a validity argument (Kane 1992).¹⁷

4591 For testing the effect of money on happiness, our manipulation was to

4592 give participants \$1000. This manipulation is clearly face valid. But

4593 how often do people just receive a windfall of cash, versus getting a

4594 raise at work or inheriting money from a relative? Is the effect caused

4595 by *having* the money, or *receiving* the money with no strings attached?

4596 We might have to do more experiments to figure out what aspect of

4597 the money manipulation was most important. Even in straightforward

4598 cases like this one, we need to be careful about the breadth of the claims

4599 we make.

4600 Sometimes validity arguments are made based on the success of the ma-

4601 nipulation in producing some change in the measurement. In the the

4602 implicit theory of mind case study we began with, the stimulus con-

4603 tained an animated Smurf character, and the argument was that par-

4604 ticipants took the Smurf's beliefs into account in making their judg-

4605 ments. This stimulus choice seems surprising—not only would partici-

4606 pants have to track the implicit beliefs of other *people*, they would also

4607 have to be tracking the beliefs of depictions of non-human, animated

4608 characters. On the other hand, based on the success of the manipula-

¹⁷ One caveat is that the validity of a manipulation incorporates the validity of the manipulation *and* the measure. You can't really have a good estimate of a causal effect if the measurement is invalid.

4609 tion, the authors made an *a fortiori* argument: if people track even an
4610 animated Smurf's beliefs, then they *must* be tracking the beliefs of real
4611 humans.

4612 Let's look at one last example to think more about manipulation validity.

4613 Walton and Cohen (2011) conducted a short intervention in which col-
4614 lege students (N=92) read about social belonging and the challenges of
4615 the transition to college and then reframed their own experiences using
4616 these ideas. This intervention led to long-lasting changes in grades and
4617 well-being. While the intervention undoubtedly had a basis in theory,
4618 part of our understanding of the validity of the intervention comes from
4619 its efficacy: sense of belonging *must* be a powerful factor if intervening
4620 on it causes such big changes in the outcome measures.¹⁸ The only dan-
4621 ger is when the argument becomes circular—a theory is correct because
4622 the intervention yielded a success, and the intervention is presumed to
4623 be valid because of the theory. The way out of this circle is through
4624 replication and generalization of the intervention. If the intervention
4625 repeatedly produces the outcome, as has been shown in replications of
4626 the sense of belonging intervention (Walton, Brady, and Crum 2020),

4627 then the manipulation becomes an intriguing target for future theories.

4628 The next step in such a research program is to understand the limitations

4629 of such interventions (sometimes called **boundary conditions**).

¹⁸ On the other hand, if the manipu-
lation *doesn't* produce a change in your
measure, maybe the manipulation is in-
valid, but the construct still exists. Sense
of belonging could still be important
even if my particular intervention failed
to alter it!

4630 9.3 Summary: Experimental design

4631 In this chapter, we started by examining some common experimental
4632 designs that allow us to measure effects associated with one or more
4633 manipulations. Our advice, in brief, was: “keep it simple!” The failure
4634 mode of many experiments is that they contain too many manipulations,
4635 and these manipulations are measured with too little precision.

4636 Start with just a single manipulation, and measure it carefully. Ideally
4637 this measurement should be done via a within-participants design un-
4638 less the manipulation is completely incompatible with this design. And
4639 if this design can incorporate a dose-response manipulation, it is more
4640 likely to provide a basis for quantitative theorizing.

4641 How do you ensure that your manipulation is valid? A careful experi-
4642 menter needs to consider possible confounds and ensure that these are
4643 controlled or randomized. They must also consider other artifacts in-
4644 cluding placebo, demand, and expectancy effects. Finally, they must
4645 begin thinking about the relation of their manipulation to the broader
4646 theoretical construct whose causal role they hope to test.



DISCUSSION QUESTIONS

1. Choose a classic study in your area of psychology. Analyze the design choices: how many factors were manipulated? How many measures were taken? Did it use a within-participants or between-participants design? Were measures repeated? Can you justify these choices with respect to trade-offs (e.g., carry-over effects, fatigue, etc.)?
2. Consider the same study. Design an alternative version that varies one of these design parameters (e.g., drops a manipulation or measure, changes within- to between-participants, etc.). What are the pros and cons of this change? Do you think your design improves on the original?

4647



READINGS

- Much of this material is covered in more depth in the classic text on research methods: Rosenthal, R. & Rosnow, R. L. 2008. *Essentials of Behavioral Research: Methods and Data Analysis*. Third Edition. New York: McGraw-Hill. <http://dx.doi.org/10.34944/dspace/66>.

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4655

10 SAMPLING

4656



LEARNING GOALS

- Discuss sampling theory and stratified sampling
- Reason about the limitations of different samples, especially convenience samples
- Consider sampling biases and how they affect your inferences
- Learn how to choose and justify an appropriate sample size for your experiment

4657

As we keep reminding you, experiments are designed to yield measurements of a causal effect. But a causal effect of what, and for whom? These are questions that are often given surprisingly little air time in our papers. Titles in our top journals read “Daxy thinking promotes fribbles,” “Doing fonzy improves smoodling,” or “Blicket practice produces more foozles than smonkers.”¹ Each of these uses generic language to state a claim that is implied to be generally true (DeJesus et al. 2019),² but for each of these, we could reasonably ask “for whom?” Is

¹ Titles changed to protect the original authors. These researchers might very well have said more specific things in the text of their paper.

² Generic language is a fascinating linguistic phenomenon. When we say things like “mosquitoes transmit malaria,” we don’t mean that *all* mosquitoes do it, only something like “it’s a valid and diagnostic generalization about mosquitoes in contrast to other relevant insects or other creatures that they are spreaders of malaria” (Tessler and Goodman 2019).

4665 it everyone? Or a particular set of people? These are questions about
4666 our key theme, GENERALIZABILITY.

4667 Let's focus on smoodling. We wouldn't let the authors get away with
4668 a fully universal version of their claim: "Doing [*any*] fonzy improves
4669 smoodling [*for everyone*]." The non-generic version states a generaliza-
4670 tion that goes way beyond the evidence we actually have. But it seems
4671 that we are often OK with authors *implying* (with generic language) that
4672 their findings generalize broadly. Imagine for a second what the com-
4673 pletely specific version of one of these titles might look like: "Reading
4674 one particular selection of fonzy for fifteen minutes in the lab improved
4675 36 college students' smoodling scores on a questionnaire." This paper
4676 sounds pretty narrow in its applicability!

4677 We've already run into generalizability in our treatment of statistical
4678 estimation and inference. When we estimated a particular quantity (say,
4679 the effect of fonzy), we did so in our own sample. But we then used
4680 inferential tools to reason about how the estimate in this **sample** related
4681 to the parameter in the **population** as a whole. How do we link up
4682 these *statistical* tools for generalization to the *scientific* questions we have
4683 about the generalizability of our findings? That's the question of this
4684 chapter.

4685 A key set of decisions in experiment planning is what population to

4686 sample from and how to sample. We'll start by talking about the basics
4687 of **sampling theory**: different ways of sampling and the generalizations
4688 they do and don't license. The second section of the chapter will then
4689 deal with **sampling biases** that can compromise our effect estimates. A
4690 final set of key decisions is about **sample size planning**. In the third part
4691 of the chapter we'll address this issue, starting with classic **power analysis**
4692 but then introducing several other ways that an experimenter can plan
4693 and justify their sample size.

4694 10.1 Sampling theory

4695 The basic idea of sampling is simple: you want to estimate some
4696 measurement for a large or infinite population by measuring a sample
4697 from that population.³ Sampling strategies are split into two categories.
4698 **Probability sampling** strategies are those in which each member of the
4699 population has some known, pre-specified probability of being selected
4700 to be in the sample—think, “generalizing to Japanese people by picking
4701 randomly from a list of everyone in Japan.” **Non-probability sampling**
4702 covers strategies in which probabilities are unknown or shifting, or in
4703 which some members of the population could never be included in
4704 the sample—think, “generalizing to Germans by sending a survey to
4705 a German email list and asking people to forward the email to their

³ There are some tools for dealing with estimation in smaller populations where your sample is a substantial fraction of the population (e.g., a survey of your department where you get responses from half of the students). We won't discuss those here; our focus is on generalizing to large populations of humans.

4706 family.”

 CASE STUDY*Is everyone bad at describing smells?*

Since Darwin, scientists have assumed that smell is a vestigial sense in humans—one that we don’t even bother to encode in language. In English we don’t even have consistent words for odors. We can say something is “stinky,” “fragrant”, or maybe “musty,” but beyond these, most of our words for smells are about the *source* of the smell, not the qualities of it. Bananas, roses, and skunks all have distinctive smells, but we don’t have any vocabulary for naming what is common or uncommon about them. And when we make up ad-hoc vocabulary, it’s typically quite inconsistent (Majid and Burenhult 2014). The same situation applies across many languages.

So, would it be a good generalization about human beings—all people—that olfaction as a sense is de-emphasized relative to, say, vision? This inference has a classic sample-to-population structure. Within several samples of participants using widely-spoken languages, we observe limited and inconsistent vocabulary for smells, as well as poor discrimination. We use these samples to license an inference to the population—in this case, the entire human population.

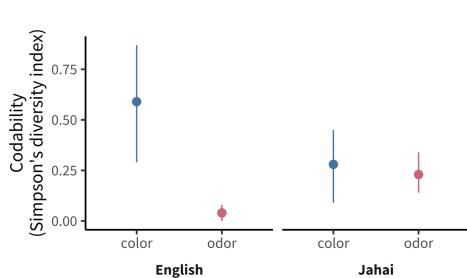


Figure 10.1

Data from Majid and Burenhult (2014) on the consistency of color and odor naming in English and Jahai speakers. Higher values indicate more consistent descriptions. Error bars show standard deviation.

But these inferences about the universal lack of olfactory vocabulary are likely based on choosing non-representative samples! Multiple hunter-gatherer groups appear to have large vocabularies for consistent smell description. For example, the Jahai, a hunter-gatherer group on the Malay Peninsula, have a vocabulary that includes at least twelve words for distinct odors, for example /cŋɔs/, which names odors with a “stinging smell” like gasoline, smoke, or bat droppings. When Jahai speakers are asked to name odors, they produce shorter and much more consistent descriptions than English speakers—in fact, their smell descriptions were as consistent as their color descriptions (figure 10.1). Further studies implicate the hunter-gatherer lifestyle as a factor: while several hunter-gatherer groups show good odor naming, nearby horticulturalist groups don’t (Majid and Kruspe 2018).

Generalizations about humans are tricky. If you want to estimate the average odor naming ability, you could take a random sample of humans and evaluate their odor naming. Most of the individuals in the sample would likely speak English, Mandarin, Hindi, or Spanish. Almost

certainly, none of them would speak Jahai, which is spoken by only a little more than a thousand people and is listed as Threatened by Ethnologue (<https://www.ethnologue.com/language/jhi>). Your estimate of low odor naming stability might be a good guess for the *majority* of the world's population, but would tell you little about the Jahai.

On the other hand, it's more complicated to jump from a statistical generalization about average ability to a richer claim, like "humans have low olfactory naming ability." Such claims about universal aspects of the human experience require much more care and much stronger evidence (Pi-antadosi and Gibson 2014). From a sampling perspective, human behavior and cognition show immense and complex heterogeneity—variability of individuals and variability across clusters. Put simply, if we want to know what people in general are like, we have to think carefully about which people we include in our studies.

4709

4710 10.1.1 *Classical probability sampling*

4711 In classical sampling theory there is some **sampling frame** containing ev-
ery member of the population—think of a giant list with every adult hu-
man's name in it. Then we use some kind of **sampling strategy**, maybe
4713 at the simplest just a completely random choice, to select N humans
4714 from that sample frame, and then we include them in our experiment.
4715 This scenario is the one that informs all of our statistical results about

4717 how sample means converge to the population mean (as in chapter 6).

4718 Unfortunately, we very rarely do sampling of this sort in psychological
4719 research. Gathering true probability samples from the large populations

4720 that we'd like to generalize to is far too difficult and expensive. Con-

4721 sider the problems involved in doing some experiment with a sample

4722 of *all adult humans*, or even *adult English-speaking humans who are located*

4723 *in the United States*. As soon as you start to think about what it would

4724 take to collect a probability sample of this kind of population, the com-

4725 plexities get overwhelming. How will you find their names—what if

4726 they aren't in the phone book? How will you contact them—what if

4727 they don't have email? How will they do your experiment—what if

4728 they don't have an up-to-date web browser? What if they don't want

4729 to participate at all?

4730 Instead, the vast majority of psychology research has been conducted

4731 with **convenience samples**: non-probability samples that feature indi-

4732 viduals who can be recruited easily, such as college undergraduates or

4733 workers on crowdsourcing platforms like Amazon Mechanical Turk or

4734 Prolific Academic (see chapter 12). We'll turn to these below.

4735 For survey research, on the other hand—think of election polling—there

4736 are many sophisticated techniques for dealing with sampling; although

4737 this field is still imperfect, it has advanced considerably in trying to pre-
4738 dict complex and dynamic behaviors. One of the basic ideas is the con-
4739 struction of **representative samples**: samples that resemble the popula-
4740 tion in their representation of one or several sociodemographic charac-
4741 teristics like gender, income, race and ethnicity, age, or political ori-
4742 entation.

4743 Representative samples can be constructed by probability sampling, but
4744 they can also be constructed through non-probability methods like re-
4745 cruiting quotas of individuals from different groups via various different
4746 convenience methods. These methods are critical for much social sci-
4747 ence research, but they have been used less frequently in experimental
4748 psychology research and aren't necessarily a critical part of the begin-
4749 ning experimentalist's toolkit.⁴

DEPTH

Representative samples and stratified sampling

Stratified sampling is a cool method that can help you get more pre-
cise estimates of your experimental effect, if you think it varies across
some grouping in your sample. Imagine you're interested in a particu-
lar measure in a population—say, attitudes towards tea drinking across
US adults—but you think that this measure will vary with one or more
characteristics such as whether the adults are frequent, infrequent, or

⁴ Readers can come up with counter-examples of recent studies that focus on representative sampling, but our guess is that they will prove the rule more generally. For example, a recent study tested the generality of growth mindset interventions for US high school students using a national sample (Yeager et al. 2019). This large-scale study sampled more than 100 high schools from a sampling frame of all registered high schools in the US, then randomly assigned students within schools that agreed to participate. They then checked that the schools that agreed to participate were representative of the broader population of schools. This study is great stuff, but we hope you agree that if you find yourself in this kind of situation—planning a multi-investigator 5 year consortium study on a national sample—you might want to consult with a statistician and not use an introductory book like this one.

non-coffee drinkers. Even worse, your measure might be more variable within one group: perhaps most frequent and infrequent coffee drinkers feel OK about tea, but as a group non-coffee drinkers tend to hate it (most don't drink any caffeinated beverages).

A simple random sample from this heterogeneous population *will* yield statistical estimates that converge asymptotically to the correct population average for tea-drinking attitudes. But it will do so more slowly than ideal because any given sample may over- or under-sample non-drinkers just by chance. In a small sample, if you happen to get too many non-coffee drinkers, your estimate of attitudes will be biased downward; if you happen to get too few, you will be biased upwards. All of this will come out in the wash eventually, but any individual sample (especially a small one) will be noisier than ideal.

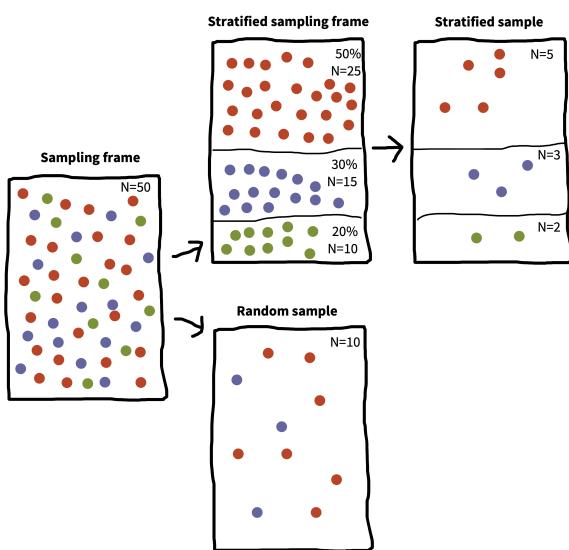


Figure 10.2
Illustration of stratified sampling. The left panel shows the sampling frame. The upper frames show the sampling frame stratified by a participant characteristic and a stratified sample. The lower frame shows a simple random sample, which happens to omit one group completely by chance.

But, if you know the proportion of frequent, infrequent, or non-coffee drinkers in the population, you can perform stratified sampling within those subpopulations to ensure that your sample is representative along this dimension (Neyman 1992). This situation is pictured in figure 10.2, which shows how a particular sampling frame can be broken up into groups for stratified sampling. The result is a sample that matches the population proportions on a particular characteristic. In contrast, a simple random sample can over- or under-sample the subgroups by chance.

Stratified sampling can lead to substantial gains in the precision of your estimate. These gains are most prominent when either the groups differ a lot in their mean or when they differ a lot in their variance. There are several important refinements of stratified sampling in case you think these methods are important for your problem. In particular, **optimal sampling** can help you figure out how to over-sample groups with higher variance. On the other hand, if the characteristic on which you stratify participants doesn't relate to your outcome at all, then estimates from stratified sampling converge just as fast as random sampling (though it's a bit more of a pain to implement).

figure 10.3 shows a simulation of the scenario in figure 10.2, in which each coffee preference group has a different tea attitude mean, and the smallest group has the biggest variance. Although the numbers here are invented, it's clear that estimation error is much smaller in the stratified group and estimation error declines much more quickly as samples get larger.

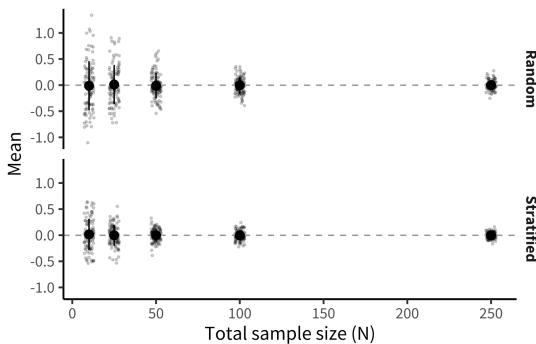


Figure 10.3

Simulation showing the potential benefits of stratification. Each dot is an estimated mean for a sample of a particular size, sampled randomly or with stratification. Red points show the mean and standard deviation of sample estimates.

Stratification is everywhere, and it's useful even in convenience samples.

For example, researchers who are interested in development typically stratify their samples across ages (e.g., recruiting equal numbers of two- and three-year-olds for a study of preschoolers). You can estimate developmental change in a pure random sample, but you are guaranteed good coverage of the range of interest when you stratify.

If you have an outcome that you think varies with a particular characteristic, it's not a bad idea to consider stratification. But don't go overboard—you can drive yourself to distraction finding the last left-handed non-binary coffee drinker to complete your sample. Focus on stratifying when you know the measure varies with the characteristic of interest.

4754 10.2 *Convenience samples, generalizability, and the*

4755 *WEIRD problem*

4756 Now let's go back to the question of generalizability. How generalizable

4757 are the experimental effect estimates that we obtain in experiments that

4758 are conducted only with convenience samples? We'll start by laying

4759 out the worst version of the problem of generalizability in experimental

4760 psychology. We'll then try to pull back from the brink and discuss some

4761 reasons why we might not want to be in despair despite some of the

4762 generalizability issues that plague the psychology literature.

4763 10.2.1 *The worst version of the problem*

4764 Psychology is the study of the human mind. But from a sampling theory

4765 standpoint, not a single estimate in the published literature is based on a

4766 simple random sample from the human population. And the situation

4767 is worse than that. Here are three of the most severe issues that have

4768 been raised regarding the generalizability of psychology research.

4769 1. **Convenience samples.** Almost all research in experimental psy-

4770 chology is performed with convenience samples. This issue has

4771 led to the remark that “the existing science of human behavior

4772 is largely the science of the behavior of sophomores” (McNemar,

4773 1946, quoted in Rosenthal and Rosnow 1984). The samples we
4774 have easy access to just don't represent the populations we want
4775 to describe! At some point there was a social media account de-
4776 voted to finding biology papers that made big claims about curing
4777 diseases and appending the qualifier "in mice" to them. We might
4778 consider whether we need to do the same to psychology papers.
4779 Would "Doing *fonzy* improves smoodling *in sophomore college un-*
4780 *dergraduates in the Western US*" make it into a top journal?

4781 2. **The WEIRD problem.** Not only are the convenience samples
4782 that we study not representative of the local or national contexts
4783 in which they are recruited, those local and national contexts
4784 are also unrepresentative of the broad range of human experi-
4785 ences. Henrich, Heine, and Norenzayan (2010) coined the term
4786 WEIRD (Western, Educated, Industrialized, Rich, and Demo-
4787 cratic) to sum up some of the ways that typical participants in
4788 psychology experiments differ from other humans. The vast over-
4789 representation of WEIRD participants in the literature has led
4790 some researchers to suggest that published results simply reflect
4791 "WEIRD psychology"—a small and idiosyncratic part of a much
4792 broader universe of human psychology.⁵

4793 3. **The item sampling issue.** As we discussed in chapter 7 and 9, we're

⁵ The term WEIRD has been very useful in drawing attention to the lack of representation of the breadth of human experiences in experimental psychology. But one negative consequence of this idea has been the response that what we need to do as a field is to sample more "non-WEIRD" people. It is not helpful to suggest that every culture outside the WEIRD moniker is the same (Syed and Kathawalla 2020)! A better starting point is to consider the way that cultural variation might guide our choices about sampling.

4794 typically not just trying to generalize to new people, we're also try-
4795 ing to generalize to new stimuli (Westfall, Judd, and Kenny 2015).

4796 The problem is that our experiments often use a very small set of
4797 items, constructed by experimenters in an ad-hoc way rather than
4798 sampled as representatives of a broader population of stimuli that
4799 we hope to generalize to with our effect size estimate. What's
4800 more, our statistical analyses sometimes fail to take stimulus vari-
4801 ation into account. Unless we know about the relationship of our
4802 items to the broader population of stimuli, our estimates may be
4803 based on unrepresentative samples in yet another way.

4804 In sum, experiments in the psychology literature primarily measure ef-
4805 fects from WEIRD convenience samples of people and unsystematic
4806 samples of experimental stimuli. Should we throw up our hands and
4807 resign ourselves to an ungeneralizable “science” of sample-specific anec-
4808 dotes (Yarkoni 2020)?

4809 10.2.2 Reasons for hope and ways forward

4810 We think the situation isn't as bleak as the arguments above might have
4811 suggested. Underlying each of the arguments above is the notion of
4812 heterogeneity, the idea that particular effects vary in the population.

4813 Let's think through a very simple version of this argument. Say we have
 4814 an experiment that measures the smoodling effect, and it turns out that
 4815 smoodling is completely universal and invariant throughout the human
 4816 population. Now, if we want to get a precise estimate of smoodling,
 4817 we can take *any* sample we want because everyone will show the same
 4818 pattern. Because smoodling is homogeneous, a non-representative sam-
 4819 ple will not cause problems. There are some phenomena like this! For
 4820 example, the Stroop task produces a consistent and similar interference
 4821 effect for almost everyone (Hedge, Powell, and Sumner 2018).

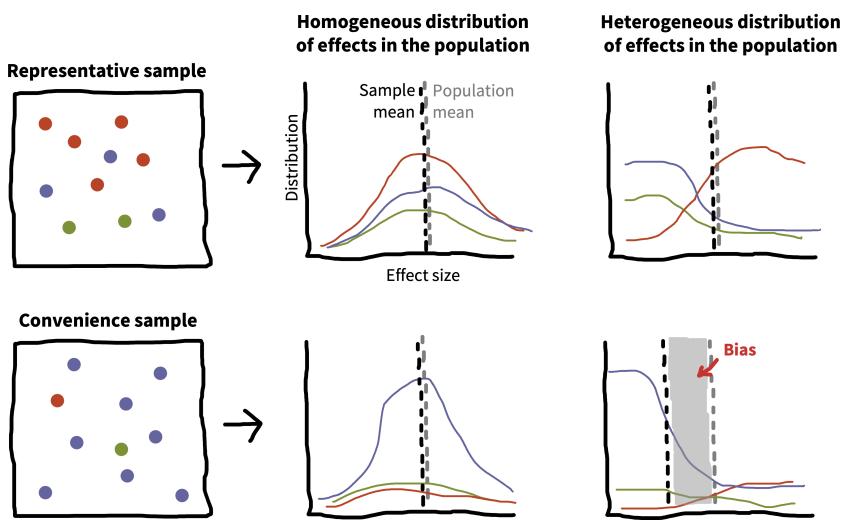


Figure 10.4
 Illustration of the interaction of heterogeneity and convenience samples. Colors indicate arbitrary population sub-groups. Left hand panels show sample composition. Individual plots show the distribution of effect sizes in each subgroup.

4822 figure 10.4 illustrates this argument more broadly. If you have a rep-
 4823 resentative sample (top), then your sample mean and your population
 4824 mean will converge to the same value, regardless of whether the effect
 4825 is homogeneous (right) or heterogeneous (right). That's the beauty of
 4826 sampling theory. If you have a convenience sample, one part of the

4827 population is over-represented in the sample. The convenience sam-
4828 ple doesn't cause problems if the size of your effect is homogeneous in
4829 the population—as with the case of smoodling or Stroop. The trou-
4830 ble comes when you have an effect that is heterogeneous. Because one
4831 group is over-represented, you get systematic bias in the sample mean
4832 relative to the population mean.

4833 So the problems listed above—convenience samples, WEIRD samples,
4834 and narrow stimulus samples—only cause issues if effects are heteroge-
4835 neous. Are they? The short answer is, *we don't know*. Convenience
4836 samples are fine in the presence of homogeneous effects, but we only
4837 use convenience samples so we may not know which effects are homo-
4838 geneous! Our metaphorical heads are in the sand.

4839 We can't do better than this circularity without a theory of what should
4840 be variable and what should be consistent between individuals.⁶ As
4841 naïve observers of human behavior, differences between people often
4842 loom large. We are keen observers of social characteristics like age, gen-
4843 der, race, class, and education. For this reason, our intuitive theories
4844 of psychology often foreground these characteristics as the primary lo-
4845 cus for variation between people. Certainly these characteristics are
4846 important, but they fail to explain many of the *invariances* of human
4847 psychology as well. An alternative line of theorizing starts with the idea

⁶ Many people have theorized about the ways that culture and language in general might moderate psychological processes (e.g., Markus and Kitayama 1991). What we're talking about is related but slightly different—a theory not of what's different, but of when there should be any difference and when there shouldn't be. As an example, Tsai (2007)'s “ideal affect” theory predicts that there should be more similarities in the distribution of actual affect across cultures, but that cultural differences should emerge in *ideal affect* (what people want to feel like) across cultures. This is a theory of when you should see homogeneity and when you should see heterogeneity.

4848 that “lower-level” parts of psychology—like perception—should be less
4849 variable than “higher-level” faculties like social cognition. This kind
4850 of theory sounds like a useful place to start, but there are also counter-
4851 examples in the literature, including cases of cultural variation in per-
4852ception (Henrich, Heine, and Norenzayan 2010).

4853 Multi-lab, multi-nation studies can help to address questions about het-
4854 erogeneity, breaking the circularity we described above. For example,
4855 ManyLabs 2 systematically investigated the replicability of a set of phe-
4856 nomena across cultures (Klein et al. 2018), finding limited variation in
4857 effects between WEIRD sites and other sites. And in a study compar-
4858 ing a set of convenience and probability samples, Coppock, Leeper, and
4859 Mullinix (2018) found limited demographic heterogeneity in another
4860 sample of experimental effects from across the social sciences. So there
4861 are at least some cases where we don’t have to worry as much about het-
4862 erogeneity. More generally, such large-scale studies offer the possibility
4863 of measuring and characterizing demographic and cultural variation—
4864 as well as how variation itself varies between phenomena!

4865 10.3 Biases in the sampling process

4866 In fields like econometrics or epidemiology that use observational meth-
4867 ods to estimate causal effects, reasoning about **sampling biases** is a critical

part of estimating generalizable effects. If your sample does not represent the population of interest, then your effect estimates will be biased.⁷

In the kind of experimental work we are discussing many of these issues are addressed by random assignment, including the first issue we treat: **collider bias**. Not so for the second one, **attrition bias**, which is an issue even in randomized experiments.

10.3.1 Collider bias

Imagine you want to measure the association between money and happiness through a (non-experimental) survey. As we discussed in chapter 1, there are plenty of causal processes that could lead to this association. Figure 10.5 shows several of these scenarios. Money could truly cause happiness (1); happiness could cause you to make more money (2); or some third factor—say having lots of friends—could cause people to be happier *and* richer (3).

But we can also create spurious associations if we are careless in our sampling. One prominent problem that we can induce is called **collider bias**. Suppose we recruited our sample from the clients of a social services agency. Unfortunately, both of our variables might affect presence in a social service agency (figure 10.5, 4): people might be interacting

⁷ There is a deep literature on correcting these biases using causal inference frameworks. These techniques are well outside of the scope of this book, but if you’re interested, you might look at some of the textbooks we recommended earlier, e.g. Cunningham (2021).

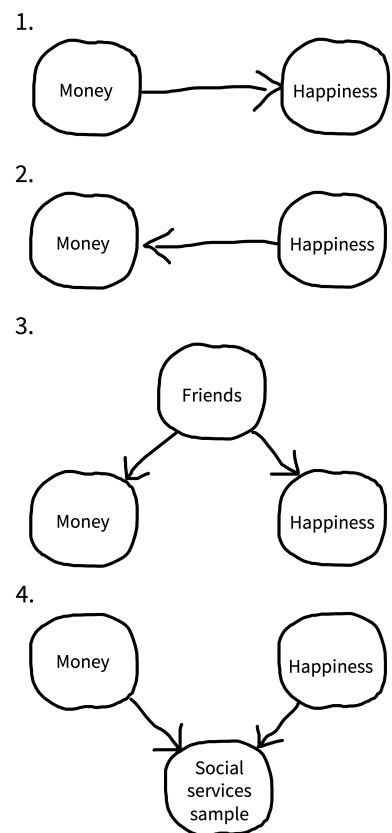


Figure 10.5
Four reasons why money and happiness can be correlated in a particular sample:
1. causal relationship, 2. reverse causality, 3. confounding with friendship, and 4. collider bias. For this last scenario, we have to assume that our measurement is *conditioned* on being in this sample, meaning we only look at the association of money and happiness within the social services sample.

4887 with the agency for financial or benefits assistance, or else for psycho-
4888 logical services (perhaps due to depression).

4889 Being in a social services sample is called a **collider** variable because the
4890 two causal arrows *collide* into it (they both point to it). If we look just
4891 within the social services sample, we might see a *negative* association
4892 between wealth and happiness—on average the people coming for fi-
4893 nancial assistance would have less wealth and more happiness than the
4894 people coming for psychological services. The take-home here is that
4895 in observational research, you need to think carefully about the causal
4896 structure of your sampling process (Rohrer 2018)!

4897 If you are doing experimental research, you are mostly protected from
4898 this kind of bias: Random assignment still “works” even in sub-selected
4899 samples. If you run a money intervention within a social-services popu-
4900 lation using random assignment, you can still make an unbiased estimate
4901 of the effect of money on happiness. But that estimate will only be valid
4902 *for members of that sub-selected population.*

4903 10.3.2 Attrition bias

4904 **Attrition** is when people drop out of your study. You should do every-
4905 thing you can to improve participants’ experiences (see chapter 12) but
4906 sometimes—especially when a manipulation is onerous for participants

4907 or your experiment is longitudinal and requires tracking participants for
 4908 some time—you will still have participants withdraw from the study.

4909 Attrition on its own can be a threat to the generalizability of an experi-
 4910 mental estimate. Imagine you do an experiment comparing a new very
 4911 intense after-school math curriculum to a control curriculum in a sam-
 4912 ple of elementary school children over the course of a year. By the end
 4913 of the year, suppose many of your participants have dropped out. The
 4914 families who have stayed in the study are likely those who care most
 4915 about math. Even if you see an effect of the curriculum intervention,
 4916 this effect may generalize only to children in families who love math.

4917 But there is a further problem with attrition, known as **selective attrition**.
 4918 If attrition is related to the outcome specifically within the treatment
 4919 group (or for that matter, specifically within the control group), you
 4920 can end up with a biased estimate, even in the presence of random as-
 4921 signment (Nunan, Aronson, and Bankhead 2018)! Imagine students in
 4922 the control condition of your math intervention experiment stayed in
 4923 the sample, but the math intervention itself was so tough that most fam-
 4924 ilies dropped out except those who were very interested in math. Now,
 4925 when you compare math scores at the end of the experiment, your esti-
 4926 mate will be biased (figure 10.6): scores in the math condition could be
 4927 higher simply because of differences in who stuck around to the end.⁸

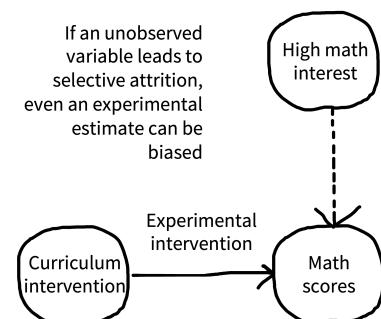


Figure 10.6
 Selective attrition can lead to a bias even in the presence of random assignment. Dashed line indicates a causal relationship that is unobserved by the researcher.

⁸ If you get deeper into drawing DAGs like we are doing here, you will want to picture attrition as its own node in the graph, but that's beyond the scope of this book.

4928 Unfortunately, it turns out that attrition bias can be pretty common
4929 even in short studies, especially when they are conducted online when
4930 a participant can drop out simply by closing a browser window. This
4931 bias can be serious enough to lead to false conclusions. For example,
4932 Zhou and Fishbach (2016) ran an experiment in which they asked on-
4933 line participants to write about either 4 happy events (low difficulty)
4934 or 12 happy events (high difficulty) from the last year and then asked
4935 the participants to rate the difficulty of the task. Surprisingly, the high
4936 difficulty task was rated as easier than the low difficulty task! Selective
4937 attrition was the culprit for this counter-intuitive conclusion: while
4938 only 26% of participants dropped out of the low difficulty condition, a
4939 full 69% dropped out of the high difficulty task. The 31% that were left
4940 found it quite easy for them to generate 12 happy events, and so they
4941 rated the objectively harder task as less difficult.

4942 Always try to track and report attrition information. That lets you—and
4943 others—understand whether attrition is leading to bias in your estimates
4944 or threats to the generalizability of your findings.⁹

4945 10.4 Sample size planning

4946 Now that you have spent some time considering your sample and what
4947 population it represents, how many people will your sample contain?

⁹ If you get interested, there is a whole field of statistics that focuses on **missing data** and provides models for reasoning about and dealing with cases where data might not be **missing completely at random** (Little and Rubin 2019 is the classic reference for these tools). The causal inference frameworks referenced above also have very useful ways of thinking about this sort of bias.

4948 Continuing to collect data until you observe a $p < .05$ in an inferen-
4949 tial test is a good way to get a false positive. This practice, known as
4950 “optional stopping,” is a good example of a practice that invalidates p -
4951 values, much like the cases of analytic flexibility discussed in chapter 3
4952 and chapter 6.

4953 Decisions about when to stop collecting data should not be data-
4954 dependent. Instead you should transparently declaring your data
4955 collection **stopping rule** in your study preregistration (see chapter 11).
4956 This step will reassure readers that there is no risk of bias from optional
4957 stopping. The simplest stopping rule is “I’ll collect data until I get to a
4958 target N ”—all that’s needed in this case is a value for N .

4959 But how do you decide N ? It’s going to be dependent on the effect
4960 that you want to measure, and how it varies in the population. Smaller
4961 effects will require larger sample sizes. Classically, N was computed
4962 using **power analysis**, which can provide a sample size for which you
4963 have a good chance of rejecting the null hypothesis (given a particular
4964 expected effect size). We’ll introduce this computation below.

4965 Classical power analysis is not the only way to plan your sample size.
4966 There are a number of other useful strategies, some of which rely on
4967 the same kinds of computations as power analysis (table 10.1). Each of

- ⁴⁹⁶⁸ these can provide a valid justification for a particular sample size, but
⁴⁹⁶⁹ they are useful in different situations.

Table 10.1
 Types of data collection stopping rules.

Method	Stopping Rule	Example
Power analysis	Stop at N for known probability of rejecting the null given known effect size	Randomized trial with strong expectations about effect size
Resource constraint	Stop collecting data after a certain amount of time or after a certain amount of resources are used	Time-limited field work
Smallest effect size of interest	Stop at N for known probability of rejecting the null for effects greater than some minimum	Measurement of a theoretically important effect with unknown magnitude
Precision analysis	Stop at N that provides some known degree of precision in measure	Experimental measurement to compare with predictions of cognitive models
Sequential analysis	Stop when a known inferential criterion is reached	Intervention trial designed to accept or reject null with maximal efficiency

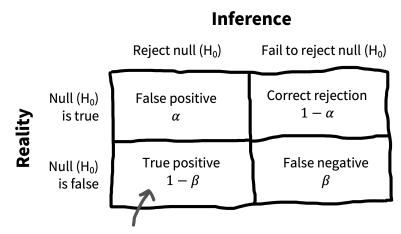


Figure 10.7
 Standard decision matrix for NHST.

4970 10.4.1 Power analysis

4971 Let's start by reviewing the null-hypothesis significance testing
4972 paradigm that we introduced in chapter 6. Recall that we introduced
4973 the Neyman-Pearson decision-theoretic view of testing in chapter 6,
4974 shown again in figure 10.7. The idea was that we've got some null
4975 hypothesis H_0 and some alternative H_1 —something like “no effect”
4976 and “yes, there is some effect with known size”—and we want to use
4977 data to decide which state we're in. α is our criterion for rejecting the
4978 null, conventionally set to $\alpha = .05$.

4979 But what if H_0 is actually false and the alternative H_1 is true? Not
4980 all experiments are equally well set up to reject the null in those cases.
4981 Imagine doing an experiment with $N = 3$. In that case, we'd almost
4982 always fail to reject the null, even if it were false. Our sample would
4983 almost certainly be too small to rule out sampling variation as the source
4984 of our observed data.

4985 Let's try to quantify our willingness to miss the effect—the false negative
4986 rate. We'll denote this probability with β . If β is the probability of
4987 missing an effect (failing to reject the null when it's really false), then
4988 $1 - \beta$ is the probability that we correctly reject the null when it is false. That's
4989 what we call the **statistical power** of the experiment.

4990 We can only compute power if we know the effect size for the alterna-
 4991 tive hypothesis. If the alternative hypothesis is a small effect, then the
 4992 probability of rejecting the null will typically be low (unless the sample
 4993 size is very large). In contrast, if the alternative hypothesis is a large
 4994 effect, then the probability of rejecting the null will be higher.

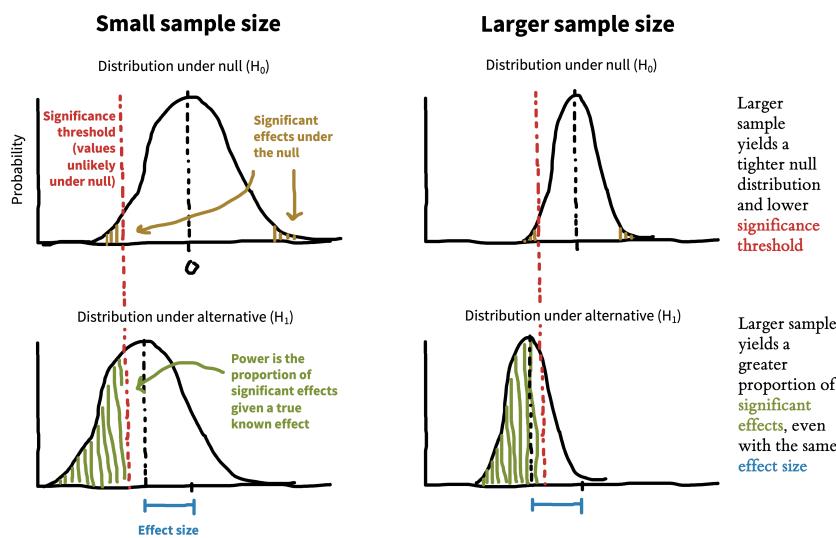


Figure 10.8
 Illustration of how larger sample sizes lead to greater power.

4995 The same dynamic holds with sample size: the same effect size will be
 4996 easier to detect with a larger sample size than with a small one. Fig-
 4997 ure 10.8 shows how this relationship works. A large sample size cre-
 4998 ates a tighter null distribution (right side) by reducing sampling error.
 4999 A tighter null distribution means you can reject the null more of the
 5000 time based on the variation in a true effect. If your sample size is too
 5001 small to detect your effect much of the time, we call this being under-
 5002 powered.¹⁰

¹⁰ You can also refer to a design as over-powered, though we object slightly to this characterization, since the value of large datasets is typically not just to reject the null but also to measure an effect with high precision and to investigate how it is moderated by other characteristics of the sample.

5003 Classical power analysis involves computing the sample size N that's
5004 necessary in order to achieve some level of power, given α and a known
5005 effect size.¹¹ The mathematics of the relationship between α , β , N , and
5006 effect size have been worked out for a variety of different statistical tests
5007 (Cohen 2013) and codified in software like G*Power (Faul et al. 2007)
5008 and the `pwr` package for R (Champely et al. 2017). For other cases
5009 (including mixed effects models), you may have to conduct a simulation
5010 in which you generate many simulated experimental runs under known
5011 assumptions and compute how many of these lead to a significant effect;
5012 luckily, R packages exist for this purpose as well, including the `simr`
5013 package (Green and MacLeod 2016).

5014 10.4.2 Power analysis in practice

5015 Let's do a power analysis for our hypothetical money and happiness
5016 experiment. Imagine the experiment is a simple two group design
5017 in which participants from a convenience population are randomly
5018 assigned either to receive \$1000 and some advice on saving money
5019 (experimental condition) vs. just receiving the advice and no money
5020 (control condition). We then follow up a month later and collect
5021 self-reported happiness ratings. How many people should we have
5022 in our study in order to be able to reject the null? The answer to

¹¹ Our focus here is on giving you a conceptual introduction to power analysis, but we refer you to Cohen (1992) for a more detailed introduction.

5023 this question depends on our desired values of α and β as well as our
5024 expected effect size for the intervention.

5025 For α we will just set a conventional significance threshold of $\alpha = .05$.

5026 But what should be our desired level of power? The usual standard in
5027 the social sciences is to aim for power above 80% (e.g., $\beta < .20$); this
5028 gives you 4 out of 5 chances to observe a significant effect. But just
5029 like $\alpha = .05$, this is a conventional value that is perhaps a little bit too
5030 loose for modern standards—a strong test of a particular effect should
5031 probably have 90% or 95% power.¹²

5032 These choices are relatively easy, compared to the fundamental issue:
5033 our power analysis requires some expectation about our effect size. This
5034 is the **first fundamental problem of power analysis**: if you knew the
5035 effect size, you might not need to do the experiment!

5036 So how are you supposed to get an estimate of effect size? Here are a
5037 few possibilities:

- 5038 – **Meta-analysis.** If there is a good meta-analysis of the effect that
5039 you are trying to measure (or something closely related), then you
5040 are in luck. A strong meta-analysis will have not only a precise ef-
5041 fect size estimate but also some diagnostics detecting and correct-
5042 ing potential publication bias in the literature (see chapter 16).

¹² Really, researchers interested in using power analysis in their work should give some thought to what sort of chance of a false negative they are willing to accept. In exploratory research perhaps a higher chance of missing an effect is reasonable; in contrast, in confirmatory research it might make sense to aim for a higher level of power.

5043 While these diagnostics are imperfect, they still can give you a
5044 sense for whether you can use the meta-analytic effect size esti-
5045 mate as the basis for a power analysis.

5046 – **Specific prior study.** A more complicated scenario is when you
5047 have only one or a handful of prior studies that you would like
5048 to use as a guide. The trouble is that any individual effect in the
5049 literature is likely to be inflated by publication and other selective
5050 reporting biases (see chapter 3). Thus, using this estimate likely
5051 means your study will be under-powered—you might not get as
5052 lucky as a previous study did!

5053 – **Pilot testing.** Many people (including us) at some point learned
5054 that one way to do a power analysis is to conduct a pilot study,
5055 estimate the effect size from the pilot, and then use this effect
5056 estimate for power analysis in the main study. We don't recom-
5057 mend this practice. The trouble is that your pilot study will have
5058 a small sample size, leading to a very imprecise estimate of effect
5059 size (Browne 1995). If you over-estimate the effect size, your
5060 main study will be very under-powered. If you under-estimate,
5061 the opposite will be true. Using a pilot for power analysis is a
5062 recipe for problems.

5063 – **General expectations about an effect of interest.** In our view, per-

5064 haps the best way you can use power analysis (in the absence of a
5065 really strong meta-analysis, at least) is to start with a general idea
5066 about the size of effect you expect and would like to be able to
5067 detect. It is totally reasonable to say, “I don’t know how big my
5068 effect is going to be, but let’s see what my power would be if it
5069 were *medium-sized* (say $d = .5$), since that’s the kind of thing we’re
5070 hoping for with our money intervention.” This kind of power
5071 analysis can help you set your expectations about what range of
5072 effects you might be able to detect with a given sample size.

5073 For our money study, using our general expectation of a medium size
5074 effect, we can compute power for $d = .5$. In this case, we’ll simply use
5075 the two-sample t -test introduced in chapter 6, for which 80% power at
5076 $\alpha = .05$ and $d = .5$ is achieved by having $N = 64$ in each group.

CODE

Classic power analysis in R is quite simple using the `pwr` package. The package offers a set of test-specific functions like `pwr.t.test()`. For each, you supply three of the four parameters specifying effect size (`d`), number of observations (`n`), significance level (`sig.level`), and power (`power`); the function computes the fourth. For classic power analysis, we leave out `n`:

```
pwr.t.test(d = .5,  
            power = .8,  
            sig.level = .05,  
            type = "two.sample",  
            alternative = "two.sided")
```

But it is also possible to use this same function to compute the power achieved at a combination of n and d , for example.

5078

5079 There's a second issue, however. The **second fundamental problem of**
5080 **power analysis** is that the real effect size for an experiment may be zero.
5081 And in that case, *no* sample size will let you correctly reject the null. Go-
5082 ing back to our discussion in chapter 6, the null hypothesis significance
5083 testing framework is just not set up to let you *accept* the null hypothesis.
5084 If you are interested in a bi-directional approach to hypothesis testing
5085 in which you can accept *and* reject the null, you may need to consider
5086 Bayes Factor or **equivalence testing** approaches (Lakens, Scheel, and Is-
5087 ager 2018), which don't fit the assumptions of classical power analysis.

5088 10.4.3 Alternative approaches to sample size planning

5089 Let's now consider some alternatives to classic power analysis that can
5090 still yield reasonable sample size justifications.

5091 1. **Resource constraint.** In some cases, there are fundamental re-
5092 source constraints that limit data collection. For example, if you
5093 are doing fieldwork, sometimes the right stopping criterion for
5094 data collection is “when the field visit is over,” since every addi-
5095 tional datapoint is valuable. When pre-specified, these kinds of
5096 sample size justifications can be quite reasonable, although they
5097 do not preclude being under-powered to test a particular hypoth-
5098 esis.

5099 2. **Smallest effect size of interest (SESOI).** SESOI analysis is a variant
5100 on power analysis that includes some resource constraint planning.
5101 Instead of trying to intuit how big your target effect is, you instead
5102 choose a level below which you might not be interested in detect-
5103 ing the effect. This choice can be informed by theory (what is
5104 predicted), applied concerns (what sort of effect might be useful
5105 in a particular context), or resource constraints (how expensive or
5106 time-consuming it might be to run an experiment). In practice,
5107 SESOI analysis simply a classic power analysis with a particular
5108 small effect as the target.

5109 3. **Precision-based sample planning.** As we discussed in chapter 6,
5110 the goal of research is not always to reject the null hypothesis!
5111 Sometimes—we’d argue that it should be most of the time—the

goal is to estimate a particular causal effect of interest with a high level of precision, since these estimates are a prerequisite for building theories. If what you want is an estimate with known precision (say, a confidence interval of a particular width), you can compute the sample size necessary to achieve that precision (Bland 2009; Rothman and Greenland 2018).¹³

4. **Sequential analysis.** Your stopping rule need not be a hard cutoff at a specific N . Instead, it's possible to plan a **sequential analysis** using either frequentist or Bayesian methods, in which you plan to stop collecting data once a particular inferential threshold is reached. For the frequentist version, the key thing that keeps sequential analysis from being *p*-hacking is that you pre-specify particular values of N at which you will conduct tests and then correct your *p*-values for having tested multiple times (Lakens 2014).

For Bayesian sequential analysis, you can actually compute a running Bayes factor as you collect data and stop when you reach a pre-specified level of evidence (Schönbrodt et al. 2017). This latter alternative has the advantage of allowing you to collect evidence *for* the null as well as against it.¹⁴

In sum, there are many different ways of justifying your sample size or your stopping rule. The most important things are 1) to pre-specify

¹³ In our experience, this kind of planning is most useful when you are attempting to gather measurements with sufficient precision to compare between computational models. Since the models can make quantitative predictions that differ by some known amount, then it's clear how tight your confidence intervals need to be.

¹⁴ Another interesting variant is sequential parameter estimation, in which you collect data until a desired level of precision is achieved (Kelley, Darku, and Chattopadhyay 2018); this approach combines some of the benefits of both precision-based analysis and sequential analysis.

5133 your strategy and 2) to give a clear justification for your choice. Ta-
5134 ble 10.2 gives an example sample size justification that draws on several
5135 different concepts discussed here, using classical power computations as
5136 one part of the justification. A reviewer could easily follow the logic of
5137 this discussion and form their own conclusion about whether this study
5138 had an adequate sample size and whether it should have been conducted
5139 given the researchers' constraints.

Table 10.2
Example sample size justification, referencing elements of SESOI, resource-limitation,
and power-based reasoning.

Element	Justification Text
Background	We did not have strong prior information about the likely effect size, so we could not compute a classical power analysis.
Smallest effect of interest	Because of our interest in meaningful factors affecting word learning, we were interested in effect sizes as small as $d=.5$.
Resource limitation	We were also limited by our ability to collect data only at our on-campus preschool.
Power computation	We calculated that based on our maximal possible sample size of $N=120$ (60 per group), we would achieve at least 80% power to reject the null for effects as small as $d = .52$.

 DEPTH

Sample sizes for replication studies

Setting the sample size for a replication study has been a persistent issue in the meta-science literature. Naïvely speaking, it seems like you should be able to compute the effect size for the original study and then simply use that as the basis for a classical power analysis.

This naïve approach has several flaws, however. First, the effect size from the original published paper is likely an overestimate of the true effect size due to publication bias (Nosek et al. 2021). Second, the power analysis will only yield the sample size at which the replication will have a particular chance of rejecting the null at some criterion. But it's quite possible that the original experiment could be $p < .05$, the replication could be $p > .05$, and 3) the original experiment and the replication results are not significantly different from each other. So a statistically significant replication of the original effect size is not necessarily what you want to aim for.

Faced with these issues, a replication sample size can be planned in several other ways. First, replicators can use standard strategies above such as SESOI or resource-based planning to rule out large effects, either with high probability or within a known amount of time or money. If the SESOI is high or limited resources are allocated, these strategies can produce an inconclusive result, however. A conclusive answer can require a very substantial commitment of resources.

Second, Simonsohn (2015) recommends the “small telescopes” approach. The idea is not to test whether there *is* an effect, but rather where there is an effect *large enough that the original study could have detected it*. The analogy is to astronomy. If a birdwatcher points their binoculars at the sky and claims to have discovered a new planet, we want to ask not just whether there is a planet at that location, but also whether there is any possibility that they could have seen it using binoculars—if not, perhaps they are right but for the wrong reasons! Simonsohn shows that, if a replicator collects 2.5 times as large a sample as the original, they have 80% power to detect any effect that was reasonably detectable by the original. This simple rule of thumb provides one good starting place for conservative replication studies.

Finally, replicators can make use of sequential Bayesian analysis, in which they attempt to gather substantial evidence relative to the support for H_1 or H_0 . Sequential bayes is an appealing option because it allows for efficient collection of data that reflects whether an effect is likely to be present in a particular sample, especially in the face of the sometimes prohibitively large samples necessary for SESOI or “small telescopes” analyses.

5141

5142 10.5 Chapter summary: Sampling

5143 Your goal as an experimenter is to estimate a causal effect. But the effect

5144 for whom? This chapter has tried to help you think about how you

5145 generalize from your experimental sample to some target population.

5146 It's very rare to be conducting an experiment based on a probability
5147 sample in which every member of the population has an equal chance of
5148 being selected. In the case that you are using a convenience sample, you
5149 will need to consider how bias introduced by the sample could relate
5150 to the effect estimate you observed. Do you think this effect is likely
5151 to be very heterogeneous in the population? Are there theories that
5152 suggest that it might be larger or smaller for the convenience sample
5153 you recruited?

5154 Questions about generalizability and sampling depend on the precise
5155 construct you are studying, and there is no mechanistic procedure for
5156 answering them. Instead, you simply have to ask yourself: how does
5157 my sampling procedure qualify the inference I want to make based on
5158 my data? Being transparent about your reasoning can be very helpful—
5159 both to you and to readers of your work who want to contextualize the
5160 generality of your findings.



DISCUSSION QUESTIONS

1. We want to understand human cognition generally, but do you think it is a more efficient research strategy to start by studying certain features of cognition (perception, for example) in WEIRD convenience populations and then later check our generalizations in non-WEIRD groups? What are the arguments against this efficiency-based strategy?

2. One alternative position regarding sampling is that the most influential experiments aren't generalizations of some number to a population; they are demonstration experiments that show that some particular effect is possible under some circumstances (think Milgram's conformity studies, see chapter 4). On this argument, the specifics of population sampling are often secondary. Do you think this position makes sense?
3. One line of argument says that we can't ever make generalizations about the human mind because so much of the historical human population is simply inaccessible to us (we can't do experiments on ancient Greek psychology). In other words, sampling from a particular population is *also* sampling a particular moment in time. How should we qualify our research interpretations to deal with this issue?

5162



READINGS

- The original polemic article on the WEIRD problem: Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The WEIRDest people in the world? *Behavioral and Brain Sciences*, 33, 61-83.
- A very accessible introduction to power analysis from its originator: Cohen, J. (1992) A power primer. *Psychological Bulletin*, 112, 155-9.
- A thoughtful and in-depth discussion of generalizability issues: Yarkoni, T. (2020). The generalizability crisis. *Behavioral and Brain Sciences*, 45, 1-37.

5163

IV

5164

EXECUTION

5165

⁵¹⁶⁶ *References*

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5171

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5172 11 PREREGISTRATION

LEARNING GOALS

- Recognize the dangers of researcher degrees of freedom
- Understand the differences between exploratory and confirmatory modes of research
- Articulate how preregistration can reduce risk of bias and increase transparency

5173

5174 When not planned beforehand, data analysis can approxi-

5175

mate a projective technique, such as the Rorschach, because

5176

the investigator can project on the data his own expectan-

5177

cies, desires, or biases and can pull out of the data almost

5178

any “finding” he may desire.

5179

— Theodore X. Barber (1976)

5180

The first principle is that you must not fool yourself—and

5181 you are the easiest person to fool... After you've not fooled
5182 yourself, it's easy not to fool other scientists. You just have
5183 to be honest in a conventional way after that.

5184 — Richard Feynman (1974)

5185 The last section of the book focused on planning a study—in particular,
5186 making decisions around measurement, design, and sampling. In this
5187 next section, we turn to the nuts and bolts of executing a study. We start
5188 with preregistration (this chapter), before discussing the logistics of data
5189 collection (chapter 12) and project management (chapter 13). These
5190 chapters touch on the themes of *transparency* and *bias reduction* through
5191 decisions about how to document and organize your data collection.

5192 Let's start with simply documenting choices about design and analysis.
5193 Although there are plenty of *incorrect* ways to design and analyse exper-
5194 iments, there is no single *correct* way. In fact, most research decisions
5195 have many justifiable choices—sometimes called “researcher degrees of
5196 freedom”. For example, will you stop data collection after 20, 200, or
5197 2000 participants? Will you remove outlier values and how will you
5198 define them? Will you conduct subgroup analyses to see whether the
5199 results are affected by sex, or age, or some other factor?

5200 Consider a simplified, hypothetical case where you have to make five

5201 analysis decisions and there are five justifiable choices for each decision
5202 – this alone would result in 3125 (5^5) unique ways to analyze the data!
5203 If you were to make these decisions **post hoc** (after observing the data)
5204 then there's a danger your decisions will be influenced by the outcome
5205 of the analysis ("data-dependent decision making") and skew towards
5206 choices that generate outcomes more aligned with your personal prefer-
5207 ences. Now think back to the last time you read a research paper. Of all
5208 the possible ways that the data could have been analyzed, how do you
5209 know that the researchers did not just select the approach that generated
5210 results most favourable to their pet hypothesis?

5211 In this chapter, we will find out why flexibility in the design, analy-
5212 sis, reporting, and interpretation of experiments, combined with data-
5213 dependent decision-making, can introduce bias, and lead to scientists
5214 fooling themselves and each other. We will also learn about **preregistra-**
5215 **tion**, the process of writing down and registering your research decisions
5216 before you observe the data. Preregistration intersects with two of our
5217 themes: it can be used to REDUCE BIAS in our data analysis, and it can pro-
5218 vide the TRANSPARENCY that other scientists need to properly evaluate
5219 and interpret our results (Hardwicke and Wagenmakers 2022).

 CASE STUDY

Undisclosed analytic flexibility?

Educational apps for children are a huge market, but relatively few randomized trials have been done to see whether or when they produce educational gains. Filling this important gap, Berkowitz et al. (2015) reported a high-quality field experiment of a free educational app, “Bedtime Math at Home,” with participants randomly assigned to either math or reading conditions over the course of a full school year. Critically, along with random assignment, the study also included standardized measures of math and reading achievement. These measures allowed the authors to compute effects in grade-level equivalents, a meaningful unit from a policy perspective.

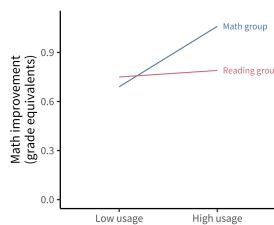


Figure 11.1
Model fits reported in Figure 1 of Berkowitz et al. (2015). Estimated years of math achievement gained over the school year across groups, as a function of app usage level.

The key result is shown in figure 11.1. Families who used the math app frequently showed greater gains in math than the control group. Although this finding appeared striking, the figure didn't directly visualize the primary causal effect of interest, namely the size of the effect of study condition on math scores. Instead the data were presented as estimated effects

for specific levels of app usage.

Because the authors made their data openly available, it was possible for Frank (2016) to do a simple analysis to examine the causal effect of interest. When not splitting the data by usage and adjusting by covariates, there was no significant main effect of the intervention on math performance figure 11.2. Since this analysis was not favorable to the primary intervention—and because it was not reported in the paper—it could have been the case that the authors had analyzed the data several ways and chosen to present an analysis that was more favorable to their hypotheses of interest.

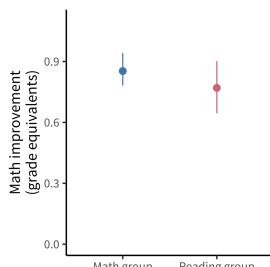


Figure 11.2
Estimated years of math achievement gained over the school year across groups in the Berkowitz et al. (2016) math app trial. Error bars show bootstrapped 95% confidence intervals. Based on Frank (2016).

As is true for many papers prior to the rise of preregistration, it's not possible to know definitively whether the reported analysis in Berkowitz et al. (2015) was influenced by the authors' desired result. As we'll see below, such data-dependent analyses can lead to substantial bias in reported effects. This uncertainty about a paper's analytic strategy can be avoided by the use of preregistration. In this case, preregistration would have convinced readers that the analyses decisions were not influenced by the data,

5222 thereby increasing the value of this otherwise high-quality study.

5223 *11.1 Lost in a garden of forking paths*

5224 One way to visualize researcher degrees of freedom is as a vast decision
5225 tree or “garden of forking paths” (figure 11.3). Each node represents
5226 a decision point and each branch represents a justifiable choice. Each
5227 unique pathway through the garden terminates in an individual research
5228 outcome.

5229 Because scientific observations typically consist of both noise (random
 5230 variation unique to this sample) and signal (regularities that will reoccur
 5231 in other samples), some of these pathways will inevitably lead to results
 5232 that are misleading (e.g., inflated effect sizes, exaggerated evidence, or
 5233 false positives). The more potential paths in the garden that you might
 5234 explore, the higher the chance of encountering misleading results.

5235 Statisticians refer to this issue as a **multiplicity** (multiple comparisons)
 5236 problem. As we talked about in chapter 6, multiplicity can be addressed
 5237 to some extent with statistical countermeasures, like the Bonferroni cor-
 5238 rection; however, these adjustment methods need to account for ev-
 5239 ery path that you *could have* taken (Gelman and Loken 2014; de Groot
 5240 1956/2014). When you navigate the garden of forking paths while
 5241 working with the data, it is easy to forget—or even be unaware of—
 5242 every path that you could have taken, so these methods can no longer
 5243 be used effectively.

5244 The signal-to-noise ratio is worse in particular situations (as com-
 5245 mon in psychology) with small effect sizes, high variation, and large
 5246 measurement errors (Ioannidis 2005). Researcher degrees of freedom
 5247 may be constrained to some extent by strong theory (Oberauer and
 5248 Lewandowsky 2019), community methodological norms, or replication
 5249 studies, though these constraints may be more implicit than explicit,

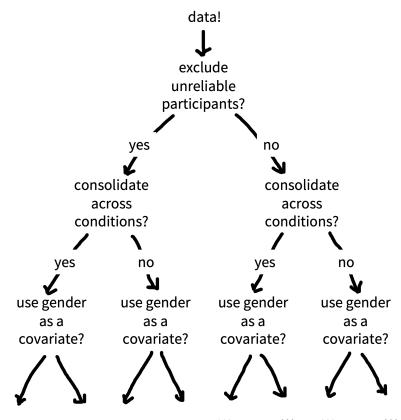


Figure 11.3

The garden of forking paths: many justifiable but different analytic choices are possible for an individual dataset.

5250 and can still leave plenty of room for flexible decision-making.

5251 *11.1.1 Data-dependent analysis*

5252 When a researcher navigates the garden of forking paths during data
5253 analysis, their choices might be influenced by the data (data-dependent
5254 decision making) which can introduce bias. If a researcher is seeking
5255 a particular kind of result (see Depth box below), then they are more
5256 likely to follow the branches that steer them in that direction.

5257 You could think of this a bit like playing a game of “hot (🔥) or cold (❄️)”
5258 where 🔥 indicates that the choice will move the researcher closer to a
5259 desirable overall result and ❄️ indicates that the choice will move them
5260 further away. Each time the researcher reaches a decision point, they
5261 try one of the branches and get feedback on how that choice affects the
5262 results. If the feedback is 🔥 then they take that branch. If the answer
5263 is ❄️, they try a different branch. If they reach the end of a complete
5264 pathway, and the result is ❄️, maybe they even retrace their steps and try
5265 some different branches earlier in the pathway. This strategy creates a
5266 risk of bias because it systematically skews results towards researcher’s
5267 preferences (Hardwicke and Wagenmakers 2022).¹

¹ We say “risk of bias” rather than just “bias” because in most scientific contexts, we do not have a known ground truth to compare the results to. So in any specific situation, we do not know the extent to which data-dependent decisions have actually biased the results.

 DEPTH

Only human: Cognitive biases and skewed incentives

There's a storybook image of the scientist as an objective, rational, and dispassionate arbiter of truth (Veldkamp et al. 2017). But in reality, scientists are only human: they have egos, career ambitions, and rent to pay! So even if we do want to live up to the storybook image, it's important to acknowledge that our decisions and behavior are also influenced by a range of cognitive biases and external incentives that can steer us away from that goal. Let's first look at some relevant cognitive biases that might lead scientists astray:

- **Confirmation bias:** Preferentially seeking out, recalling, or evaluating information in a manner that reinforces one's existing beliefs (Nickerson 1998).
- **Hindsight bias:** Believing that past events were always more likely to occur relative to our actual belief in their likelihood before they happened ("I knew it all along!") (Slovic and Fischhoff 1977).
- **Motivated reasoning:** Rationalizing prior decisions so they are framed in a favorable light, even if they were irrational (Kunda 1990).
- **Apophenia:** Detecting seemingly meaningful patterns in noise (Gilovich, Vallone, and Tversky 1985).

To make matters worse, the incentive structure of the scientific ecosystem often adds additional motivation to get things wrong. The allocation

of funding, awards, and publication prestige is often based on the nature of research results rather than research quality (Smaldino and McElreath 2016; Nosek, Spies, and Motyl 2012). For example, many academic journals, especially those that are widely considered to be the most prestigious, appear to have a preference for novel, positive, and statistically significant results over incremental, negative, or null results (Bakker, Dijk, and Wicherts 2012). There is also pressure to write articles with concise, coherent, and compelling narratives (Giner-Sorolla 2012). This set of forces incentivizes scientists to be “impressive” over being right and encourages questionable research practices. The process of iteratively p-hacking and HARKing one’s way to a “beautiful” scientific paper has been dubbed “The Chrysalis Effect” (O’Boyle, Banks, and Gonzalez-Mulé 2017), illustrated in figure 11.4.

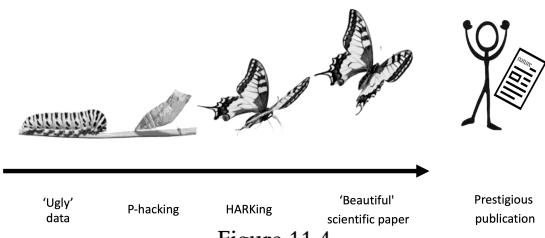


Figure 11.4

The Chrysalis Effect, when ugly truth becomes a beautiful fiction.

In sum, scientists’ human flaws—and the scientific ecosystem’s flawed incentives—highlight the need for transparency and intellectual humility when reporting the findings of our research (Hoekstra and Vazire 2021).

5270 In the most egregious cases, a researcher may try multiple pathways until
5271 they obtain a desirable result and then **selectively report** that result, ne-
5272 glecting to mention that they have tried several other analysis strategies
5273 (also known as *p*-hacking, a practice we've discussed throughout the
5274 book).² You may remember an example of this practice in chapter 3,
5275 where participants apparently became younger when they listened to
5276 "When I'm 64" by The Beatles. Another example of how damaging
5277 the garden of forking paths can be comes from the "discovery" of brain
5278 activity in a dead Atlantic Salmon! Researchers deliberately exploited
5279 flexibility in the fMRI analysis pipeline and avoided multiple compar-
5280 isons corrections, allowing them to find brain activity where there was
5281 only dead fish figure 11.5.

5282 11.1.1 Hypothesizing after results are known

5283 In addition to degrees of freedom in experimental design and analysis,
5284 there is additional flexibility in how researchers *interpret* research results.
5285 As we discussed in chapter 2, theories can accommodate even conflict-
5286 ing results in many different ways—for example, by positing auxiliary
5287 hypotheses that explain why a particular datapoint is special.
5288 The practice of selecting or developing your hypothesis after observing
5289 the data has been called "Hypothesizing After the Results are Known",

² "If you torture the data long enough, it will confess" (Good 1972).

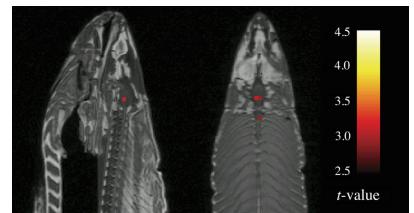


Figure 11.5
By deliberately exploiting analytic flexibility in the processing pipeline of fMRI data, Bennett, Miller, and Wolford (2009) were able to identify 'brain activity' in a dead Atlantic Salmon. From Bennett, Miller, and Wolford (2009) (licensed under CC BY).

5290 or “HARKing” (Kerr 1998). HARKing is potentially problematic be-
 5291 cause it expands the garden of forking paths and helps to justify the
 5292 use of various additional design and analysis decisions (figure 11.6). For
 5293 example, you may come up with an explanation for why an interven-
 5294 tion is effective in men but not in women in order to justify a post-hoc
 5295 subgroup analysis based on sex (see Case Study. The extent to which
 5296 HARKing is problematic is contested (for discussion see Hardwicke and
 5297 Wagenmakers 2022). But at the very least it’s important to be honest
 5298 about whether hypotheses were developed before or after observing the
 5299 data.

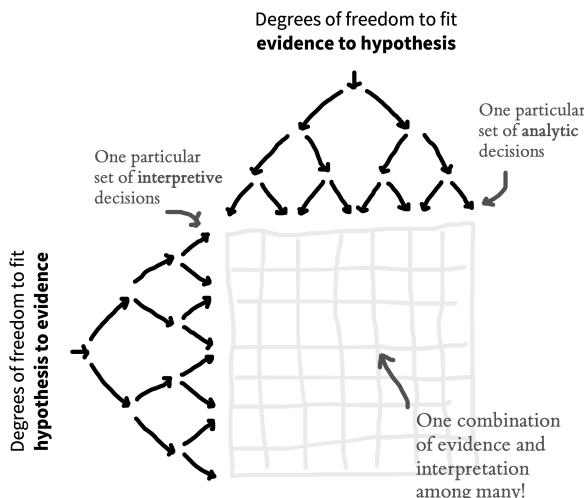


Figure 11.6

A grid of individual research results. The horizontal axis provides a simplified illustration of the many justifiable design and analysis choices that a scientist can use to generate the evidence. The vertical axis illustrates that there are often several potential hypotheses which could be constructed or selected when interpreting the evidence. An unconstrained scientist can simultaneously fit evidence to hypotheses and fit hypotheses to evidence in order to obtain their preferred overall result.

5300 But hang on a minute! Isn’t it a good thing to seek out interesting results
 5301 if they are there in the data? Shouldn’t we “let the data speak”? The
 5302 answer is yes! But it’s crucial to understand the distinction between ex-
 5303 ploratory and confirmatory modes of research.³ Confirmation involves

³ In practice, an individual study may contain both exploratory and confirmatory aspects which is why we describe them as different “modes.”

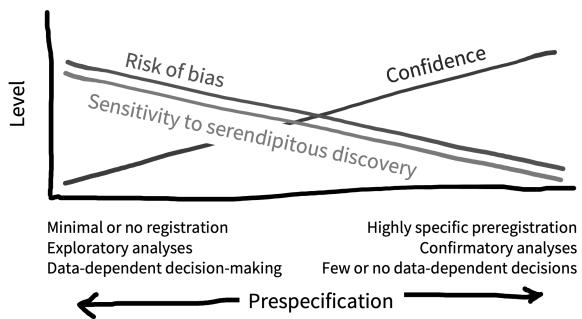
5304 making research decisions *before* you've seen the data whereas explo-
5305 ration involves making research decisions *after* you've seen data.

5306 The key things to remember about exploratory research are that you
5307 need to (1) be aware of the increased risk of bias arising from data-
5308 dependent decision making and calibrate your confidence in the results
5309 accordingly; (2) be honest with other researchers about your analysis
5310 strategy so they are also aware of the risk of bias and can calibrate *their*
5311 confidence in the outcomes accordingly. In the next section, we will
5312 learn about how preregistration helps us to make this important distinc-
5313 tion between exploratory and confirmation research.

5314 *11.2 Reducing risk of bias, increasing transparency, and*
5315 *calibrating confidence with preregistration*

5316 You can counter the problem of researcher degrees of freedom and data-
5317 dependent decision-making by making research decisions before you
5318 have seen the data—like planning your route through the garden of fork-
5319 ing paths before you start your journey (Wagenmakers et al. 2012; Hard-
5320 wicke and Wagenmakers 2022). If you stick to the planned route, then
5321 you have eliminated the possibility that your decisions were influenced
5322 by the data.

5323 Preregistration is the process of declaring your research decisions in
 5324 a public registry before you analyze (and often before you collect)
 5325 the data. Preregistration ensures that your research decisions are
 5326 data-independent, which reduces risk of bias arising from the issues
 5327 described above. Preregistration also transparently conveys to others
 5328 what you planned, helping them to determine the risk of bias and
 5329 calibrate their confidence in the research results. In other words,
 5330 preregistration can dissuade researchers from engaging in questionable
 5331 research practices like p-hacking and HARKing, because they can
 5332 be held accountable to their original plan, while also providing the
 5333 context needed to properly evaluate and interpret research.



5334 Preregistration does not require that you specify all research decisions
 5335 in advance, only that you are transparent about what was planned, and
 5336 what was not planned. This transparency helps to make a distinction be-
 5337 tween which aspects of the research were exploratory and which were
 5338 confirmatory (figure 11.7). All else being equal, we should have more
 5339 confidence in confirmatory results, because there is a lower risk of bias.

Figure 11.7

Preregistration clarifies where research activities fall on the continuum of pre-specification. When the preregistration provides little constraint over researcher degrees of freedom (i.e., more exploratory research), decisions are more likely to be data-dependent, and consequently there is a higher risk of bias. When preregistration provides strong constraint over researcher degrees of freedom (i.e., more confirmatory research), decisions are less likely to be data-dependent, and consequently there is a lower risk of bias. Exploratory research activities are more sensitive to serendipitous discovery, but also have a higher risk of bias relative to confirmatory research activities. Preregistration transparently communicates where particular results are located along the continuum, helping readers to appropriately calibrate their confidence.

5340 Exploratory results have a higher risk of bias, but they are also more
5341 sensitive to serendipitous (unexpected discoveries. So the confirmatory
5342 mode is best suited to testing hypotheses and the exploratory mode is
5343 best suited to generating them. Therefore, exploratory and confirma-
5344 tory research are both valuable activities—it is just important to differen-
5345 tiate them (Tukey 1980)! Preregistration offers the best of both worlds
5346 by clearly separating one from the other.

5347 In addition to the benefits described above, preregistration may improve
5348 the quality of research by encouraging closer attention to study plan-
5349 ning. We've found that the process of writing a preregistration really
5350 helps facilitate communication between collaborators, and can catch
5351 addressable problems before time and resources are wasted on a poorly
5352 designed study. Detailed advanced planning can also create opportuni-
5353 ties for useful community feedback, particularly in the context of Reg-
5354 istered Reports (see Depth box below), where dedicated peer reviewers
5355 will evaluate your study before it has even begun.

 DEPTH

Preregistration and friends: A toolbox to address researcher degrees of freedom

Several useful tools can be used to complement or extend preregistration.

In general, we would recommend that these tool are combined with pre-registration, rather than used as a replacement because preregistration provides transparency about the research and planning process (Hardwicke and Wagenmakers 2022). The first two of these are discussed in more detail in the last section of chapter 7.

Robustness checks. Robustness checks (also called “sensitivity analyses”) assess how different decision choices in the garden of forking paths affect the eventual pattern of results. This technique is particularly helpful when you have to choose between several justifiable analytic choices, neither of which seem superior to the other, or which have complementary strengths and weaknesses. For example, you might run the analysis three times using three different methods for handling missing data. Robust results should not vary substantially across the three different choices.

Multiverse analyses. Recently, some researchers have started running large-scale robustness checks called “multiverse” (Steegen et al. 2016) or “specification curve” (Simonsohn, Simmons, and Nelson 2020) analyses. We discussed these a bit in chapter 7. Some have argued that these large-scale robustness checks make preregistration redundant; after all, why pre-

specify a single path if you can explore them all (Rubin 2020; Oberauer and Lewandowsky 2019)? But interpreting the results of a multiverse analysis are not straightforward; for example, it seems unlikely that all of the decision choices are equally justifiable (Giudice and Gangestad 2021). Furthermore, if multiverse analyses are not preregistered, then they introduce researcher degrees of freedom, and create an opportunity for selective reporting, which increases risk of bias.

Held-out sample. One option to benefit from both exploratory and confirmatory research modes is to split your data into **training** and **test** samples. (The test sample is commonly called the “held out” because it is “held out” from the exploratory process.) You can generate hypotheses in an exploratory mode in the training sample and use that as the basis to preregister confirmatory analyses in the hold-out sample. A notable disadvantage of this strategy is that splitting the data reduces statistical power, but in cases where data are plentiful—including in much of machine learning—this technique is the gold standard.

Masked analysis (traditionally called “blind analysis”). Sometimes problems, such as missing data, attrition, or randomization failure that you did not anticipate in your preregistered plan can arise during data collection. How do you diagnose and address these issues without increasing risk of bias through data-dependent analysis? One option is masked analysis, which disguises key aspects of the data related to the results (for example, by shuffling condition labels or adding noise) while still allowing some degree of data inspection (Dutilh, Sarafoglou, and Wagenmakers 2019). Af-

ter diagnosing a problem, you can adjust your preregistered plan without increasing risk of bias, because your decisions have not been influenced by the results.

Standard Operating Procedures. Community norms, perhaps at the level of your research field or lab, can act as a natural constraint on researcher degrees of freedom. For example, there may be a generally accepted approach for handling outliers in your community. You can make these constraints explicit by writing them down in a Standard Operating Procedures document—a bit like a living meta-preregistration (Lin and Green 2016).

Open lab notebooks. Maintaining a lab notebook can be a useful way to keep a record of your decisions as a research project unfolds. Preregistration is bit like taking a snapshot of your lab notebook at the start of the project, when all you have written down is your research plan. Making your lab notebook publicly available is a great way to transparently document your research and departures from the preregistered plan.



Figure 11.8
Registered Reports (from <https://www.cos.io/initiatives/registered-reports>, licensed under CC BY 4.0).

Registered Reports. Registered Reports are a type of article format that embeds preregistration directly into the publication pipeline , figure 11.8. The idea is that you submit your preregistered protocol to a journal and

it is peer reviewed, before you've even started your study. If the study is approved, the journal agrees to publish it, regardless of the results. This is a radical departure from traditional publication models where peer reviewers and journals evaluate your study *after* its been completed and the results are known. Because the study is accepted for publication independently of the results, Registered Reports can offer the benefits of preregistration with additional protection against publication bias. They also provide a great opportunity to obtain feedback on your study design while you can still change it!

5359

5360 11.3 How to preregister

5361 High-stakes studies such as medical trials must be preregistered (Dick-
5362 ersin and Rennie 2012). In 2005, a large international consortium of
5363 medical journals decided that they would not publish unregistered tri-
5364 als. The discipline of economics also has strong norms about study reg-
5365 istration (see e.g. <https://www.socialscienceregistry.org>). But preregis-
5366 tration is pretty new to psychology (Nosek et al. 2018), and there's still
5367 no standard way of doing it—you're already at the cutting edge!

5368 We recommend using the Open Science Framework (OSF) as your reg-
5369 istry. OSF is one of the most popular registries in psychology and you
5370 can do lots of other useful things on the platform to make your research

5371 transparent, like sharing data, materials, analysis scripts, and preprints.

5372 On OSF it is possible to “register” any file you have uploaded. When

5373 you register a file, it creates a time-stamped, read-only copy, with a ded-

5374 icated link. You can add this link to articles reporting your research.

Table 11.1
Preregistration template outline.

Question
1 Data collection. Have any data been collected for this study already?
2 Hypothesis. What's the main question being asked or hypothesis being tested in this study?
3 Dependent variable. Describe the key dependent variable(s) specifying how they will be measured.
4 Conditions. How many and which conditions will participants be assigned to?
5 Analyses Specify exactly which analyses you will conduct to examine the main question/hypothesis.
6 Outliers and Exclusions. Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
7 Sample Size. How many observations will be collected or what will determine sample size? No need to justify decision, but be precise about exactly how the number will be determined.
8 Other. Anything else you would like to pre-register? (e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)

5375 One approach to preregistration is to write a protocol document that
 5376 specifies the study rationale, aims or hypotheses, methods, and analysis
 5377 plan, and register that document.⁴ OSF also has a collection of dedicated
 5378 preregistration templates that you can use if you prefer. An outline of such a template is shown in table 11.1. These templates are
 5379

⁴ You can think of a study protocol a bit like a research paper without a results and discussion section (here's an example from one of our own studies: <https://osf.io/2cnkq/>).

5380 often tailored to the needs of particular types of research. For exam-
5381 ple, there are templates for general quantitative psychology research
5382 (“PRP-QUANT,” Bosnjak et al. 2022), cognitive modelling (Crüwell
5383 and Evans 2021), and secondary data analysis (Akter et al. 2019). The
5384 OSF interface may change, but currently this guide⁵ provides a set of
5385 steps to create a preregistration.

5 [5386 Once you’ve preregistered your plan, you just go off and run the study
5387 and report the results, right? Well hopefully... but things might not
5388 turn out to be that straightforward. It’s quite common to forget to in-
5389 clude something in your plan or to have to depart from the plan due
5390 to something unexpected. Preregistration can actually be pretty hard in
5391 practice \(Nosek et al. 2019\)!](https://help.osf.io/hc/en-us/articles/360019738834>Create-a-Preregistration</p></div><div data-bbox=)

5392 Don’t worry though – remember that a key goal of preregistration
5393 is transparency to enable others to evaluate and interpret research
5394 results. If you decide to depart from your original plan and conduct
5395 data-dependent analyses, then this decision may increase the risk of
5396 bias. But if you communicate this decision transparently to your
5397 readers, they can appropriately calibrate their confidence in the results.
5398 You may even be able to run both the planned and unplanned analyses
5399 as a robustness check (see Depth box) to evaluate the extent to which
5400 this particular choice impacts the results.

5401 When you report your study, it is important to distinguish between
5402 what was planned and what was not. If you ran a lot of data-dependent
5403 analyses, then it might be worth having separate exploratory and confir-
5404 matory results sections. On the other hand, if you mainly stuck to your
5405 original plan, with only minor departures, then you could include a ta-
5406 ble (perhaps in an appendix) that outlines these changes (for example,
5407 see Supplementary Information A of this article⁶).

⁶ <https://doi.org/10.31222/osf.io/wt5ny>

5408 11.4 Chapter summary: Preregistration

5409 We've advocated here for preregistering your study plan. This practice
5410 helps to reduce the risk of bias caused by data-dependent analysis (the
5411 "garden of forking paths" that we described) and transparently commu-
5412 nicate the risk of bias to other scientists. Importantly, preregistration is
5413 a "plan, not a prison"⁷: in most cases preregistered, confirmatory anal-
5414 yses coexist with exploratory analyses. Both are an important part of
5415 good research—the key is to disclose which is which!

⁷ <https://www.cos.io/blog/preregistration-plan-not-prison>



DISCUSSION QUESTIONS

1. P-hack your way to scientific glory! To get a feel for how data-dependent analyses might work in practice, have a play around with this app: <https://projects.fivethirtyeight.com/p-hacking/>. Do you think preregistration would affect your confidence in claims made

about this dataset?

2. Preregister your next experiment! The best way to get started with preregistration is to have a go with your next study. Head over to <https://osf.io/registries/osf/new> and register your study protocol or complete one of the templates. What aspects of preregistration did you find most difficult and what benefits did it bring?

5417

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5426

12 DATA COLLECTION



LEARNING GOALS

- Outline key features of informed consent and participant debriefing
- Identify additional protections necessary for working with vulnerable populations
- Review best practices for online and in-person data collection
- Implement data integrity checks, manipulation checks, and pilot testing

5427

5428 You have selected your measure and manipulation and planned your
5429 sample. Your preregistration is set. Now it's time to think about the
5430 nuts and bolts of collecting data. Though the details may vary between
5431 contexts, this chapter will describe some general best practices for data
5432 collection.¹ We organize our discussion of these practices around two
5433 perspectives: the participant and the researcher.

5434 The first section takes the perspective of a participant. We begin by

¹ The metaphor of “collection” implies to some researchers that the data exist independent of the researcher’s own perspective and actions, so they reject it in favor of the term “data generation.” Unfortunately, this alternative label doesn’t distinguish generating data via interactions with participants on the one hand and generating data from scratch via statistical simulations on the other. We worry that “data generation” sounds too much like the kinds of fraudulent data generation that we talked about in chapter 4, so we have opted to keep the more conventional “data collection” label.

5435 reviewing the importance of informed consent. A key principle of run-
5436 ning experiments with human participants is that we respect their au-
5437 tonomy, which includes their right to understand the study and choose
5438 whether to take part. When we neglect the impact of our research on
5439 the people we study, we not only violate regulations governing research,
5440 we also create distrust that undermines the moral basis of scientific re-
5441 search.

5442 In the second section, we begin to shift perspectives, discussing the
5443 choice of online vs. in-person data collection and some of the advan-
5444 tages of online data collection for TRANSPARENCY. We consider how to
5445 optimize the experimental experience for participants in both settings.
5446 We then end by taking the experimenter's perspective more fully, dis-
5447 cussing how we can maximize data quality (contributing to MEASURE-
5448 MENT PRECISION) using pilot testing, manipulation checks, and attention
5449 checks, while still being cognizant of both changes to the participant's
5450 experience and the integrity of statistical inferences (both contributing
5451 to BIAS REDUCTION).

CASE STUDY

The rise of online data collection

Since the rise of experimental psychology laboratories in university set-
5452 tings during the period after World War 2 (Benjamin 2000), experiments

have typically been conducted by recruiting participants from what has been referred to as the “subject pool.” This term denotes a group of people who can be recruited for experiments, typically students from introductory psychology courses (Sieber and Saks 1989) who are required to complete a certain number of experiments as part of their course work. The ready availability of this convenient population inevitably led to the massive over-representation of undergraduates in published psychology research, undermining its generalizability (Sears 1986; Henrich, Heine, and Norenzayan 2010).

Yet over the last couple of decades, there has been a revolution in data collection. Instead of focusing on university undergraduates, increasingly, researchers recruit individuals from crowdsourcing websites like Amazon Mechanical Turk and Prolific Academic. Crowdsourcing services were originally designed to recruit and pay workers for ad-hoc business tasks like retyping receipts, but they have also become marketplaces to connect researchers with research participants who are willing to complete surveys and experimental tasks for small payments (Litman, Robinson, and Abberbock 2017). As of 2015, more than a third of studies in top social and personality psychology journals were conducted on crowdsourcing platforms (another third were still conducted with college undergraduates) and this proportion is likely continuing to grow (Anderson et al. 2019).

Initially, many researchers worried that crowdsourced data from online convenience samples would lead to a decrease in data quality. However,

several studies suggest that data quality from online convenience samples is typically comparable to in-lab convenience samples (Mason and Suri 2012; Buhrmester, Kwang, and Gosling 2011). In one particularly compelling demonstration, a set of online experiments were used to replicate a group of classic phenomena in cognitive psychology, with clear successes on every experiment except those requiring sub-50 millisecond stimulus presentation (Crump, McDonnell, and Gureckis 2013). Further, as we discuss below, researchers have developed a suite of tools to ensure that online participants understand and comply with the instructions in complex experimental tasks.

Since these initial successes, however, attention has moved away from the validity of online experiments to the ethical challenges of engaging with crowdworkers. In 2020, nearly 130,000 people completed MTurk studies (Moss et al. 2020). Of those, an estimated 70% identified as White, 56% identified as women, and 48% had an annual household income below \$50,000. A sampling of crowd work determined that the average wage earned was just \$2.00 per hour, and less than 5% of workers were paid at least the federal minimum wage (Hara et al. 2018). Further, many experimenters routinely withheld payment from workers based on their performance in experiments. These practices clearly violate ethical guidelines for research with human participants, but are often overlooked by institutional review boards who may be unfamiliar with online recruitment platforms or consider that platforms are offering a “service” rather than simply being alternative routes for paying individuals.

With greater attention to the conditions of workers (e.g., Salehi et al. 2015), best practices for online research have progressed considerably. As we describe below, working with online populations requires attention to both standard ethical issues of consent and compensation, as well as new issues around the “user experience” of participating in research. The availability of online convenience samples can be transformative for the pace of research, for example by enabling large studies to be run in a single day rather than over many months. But online participants are vulnerable in different ways than university convenience samples, and we must take care to ensure that research online is conducted ethically.

5455

5456 12.1 *Informed consent and debriefing*

5457 As we discussed in chapter 4, experimenters must respect the autonomy
5458 of their participants: they must be informed about the risks and bene-
5459 fits of participation before they agree to participate. Researchers must
5460 also discuss and contextualize the research by debriefing participants af-
5461 ter they have completed the study. Here we look at the nuts and bolts
5462 of each of these processes, ending with guidance on the special protec-
5463 tions that are required to protect the autonomy of especially vulnerable
5464 populations.

5465 12.1.1 *Getting consent*

5466 Experimental participants must give consent. In most regulatory frame-
5467 works, there are clear guidelines about what the process of giving con-
5468 sent should look like. Typically participants are expected to read and
5469 sign a **consent form**: a document that explains the goals of the research
5470 and its procedures, describes potential risks and benefits, and asks for
5471 participants' explicit consent to participate voluntarily. Table 12.1 gives
5472 the full list of consent form requirements from the US Office for Hu-
5473 man Research Protections, and figure 12.1 shows how these individual
5474 requirements are reflected in a real consent form used in our research.

Table 12.1
US Office of Human Research Protections requirements for a consent form (edited for length).

Requirement
1 A statement that the study involves research
2 An explanation of the purposes of the research
3 The expected duration of the subject's participation
4 A description of the procedures to be followed
5 Identification of any procedures which are experimental
6 A description of any reasonably foreseeable risks or discomforts to the subject
7 A description of any benefits to the subject or to others which may reasonably be expected from the research
8 A disclosure of appropriate alternative procedures or courses of treatment, if any, that might be advantageous to the subject

Requirement

- 9 A statement describing the extent, if any, to which confidentiality of records identifying the subject will be maintained
 - 10 For research involving more than minimal risk, an explanation as to whether any compensation or medical treatments are available if injury occurs
 - 11 An explanation of whom to contact for answers to pertinent questions about the research and research subjects' rights
 - 12 A statement that participation is voluntary, refusal to participate will involve no penalty, and that subject may discontinue participation at any time without penalty
-

STANFORD UNIVERSITY Research Consent Form		IRB USE ONLY Approval Date: Expiration Date:
Protocol Director: Michael C. Frank, Ph.D.		
Protocol Title: Investigations of language learning and social cognition in infants, children and adults		
<p>DESCRIPTION: In this study, we are investigating the development of language and communication. Our research explores how infants and young children learn about their native language. We observe how children at different ages learn new words and comprehend familiar words. All of the activities in our studies are designed to be age-appropriate and fun for children. In a typical session, we may invite your child to play a short game, or we may use an eye-tracker (a special camera that keeps track of where a child is looking on a computer screen) to help us understand what your child is looking at while they listen to recorded speech and/or view movies of adults, children, puppets, or animated characters playing and talking. Sometimes some of the speech they hear will be from a foreign or made-up language.</p>		
<p>2 RISKS AND BENEFITS: There are no foreseeable risks or discomforts to you or your child in participating in this research. All our procedures are observational and non-intrusive. We pace each session appropriately and give breaks as needed to enable your child to enjoy and complete the session. Your child will not be pressured to continue in the event that he or she becomes upset, tired, or resistant at any point during the session. If for any reason you or your child do not want to continue, the session will be ended immediately with no penalty.</p>		
<p>7 We cannot and do not guarantee or promise that you will receive any benefits from this study, apart from the honorarium and the satisfaction of participating in developmental research. If appropriate, we provide information regarding resources that may be helpful in addressing any concerns regarding your child's development.</p>		
<p>3 TIME INVOLVEMENT: Each session typically lasts from 5-10 minutes, depending on the nature of the study. Most studies involve a single session, but in some cases you and your child will be invited to participate in more than one session.</p>		
<p>6 PAYMENTS: You will not receive a cash payment for your participation in this research. However, based on the number and length of sessions we arrange with you during scheduling, your child will receive one of the following gifts in appreciation of your time and cooperation: a children's book, T-shirt, or certificate of appreciation.</p>		
<p>12 SUBJECT'S RIGHTS: If you have read this form and have decided to allow your child to participate in this project, please understand your child's participation is voluntary and your child has the right to withdraw his/her consent or discontinue participation at any time without penalty or loss of benefits to which he/she is otherwise entitled. Your child has the right to refuse to answer particular questions. The video record of the session will be identified by a code number, not by name. This record will be accessible only to the project director and members of the project staff, unless you give your explicit permission below for others to view it for scientific or educational purposes. All records will be stored securely so that your child's individual privacy will be maintained. In addition, your child's identity will remain private in all publications resulting from the study.</p>		
<p>11 CONTACT INFORMATION:</p> <ul style="list-style-type: none"> * Questions, Concerns, or Complaints: If you have any questions, concerns or complaints about this research study, its procedures, risks, and benefits you should contact the Protocol Director, Dr. Michael Frank, phone: (650) 721-9270, email: langcoglab@stanford.edu, webpage: http://langcog.stanford.edu * Independent Contact: If you are not satisfied with how this study is being conducted, or if you have any concerns, complaints, or general questions about the research or your rights as a participant, please contact the Stanford Institutional Review Board (IRB) to speak to someone independent of the research team at (650) 723-2480 or toll free at 1-866-680-2906. You can also write to the Stanford IRB, Stanford University, 1705 El Camino Real, Palo Alto, CA 94306. 		
<p>CONSENT I give consent for my child to be videotaped during this study. please initial: _____ Yes _____ No</p>		
<p>I give consent for your child's image (from the video recording) to be shown to people not directly involved with this research during class, seminars, or scientific presentations. please initial: _____ Yes _____ No</p>		
<p>Please sign below.</p>		
<p>Signature of Parent, Guardian or Conservator _____ Date _____ <small>The IRB determined that the permission of one parent is sufficient for research to be conducted under 45 CFR 46.404, in accordance with 45 CFR 46.408(b).</small></p>		
<p>The extra copy of this consent form is for you to keep.</p>		
<p>For Office Use Only Study: _____ SubjID: _____</p>		

Figure 12.1

Consent form annotated to show how specific text fulfills the requirements in table 12.1. Categories 5, 8, and 10 were not required for this minimal risk psychology experiment.

- 5475 These are just samples. Since ethics regulation is almost always man-
 aged at the institutional level, your local ethics board will often provide
 5477 guidance on the specific information you should include in the consent
 5478 form and they will almost always need to approve the form before you
 5479 are allowed to begin recruiting participants.
- 5480 When providing consent information, researchers should focus on what

5481 someone might think or feel as a result of participating in the study. Are
5482 there any physical or emotional risks associated? What should someone
5483 know about the study that may give them pause about agreeing to par-
5484 ticipate in the first place? Our advice is to center the *participant* in the
5485 consent process rather than the research question. Information about
5486 specific research goals can typically be provided during debriefing.²

5487 If there are specific pieces of information that about study goals or proce-
5488 dures that *must* be withheld from participants during consent, **deception**
5489 of participants may be warranted. Deception can be approved by ethics
5490 boards as long as it poses little risk and is effectively addressed via more
5491 extensive debriefing. But an experimental protocol that includes de-
5492 ception will likely undergo greater scrutiny during ethics review, as it
5493 must be justified by a specific experimental need.

5494 During the consent process, researchers should explain to participants
5495 what will be done with their data. Requirement 9 in table 12.1 asks for
5496 a statement about data confidentiality, but such a statement is a mere
5497 minimum. Some modern consent forms explicitly describe different
5498 uses of the data and ask for consent for each. For example, the form in
5499 figure 12.1 asks permission for showing recordings as part of presenta-
5500 tions.³

² Some experimenters worry that informing participants about the study that they are about to participate in may influence their behavior in the study via so-called “demand characteristics”, discussed in chapter 9. But the goal of a consent form is not to explain the specific psychological construct being manipulated. Instead, a consent form typically focuses on the experience of being in the study (for example, that a participant would be asked to provide quick verbal responses to pictures). This sort of general explanation should not create demand characteristics.

5501 *12.1.2 Prerequisites of consent*

5502 In order to give consent, participants must have the cognitive capacity
5503 to make decisions (competence), understand what they are being asked
5504 to do (comprehension), and know that they have the right to withdraw
5505 consent at any time (voluntariness) (Kadam 2017).

5506 Typically, we assume competence for adult volunteers in our experi-
5507 ments, but if we are working with children or other vulnerable popula-
5508 tions (see below), we may need to consider whether they are legally com-
5509 petent to provide consent. Participants who cannot consent on their
5510 own should still be informed about participation in an experiment and,
5511 if possible, you should still obtain their **assent** (informal agreement) to
5512 participate. When a person has no legal ability to consent, you must
5513 obtain consent from their legal guardian. But if they do not assent, you
5514 should also respect their decision not to participate—even if you previ-
5515 ously obtained consent from their guardian.

5516 The second prerequisite is comprehension. It is good practice to dis-
5517 cuss consent forms verbally with participants, especially if the study is
5518 involved and takes place in person. If the study is online, ensure that
5519 participants know how to contact you if they have questions about the
5520 study. The consent form itself must be readable for a broad audience,

³ Some ethics boards will ask for con-
sent for sharing even anonymized data
files. As we discuss in chapter 13, fully
anonymized data can often be shared
without explicit consent. You may still
choose to ask participants' permission,
but this practice may lead to an awkward
situation, for example, a dataset with
heterogeneous sharing permissions such
that most but not all data can be shared
publicly. Norms around anonymized
data sharing are shifting, so it's worth
having a conversation with your ethics
board about how they interpret your par-
ticular regulatory obligations.

meaning care should be taken to use accessible language and clear formatting. Consider giving participants a copy of the consent form in advance so they can read at their own pace, think of any questions they might have, and decide how to proceed without any chance of feeling coerced (Young, Hooker, and Freeberg 1990).

Finally, participants must understand that their involvement is voluntary, meaning that they are under no obligation to be involved in a study and always have the right to withdraw at any time. Experimenters should not only state that participation is voluntary, they should also pay attention to other features of the study environment that might lead to structural coercion (Fisher 2013). For example, high levels of compensation can make it difficult for lower-income participants to withdraw from research. Similarly, factors like race, gender, and social class can lead participants to feel discomfort around discontinuing a study. It is incumbent on experimenters to provide a comfortable study environment and to avoid such coercive factors wherever possible.

12.1.3 Debriefing participants

Once a study is completed, researchers should always debrief participants. A debriefing is composed of several parts: (1) gratitude, (2) discussion of goals, (3) explanation of deception (if relevant), and (4) ques-

5541 tions and clarification (Allen 2017). Together these serve to contextualize
5542 the experience for the participant and to mitigate any potential
5543 harms from the study.

5544 1. **Gratitude.** Thank participants for their contribution! Sometimes
5545 thanks is enough (for a short experiment), but many studies also
5546 include monetary compensation or course credit. Compensation
5547 should be commensurate with the amount of time and effort re-
5548 quired for participation. Compensation structures vary widely
5549 from place to place; typically local ethics boards will have specific
5550 guidelines.

5551 2. **Discussion of goals.** Researchers should share the purpose of the
5552 research with participants in, aiming for a short and accessible
5553 statement that avoids technical jargon. Sharing goals is especially
5554 important when some aspect of the study appears evaluative—
5555 participants will often be interested in knowing how well they
5556 performed against their peers. For example, a parent whose child
5557 completed a word-recognition task may request information
5558 about their child’s performance. It can assuage parents’ worries
5559 to highlight that the goals of the study are about measuring a
5560 particular experimental effect, not about individual evaluation
5561 and ranking.⁴

⁴ At the study’s conclusion, you might also consider sharing any findings with participants—many participants appreciate learning about research findings that they contributed to, even months or years after participation.

5562 3. **Explanation of deception.** Researchers must reveal any deception
5563 during debriefing, regardless of how minor the deception seems
5564 to the researcher. This component of the debriefing process can
5565 be thought of as “dehoaxing” because it is meant to illuminate
5566 any aspects of the study that were previously misleading or inac-
5567 curate (Holmes 1976). The goal is both to reveal the true intent
5568 of the study and to alleviate any potential anxiety associated with
5569 the deception. Experimenters should make clear both where in
5570 the study the deception occurred and why the deception was nec-
5571 essary for the study’s success.

5572 4. **Questions and clarification.** Finally, researchers should answer
5573 any questions or address any concerns raised by participants.
5574 Many researchers use this opportunity to ask participants about
5575 their own ideas about the study goals. This practice not only
5576 illuminates aspects of the study design that may have been unclear
5577 to or hidden from participants, it also begins a discussion where
5578 both researchers and participants can communicate about this
5579 joint experience. This step is also helpful in identifying negative
5580 emotions or feelings resulting from the study (Allen 2017).
5581 When participants do express negative emotions, researchers are
5582 responsible for sharing resources participants can use to help
5583 them.⁵

⁵ In the case that participants report substantial concerns or negative reactions to an experiment—during debriefing or otherwise—researchers will typically have an obligation to report these to their ethics board.

5584 *12.1.4 Special considerations for vulnerable populations*

5585 Regardless of who is participating in research, investigators have an obli-
5586 gation to protect the rights and well-being of all participants. Some pop-
5587 ulations are considered especially **vulnerable** because of their decreased
5588 agency—either in general or in the face of potentially coercive situa-
5589 tions. Research with these populations receives additional regulatory
5590 oversight. In this section, we will consider several vulnerable popula-
5591 tions.

5592 **Children.** Children are some of the most commonly used vulner-
5593 able populations in research because the study of development can
5594 contribute both to children’s welfare and to our understanding of
5595 the human mind. In the US, children under the age of 18 may only
5596 participate in research with written consent from a parent or guardian.

5597 Unless they are pre-verbal, children should additionally be asked for
5598 their assent. The risks associated with a research study focusing on
5599 children also must be no greater than minimal unless participants may
5600 receive some direct benefit from participating or participating in the
5601 study may improve a disorder or condition the participant was formally
5602 diagnosed with.

5603 **People with disabilities.** There are thousands of disabilities that affect
5604 cognition, development, motor ability, communication, and decision-

5605 making with varying degrees of interference, so it is first important to
5606 remember that considerations for this population will be just as diverse
5607 as its members. No laws preclude people with disabilities from partici-
5608 pating in research. However, those with cognitive disabilities who are
5609 unable to make their own decisions may only participant with written
5610 consent from a legal guardian and with their individual assent (if ap-
5611 plicable). Those retaining full cognitive capacity but who have other
5612 disabilities that make it challenging to participate normally in the study
5613 should receive appropriate assistance to access information about the
5614 study, including the risks and benefits of participation.

5615 **Incarcerated populations.** Nearly 2.1 million people are incarcerated in
5616 the United States alone (Gramlich 2021). Due to early (and repugnant)
5617 use of prisoners as a convenience population that could not provide con-
5618 sent, the use of prisoners in research has been a key focus of protective
5619 efforts. The US Office for Human Research Protections (OHRP) sup-
5620 ports their involvement in research under very limited circumstances—
5621 typically when the research specifically focuses on issues relevant to in-
5622 carcerated populations (Office for Human Research Protections 2003).

5623 When researchers propose to study incarcerated individuals, the local
5624 ethics board must reconfigure to include at least one active prisoner (or
5625 someone who can speak from a prisoner's perspective) and ensure that
5626 less than half of the board has any affiliation to the prison system, pub-

lic or private. Importantly, researchers must not suggest or promise that participation will have any bearing on an individual's prison sentence or parole eligibility, and compensation must be otherwise commensurate with their contribution.

Low-income populations. Participants with fewer resources may be more persuaded to participate by monetary incentives, creating a potentially coercive situation. Researchers should consult with their local ethics board to conform to local standards for non-coercive payment.

Indigenous populations. There is a long and negative history of the involvement of indigenous populations in research without their consent. In the case that research requires the participation of indigenous individuals—because of potential benefits to their communities, rather than due to convenience—then community leadership must be involved to discuss the appropriateness of the research as well as how the consent process should be structured (Fitzpatrick et al. 2016).

Crowdworkers. Ethics boards do not usually consider crowdworkers on platforms like Amazon Mechanical Turk to be a specific vulnerable population, but many of the same concerns about diminished autonomy and greater need for protection still arise (see Depth Box below). Without platform or ethics board standards, it is up to individual experimenters to commit to fair pay, which should ideally match or exceed

5648 the applicable minimum wage (e.g., the US federal minimum wage).
5649 Further, in the context of reputation management systems like those of
5650 Amazon Mechanical Turk, participants can be penalized for withdraw-
5651 ing from an experiment—once they have their work “rejected” by an
5652 experimenter, it can be harder for them to find new jobs, causing serious
5653 long-term harm to their ability to earn on the platform.

5654 *12.2 Designing the “research experience”*

5655 For the majority of psychology experiments, the biggest factor that gov-
5656 erns whether a participant has a positive or negative experience of an ex-
5657 periment is not its risk profile, since for many psychology experiments
5658 the quantifiable risk to participants is minimal.⁶ Instead, it is the partic-
5659 ipants’ experience. Did they feel welcome? Did they understand the
5660 instructions? Did the software work as designed? Was their compensa-
5661 tion clearly described and promptly delivered? These aspects of “user
5662 experience” are critical both for ensuring that participants have a good
5663 experience in the study (an ethical imperative) and for gathering good
5664 data. An experiment that leaves participants unhappy typically doesn’t
5665 satisfy either the ethical or the scientific goals of research. In this sec-
5666 tion, we’ll discuss how to optimize the research experience for both
5667 in-person and online experiments, as well as providing some guidance

⁶ There are of course exceptions, includ-
ing research with more sensitive content.
Even in these cases, however, attention
to the participant’s experience can be
important for ensuring good scientific
outcomes.

5668 on how to decide between these two administration contexts.

5669 *12.2.1 Ensuring good experiences for in-lab participants*

5670 A participant's experience begins even before they arrive at the lab.

5671 Negative experiences with the recruitment process (e.g., unclear con-

5672 sent forms, poor communication, complicated scheduling) or transit to

5673 the lab (e.g., difficulty navigating or finding parking) can lead to frus-

5674 trated participants with a negative view of your research. Anything

5675 you can do to make these experiences smoother and more predictable—

5676 prompt communication, well-tested directions, reserved parking slots,

5677 etc.—will make your participants happier and increase the quality of

5678 your data.⁷

5679 Once a participant enters the lab, every aspect of the interaction with

5680 the experimenter can have an effect on their measured behavior (Gass

5681 and Seiter 2018)! For example, a likable and authoritative experimenter

5682 who clearly describes the benefits of participation is following general

5683 principles for persuasion (Cialdini and Goldstein 2004). This interac-

5684 tion should lead to better compliance with experimental instructions,

5685 and hence better data, than an interaction with an unclear or indiffer-

5686 ent experimenter.

⁷ For some reason, the Stanford Psychology Department building is notoriously difficult to navigate. This seemingly minor issue has resulted in a substantial number of late, frustrated, and flustered participants over the years.

5687 Any interaction with participants must be scripted and standardized so
5688 that all participants have as similar an experience as possible. A lack
5689 of standardization can result in differential treatment for participants
5690 with different characteristics, which could result in data with greater
5691 variability or even specific sociodemographic biases. An experimenter
5692 that was kinder and more welcoming to one demographic group would
5693 be acting unethically, and they also might find a very different result
5694 than they intended.

5695 Even more importantly, experimenters who interact with participants
5696 should ideally be unaware of the experimental condition each partic-
5697 ipant is assigned to. This practice is often called “blinding” or “mask-
5698 ing”. Otherwise it is easy for experimenter knowledge to result in small
5699 differences in interaction across conditions, which in turn can influence
5700 participants’ behavior, resulting in experimenter expectancy effects (see
5701 chapter 9)! Even if the experimenter must know a participant’s condi-
5702 tion assignment—as is sometimes the case—this information should be
5703 revealed at the last possible moment to avoid contamination of other
5704 aspects of the experimental session.⁸

⁸ In some experiments, an experimenter delivers a manipulation and hence it cannot be masked from them. In such cases, it’s common to have two experimenters such that one delivers the manipulation and another (masked to condition) collects the measurements. This situation often comes up with studies of infancy, since stimuli are often delivered via an in-person puppet show; at a minimum, behavior should be coded by someone other than the puppeteer.

5705 *12.2.2 Ensuring good experiences for online participants*

5706 The design challenges for online experiments are very different than for
5707 in-lab experiments. As the experimental procedure is delivered through
5708 a web browser, experimenter variability and potential expectancy ef-
5709 fects are almost completely eliminated. On the other hand, some online
5710 participants do many hours of online tasks a day and many are multi-
5711 tasking in other windows or on other devices. It can be much harder
5712 to induce interest and engagement in your research when your manip-
5713 ulation is one of dozens the participant has experienced that day and
5714 when your interactions are mediated by a small window on a computer
5715 screen.

5716 When creating an online experimental experience, we consider four
5717 issues: (1) design, (2) communication, (3) payment policies, and (4) ef-
5718 fective consent and debriefing.⁹

⁹ For extensive further guidance on this topic, see Litman and Robinson (2020).

5719 **Basic UX design.** Good experiment design online is a subset of good
5720 web user experience (UX) design more generally. If your experi-
5721 ment is unpleasant to interact with, participants will likely become con-
5722 fused and frustrated. They will either drop out or provide data that are
5723 lower quality. A good interface should be clean and well-tested and
5724 should offer clear places where the participant must type or click to

5725 interact. If a participant presses a key at an appropriate time, the experi-
5726 ment should offer a response—otherwise the participant will likely press
5727 it again. If the participant is uncertain how many trials are left, they
5728 may be more likely to drop out of the experiment so it is also helpful
5729 to provide an indication of their progress. And if they are performing
5730 a speeded paradigm, they should receive practice trials to ensure that
5731 they understand the experiment prior to beginning the critical blocks
5732 of trials.

5733 **Communication.** Many online studies involve almost no direct contact
5734 with participants. When participants do communicate with you it is
5735 very important to be responsive and polite (as it is with in-lab partic-
5736 ipants, of course). Unlike the typical undergraduate participant, the
5737 work that a crowdworker is doing for your study may be part of how
5738 they earn their livelihood, and a small issue in the study for you may
5739 feel very important for them. For that reason, rapid resolution of is-
5740 sues with studies—typically through appropriate compensation—is very
5741 important. Crowdworkers often track the reputation of specific labs
5742 and experimenters [sometimes through forums or specialized software;
5743 Irani and Silberman (2013)]. A quick and generous response to an issue
5744 will ensure that future crowdworkers do not avoid your studies.

5745 **Payment policies.** Unclear or punitive payment policies can have a ma-

5746 jor impact on crowdworkers. We strongly recommend *always* paying
5747 workers if they complete your experiment, regardless of result. This
5748 policy is comparable to standard payment policies for in-lab work. We
5749 assume good faith in our participants: if someone comes to the lab, they
5750 are paid for the experiment, even if it turns out that they did not per-
5751 form correctly. The major counterargument to this policy is that some
5752 online marketplaces have a population of workers who are looking to
5753 cheat by being non-compliant with the experiment (e.g., entering gib-
5754 berish or even using scripts or artificial intelligence tools to progress
5755 quickly through studies). Our recommendation is to address this issue
5756 through the thoughtful use of “check” trials (see below)—not through
5757 punitive non-payment. The easiest way for a participant to complete
5758 your experiment should be by complying with your instructions.

Table 12.2
Sample online consent statement from our course.

By answering the following questions, you are participating in a study being performed by cognitive scientists in the Stanford Department of Psychology. If you have questions about this research, please contact us at stanfordpsych251@gmail.com. You must be at least 18 years old to participate. Your participation in this research is voluntary. You may decline to answer any or all of the following questions. You may decline further participation, at any time, without adverse consequences. Your anonymity is assured; the researchers who have requested your participation will not receive any personal information about you.

5759 **Consent and debriefing.** Because online studies are typically fully au-
5760 tomated, participants do not have a chance to interact with researchers
5761 around consent and debriefing. Further, engagement with long con-
5762 sent forms may be minimal. In our work we have typically relied on
5763 short consent statements such as the one from our class that is shown
5764 in table 12.2. Similarly, debriefing often occurs through a set of pages
5765 that summarize all components of the debriefing process (participation
5766 gratitude, discussion of goals, explanation of deception if relevant, and
5767 questions and clarification). Because these interactions are so short, it
5768 is especially important to include contact information prominently so
5769 that participants can follow up.

5770 12.2.3 When to collect data online?

5771 Online data collection is increasingly ubiquitous in the behavioral
5772 sciences. Further, the web browser—alongside survey software like
5773 Qualtrics or packages like jsPsych (De Leeuw 2015)—can be a major
5774 aid to transparency in sharing experimental materials. Replication
5775 and reuse of experimental materials is vastly simpler if readers and
5776 reviewers can click a link and share the same experience as a participant
5777 in your experiment. By and large, well-designed studies yield data that
5778 are as reliable as in-lab data (Buhrmester, Kwang, and Gosling 2011;
5779 Mason and Suri 2012; Crump, McDonnell, and Gureckis 2013).

5780 Still, online data collection is not right for every experiment. Studies
5781 that have substantial deception or induce negative emotions may require
5782 an experimenter present to alleviate ethical concerns or provide debrief-
5783 ing. Beyond ethical issues, we discuss four broader concerns to consider
5784 when deciding whether to conduct data collection online: (1) popula-
5785 tion availability, (2) the availability of particular measures, (3) the feasi-
5786 bility of particular manipulations, and (4) the length of experiments.

5787 **Population.** Not every target population can be tested online. Indeed,
5788 initially, convenience samples from Amazon Mechanical Turk were the
5789 only group easily available for online studies. More recently, new tools
5790 have emerged to allow pre-screening of crowd participants, including
5791 sites like Cloud Research and Prolific (Eyal et al. 2021; Peer et al.
5792 2021).¹⁰ And it may initially have seemed implausible that children
5793 could be recruited online, but during the COVID-19 pandemic a
5794 substantial amount of developmental data collection moved online,
5795 with many studies yielding comparable results to in-lab studies (e.g.,
5796 Chuey et al. 2021).¹¹ Finally, new, non-US crowdsourcing platforms
5797 continue to grow in popularity, leading to greater global diversity in
5798 the available online populations.

5799 **Online measures.** Not all measures are available online, though more
5800 and more are. Although online data collection was initially restricted

¹⁰ These tools still have significant weaknesses for accessing socio-demographically diverse populations within and outside the US, however—screening tools can remove participants, but if the underlying population does not contain many participants from a particular demographic, it can be hard to gather large enough samples. For an example of using crowdsourcing and social media sites to gather diverse participants, see DeMayo et al. (2021).

¹¹ Sites like LookIt (<https://lookit.mit.edu>) now offer sophisticated platforms for hosting studies for children and families (Scott and Schulz 2017).

5801 to the use of survey measures—including ratings and text responses—
5802 measurement options have rapidly expanded. The widespread use of
5803 libraries like jsPsych (De Leeuw 2015) has meant that millisecond accu-
5804 racy in capturing response times is now possible within web-browsers;
5805 thus, most reaction time tasks are quite feasible (Crump, McDonnell,
5806 and Gureckis 2013). The capture of sound and video is possible with
5807 modern browser frameworks (Scott and Schulz 2017). Further, even
5808 measures like mouse- and eye-tracking are beginning to become
5809 available (Maldonado, Dunbar, and Chemla 2019; Slim and Hartsuiker
5810 2023). In general, almost any variable that can be measured in the
5811 lab without specialized apparatus can also be collected online. On
5812 the other hand, studies that measure a broader range of physiological
5813 variables (e.g., heart rate or skin conductance) or a larger range of
5814 physical behaviors (e.g., walking speed or pose) are still likely difficult
5815 to implement online.

5816 **Online manipulations.** Online experiments are limited to the set of ma-
5817 nipulations that can be created within a browser window—but this re-
5818 striction excludes many different manipulations that involve real-time
5819 social interactions with a human being.¹² Synchronous chat sessions can
5820 be a useful substitute (Hawkins, Frank, and Goodman 2020), but these
5821 focus the experiment on the content of what is said and exclude the
5822 broader set of non-verbal cues available to participants in a live interac-

12 So-called “moderated” experiments—in which the experimental session is administered through a synchronous video chat have been used widely in online experiments for children but these designs are less common in experiments with adults because they are expensive and time-consuming to administer (Chuey et al. 2021).

5823 tion (e.g., gaze, race, appearance, accent, etc.). Creative experimenters
5824 can circumvent these limitations by using pictures, videos, and other
5825 methods. But more broadly, an experimenter interested in implement-
5826 ing a particular manipulation online should ask how compelling the
5827 online implementation is compared with an in-lab implementation. If
5828 the intention is to induce some psychological state—say stress, fear, or
5829 disgust—experimenters must trade off the greater ease of recruitment
5830 and larger scale of online studies with the more compelling experience
5831 they may be able to offer in a controlled lab context.

5832 **The length of online studies.** One last concern is about attention and
5833 focus in online studies. Early guidance around online studies tended to
5834 focus on making studies short and easy, with the rationale that crowd-
5835 sourcing workers were used to short jobs. Our sense is that this guidance
5836 no longer holds. Increasingly, researchers are deploying long and com-
5837 plex batteries of tasks to relatively good effect (e.g., Enkavi et al. 2019)
5838 and conducting repeated longitudinal sampling protocols (discussed in
5839 depth in Litman and Robinson 2020). Rather than relying on hard and
5840 fast rules about study length, a better approach for online testing is to
5841 ensure that participants' experience is as smooth and compelling as pos-
5842 sible. Under these conditions, if an experiment is viable in the lab, it is
5843 likely viable online.

5844 Online testing tools continue to grow and change but they are already
5845 mature enough that using them should be part of most behavioral re-
5846 searchers' basic toolkit.¹³

5847 *12.3 Ensuring high quality data*

5848 In the final section of this chapter, we review some key data collection
5849 practices that can help researchers collect high quality data while re-
5850 specting our ethical obligations to participants. By "high quality," here
5851 we especially mean datasets that are uncontaminated by responses gen-
5852 erated by misunderstanding of instructions, fatigue, incomprehension,
5853 or intentional neglect of the experimental task.

5854 We'll begin by discussing the issue of pilot testing; we recommend a
5855 systematic procedure for piloting that can maximize the chance of col-
5856 lecting high quality data. Next, we'll discuss the practice of checking
5857 participants' comprehension and attention and what such checks should
5858 and shouldn't be used for. Finally, we'll discuss the importance of main-
5859 taining consistent data collection records.

¹³ It is of course import to keep in mind that if a person works part- or full-time on a crowdsourcing platform, they are not a representative sample of the broader national population. Unfortunately, similar caveats hold true for in-person convenience samples (see chapter 10). Ultimately, researchers must reason about what their generalization goal is and whether that goal is consistent with the samples they can access (online or otherwise).

5860 12.3.1 *Conduct effective pilot studies*

5861 A **pilot study** is a small study conducted before you collect your main
5862 sample. The goal is to ensure smooth and successful data collection by
5863 first checking if your experimental procedures and data collection work-
5864 flow are working correctly. Pilot studies are also an opportunity to get
5865 feedback from participants about their experience of the experimental
5866 task, for example, is it too easy, too difficult, or too boring.

5867 Because pilot studies usually involve a small number of participants, they
5868 are not a reliable indicator of the study results, such as the expected ef-
5869 fect size or statistical significance (as we discussed in chapter 10). *Don't*
5870 use pilots to check if your effect is present or to estimate an effect size
5871 for power analysis. What pilots *can* do is tell you about whether your
5872 experimental procedure is viable. For example, pilot studies can re-
5873 veal:

- 5874 – if your code crashes under certain circumstances
- 5875 – if your instructions confuse a substantial portion of participants
- 5876 – if you have a very high dropout rate
- 5877 – if your data collection procedure fails to log variables of interest
- 5878 – if participants are disgruntled by the end of the experiment

5879 We recommend that all experimenters perform—at the very
5880 minimum—two pilot studies before they launch a new experiment.¹⁴

5881 The first pilot, which we call your **non-naïve participant pilot**, can make
5882 use of participants who know the goals of the experiment and under-
5883 stand the experimental manipulation—this could be a friend, collabo-
5884 rator, colleague, or family member.¹⁵ The goal of this pilot study is to
5885 ensure that your experiment is comprehensible, that participants can
5886 complete it, and that the data are logged appropriately. You must *ana-*
5887 *lyze* the data from the non-naive pilot, at least to the point of checking
5888 that the relevant data about each trial is logged.

5889 The second pilot, your **naïve participant pilot**, should consist of a test of
5890 a small set of participants recruited via the channel you plan to use for
5891 your main study. The number of participants you should pilot depends
5892 on the cost of the experiment in time, money, and opportunity as well
5893 as its novelty. A brand new paradigm is likely more prone to error than a
5894 tried and tested paradigm. For a short online survey-style experiment, a
5895 pilot of 10–20 people is reasonable. A more time-consuming laboratory
5896 study might require piloting just two or three people.¹⁶

5897 The goal of the naïve pilot study is to understand properties of the par-
5898 ticipant experience. Were participants confused? Did they withdraw
5899 before the study finished? Even a small number of pilots can tell you

¹⁴ We mean especially when deploying a new experimental paradigm or when collecting data from a new population. Once you have run many studies with a similar procedure and similar sample, extensive piloting is less important. Any time you change something, it's always good to run one or two pilots, though, just to check that you didn't inadvertently mess up your experiment.

¹⁵ In a pinch you can even run yourself through the experiment a bunch of times (though this isn't preferable because you're likely to miss a lot of aspects of the experience that you are habituated to, especially if you've been debugging the experiment already).

5900 that your dropout rate is likely too high: for example, if 5 of 10 pilot
5901 participants withdraw you likely need to reconsider aspects of your de-
5902 sign. It's critical for your naïve participant pilot that you debrief more
5903 extensively with your participants. This debriefing often takes the form
5904 of an interview questionnaire after the study is over. "What did you
5905 think the study was about?" and "is there any way we could improve
5906 the experience of being in the study?" can be helpful questions. Often
5907 this debriefing is more effective if it is interactive, so even if you are
5908 running an online study you may want to find some way to chat with
5909 your participants.

5910 Piloting—especially piloting with naïve participants to optimize the par-
5911 ticipant experience—is typically an iterative process. We frequently
5912 launch an experiment for a naive pilot, then recognize from the data
5913 or from participant feedback that the experience can be improved. We
5914 make tweaks and pilot again. Be careful not to over-fit to small dif-
5915 ferences in pilot data, however. Piloting should be more like work-
5916 shopping a manuscript to remove typos than doing statistical analysis. If
5917 someone has trouble understanding a particular sentence—whether in
5918 your manuscript or in your experiment instructions—you should edit
5919 to make it clearer!

¹⁶ In the case of especially expensive experiments, it can be a dilemma whether to run a larger pilot to identify difficulties since such a pilot will be costly. In these cases, one possibility is to plan to include the pilot participants in the main dataset if no major procedural changes are required. In this case, it is helpful to preregister a contingent testing strategy to avoid introducing data-dependent bias (see chapter 11). For example, in a planned sample of 100 participants, you could preregister running 20 as a pilot sample with the stipulation that you will look only at their dropout rate—and not at any condition differences. Then the preregistration can state that, if the dropout rate is lower than 25%, you will collect the next 80 participants and analyze the whole dataset, including the initial pilot, but if dropout rate is higher than 25%, you will discard the pilot sample and make changes. This kind of strategy can help you split the difference between cautious piloting and conservation of rare or costly data.

 ACCIDENT REPORT*Data logging much?*

When Mike was in graduate school, his lab got a contract to test a very large group of participants in a battery of experiments, bringing them into the lab over the course of a series of intense bursts of participant testing. He got the opportunity to add an experiment to the battery, allowing him to test a much larger sample than resources would otherwise allow. He quickly coded up a new experiment as part of a series of ongoing studies and began deploying it, coming to the lab every weekend for several months to help move participants through the testing protocol. Eagerly opening up the data file to reap the reward of this hard work, he found that the condition variable was missing from the data files. Although the experimental manipulation had been deployed properly, there was no record of which condition each participant had been run in, and so the data were essentially worthless. Had he run a quick pilot (even with non-naive participants) and attempted to analyze the data, this error would have been detected, and many hours of participant and experimenter effort would not have been lost.

5920

5921 12.3.1 *Measure participant compliance*

5922 You've constructed your experiment and piloted it. You are almost
5923 ready to go—but there is one more family of tricks for helping to
5924 achieve high quality data: integrating measures of participant com-

pliance into your paradigm. Collecting data on compliance (whether participants followed the experimental procedures as expected) can help you quantify whether participants understood your task, engaged with your manipulation, and paid attention to the full experimental experience. These measures in turn can be used both to modify your experimental paradigm and to exclude specific participants that were especially non-compliant (Hauser, Ellsworth, and Gonzalez 2018; Ejelöv and Luke 2020).

Below we discuss four types of compliance checks: (1) passive measures, (2) comprehension checks, (3) manipulation checks, and (4) attention checks. Passive measures and comprehension checks are very helpful for enhancing data quality. Manipulation checks also often have a role to play. In contrast, we typically caution in the use of attention checks.

1. **Passive measures of compliance.** Even if you do not ask participants anything extra in an experiment, it is often possible to tell if they have engaged with the experimental procedure simply by how long it takes them to complete the experiment. If you see participants with completion times substantially above or below the median, there is a good chance that they are either multi-tasking or rushing through the experiment without engaging.¹⁷ Passive measures cost little to implement and should be inserted

¹⁷ Measurements of per-page or per-element completion times can be even more specific since they can, for example, identify participants that simply did not read an assigned passage.

5946 whenever possible in experiments.¹⁸

5947 2. **Comprehension checks.** For tasks with complex instructions or
5948 experimental materials (say a passage that must be understood for
5949 a judgment to be made about it), it can be very helpful to get
5950 a signal that participants have understood what they have read
5951 or viewed. Comprehension checks, which ask about the content
5952 of the experimental instructions or materials, are often included
5953 for this purpose. For the comprehension of instructions, the best
5954 kinds of questions simply query the knowledge necessary to suc-
5955 ceed in the experiment, for example, “what are you supposed to
5956 do when you see a red circle flash on the screen?” In many plat-
5957 forms, it is possible to make participants reread the instructions
5958 again until they can answer these correctly. This kind of repeti-
5959 tion is nice because it corrects participants’ misconceptions rather
5960 than allowing them to continue in the experiment when they do
5961 not understand.¹⁹

5962 3. **Manipulation checks.** If your experiment involves more than
5963 a very transient manipulation—for example, if you plan to in-
5964 duce some state in participants or have them learn some content—
5965 then you can include a measure in your experiment that confirms
5966 that your manipulation succeeded (Ejelöv and Luke 2020). This

¹⁸ One variation that we endorse in certain cases is to force participants to engage with particular pages for a certain amount of time through the use of timers. Though, beware, this kind of feature can lead to an adversarial relationship with participants—in the face of this kind of coercion, many will opt to pull out their phone and multi-task until the timer runs down.

¹⁹ If you are querying comprehension of experimental materials rather than instructions, you may not want to re-expose participants to the same passage again in order to avoid confounding a participants’ initial comprehension and the amount of exposure that they receive.

measure is known as a manipulation check because it measures some prerequisite difference between conditions that is not the key causal effect of interest but is causally prerequisite to this effect. For example, if you want to see if anger affects moral judgment, then it makes sense to measure whether participants in your anger induction condition rate themselves as angrier than participants in your control condition. Manipulation checks are useful in the interpretation of experimental findings because they can decouple the failure of a manipulation from the failure of a manipulation to affect your specific measure of interest.²⁰

4. **Attention checks.** A final type of compliance check is a check that participants are paying attention to the experiment at all. One simple technique is to add questions that have a known and fairly obvious right answer (e.g., “what’s the capital of the United States.”). These trials can catch participants that are simply ignoring all text and “mashing buttons”, but they will not find participants who are mildly inattentive. Sometimes experimenters also use trickier compliance checks, such as putting an instruction for participants to click a particular answer deep within a question text that otherwise would have a different answer (Oppenheimer, Meyvis, and Davidenko 2009) (figure 12.2). Such compliance checks decrease so-called “satisficing” behavior,

²⁰ Hauser, Ellsworth, and Gonzalez (2018) worry that manipulation checks can themselves change the effect of a manipulation—this worry strikes us as sensible, especially for some types of manipulations like emotion inductions. Their recommendation is to test the efficacy of the manipulation in a separate study, rather than trying to nest the manipulation check within the main study.

5989 in which participants read as quickly as they can get away with
 5990 (doing only the minimum. On the other hand, participants may
 5991 see such trials as indications that the experimenter is trying to
 5992 trick them, and adopt a more adversarial stance towards the
 5993 experiment, which may result in less compliance with other
 5994 aspects of the design (unless they are at the end of the experiment,
 5995 [Hauser, Ellsworth, and Gonzalez 2018](#)). If you choose to include
 5996 attention checks like these, be aware that you are likely reducing
 5997 variability in your sample—trading off representativeness for
 5998 compliance.

Sports Participation

Most modern theories of decision making recognize the fact that decisions do not take place in a vacuum. Individual preferences and knowledge, along with situational variables can greatly impact the decision process. In order to facilitate our research on decision making we are interested in knowing certain factors about you, the decision maker. Specifically, we are interested in whether you actually take the time to read the directions; if not, then some of our manipulations that rely on changes in the instructions will be ineffective. So, in order to demonstrate that you have read the instructions, please ignore the sports items below, as well as the continue button. Instead, simply click on the title at the top of this screen (i.e., "sports participation") to proceed to the next screen.
 Thank you very much.

Which of these activities do you engage in regularly?
 (click on all that apply)

skiing	soccer	snowboarding	running	hockey
football	swimming	tennis	basketball	cycling

[Continue](#)

Figure 12.2

An attention check trial based on Oppenheimer, Meyvis, and Davidenko (2009). These trials can decrease variability in participant attention, but at the cost of selecting a subsample of participants, so they should be used cautiously.

5999 Data from all of these types of checks are used in many different—often
 6000 inconsistent—ways in the literature. We recommend that you:

- 6001 1. Use passive measures and comprehension checks as pre-registered
 6002 exclusion criteria to eliminate a (hopefully small) group of partic-

6003 ipants who might be non-compliant with your experiment.

6004 2. Check that exclusions are low and that they are uniform across
6005 conditions. If exclusion rates are high, your design may have
6006 deeper issues. If exclusions are asymmetric across conditions, you
6007 may be compromising your randomization by creating a situation
6008 in which (on average) different kinds of participants are included
6009 in one condition compared with the other. Both of these situa-
6010 tions substantially compromise any estimate of the causal effect of
6011 interest.

⚠ ACCIDENT REPORT

Does data quality vary throughout the semester?

Every lab that collects empirical data repeatedly using the same popula-
tion builds up lore about how that population varies in different contexts.
Many researchers who conducted experiments with college undergrad-
uates were taught never to run their studies at the end of the semester.
Exhausted and stressed students would likely yield low-quality data, or so
the argument went. Until the rise of multi-lab collaborative projects like
ManyLabs (see chapter 3), such beliefs were almost impossible to test.

ManyLabs 3 aimed specifically to evaluate data quality variation across
the academic calendar (Ebersole et al. 2016). With 2,696 participants
at 20 sites, the study conducted replications of 13 previously published
findings. Although only six of these findings showed strong evidence of

replicating across sites, none of the six effects was substantially moderated by being collected later in the semester. The biggest effect they observed was a change in the Stroop effect from $d = .89$ during the beginning and middle of the semester to $d = .92$ at the end. There was some evidence that participants *reported* being less attentive at the end of the semester, but this trend wasn't accompanied by a moderation of experimental effects.

Researchers are subject to the same cognitive illusions and biases as any human. One of these biases is the search to find meaning in the random fluctuations they sometimes observe in their experiments. The intuitions formed through this process can be helpful prompts for generating hypotheses—but beware of adopting them into your “standard operating procedures” without further examination. Labs that avoided data collection during the end of the semester might have sacrificed 10–20% of their data collection capacity for no reason!

6013

6014 3. Deploy manipulation checks if you are concerned about whether
6015 your manipulation effectively induces a difference between
6016 groups. Analyze the manipulation check separately from the
6017 dependent variable to test whether the manipulation was causally
6018 effective (Ejelöv and Luke 2020).

6019 4. Make sure that your attention checks are not confounded in any
6020 way with condition—remember our cautionary tale from chap-
6021 ter 9, in which an attention check that was different across condi-

6022 tions actually created an experimental effect.

6023 5. *Do not* include any of these checks in your analytic models as a
6024 covariate, as including this information in your analysis compro-
6025 mises the causal inference from randomization and introduces bias
6026 in your analysis (Montgomery, Nyhan, and Torres 2018).²¹

6027 Used appropriately, compliance checks can provide both a useful set
6028 of exclusion criteria and a powerful tool for diagnosing potential issues
6029 with your experiment during data analysis and correcting them down
6030 the road.

²¹ Including this information means you are “conditioning on a post-treatment variable,” as we described in chapter 7. In medicine, analysts distinguish “intent-to-treat” analysis, where you analyze data from everyone you gave a drug, and “as treated” analysis, where you analyze data depending on how much of the drug people actually took. In general, intent-to-treat gives you the generalizable causal estimate. In our current situation, if you include compliance as a covariate, you are essentially doing an “as treated” analysis and your estimate can be biased as a result. Although there is occasional need for such analyses, in general you probably want to avoid them.

6031 12.3.1 *Keep consistent data collection records*

6032 As an experimentalist, one of the worst feelings is to come back to
 6033 your data directory and see a group of data files, `run1.csv`, `run2.csv`,
 6034 `run3.csv` and not know what experimental protocol was run for each.
 6035 Was `run1` the pilot? Maybe a little bit of personal archaeology with
 6036 timestamps and version history can tell you the answer, but there is no
 6037 guarantee.²²

	A	B	C	D	E	F	G
1	DOT	RA	SID	DOB	Gender	Consent	Source
2	12/14/12	ak, fp	ASD_01	9/19/98	m	1	fp
3	12/17/12	ak, fp	ASD_02	6/17/90	f	0	fp
4	12/18/12	ak, fp	ASD_03	8/15/90	f	1	fp
5	12/20/12	mf, fp	ASD_04	9/21/08	m	1	fp
6	1/21/13	mf, fp	ASD_05	8/31/07	m	1	fp
7	1/29/13	ak, ca	ASD_06	8/30/10	f	1	ah
8	1/31/13	ak, fp	ASD_07	10/26/05	m	1	fp

²² We'll have a lot to say about this issue in chapter 13.

Figure 12.3
Part of a run sheet for a developmental study.

6038 As well as collecting the actual data in whatever form they take (e.g.,
 6039 paper surveys, videos, or files on a computer), it is important to log
 6040 metadata—data about your data—including relevant information like
 6041 the date of data collection, the sample that was collected, the experi-
 6042 ment version, the research assistants who were present, etc. The rele-
 6043 vant meta-data will vary substantially from study to study—the impor-
 6044 tant part is that you keep detailed records. Figure 12.3 and figure 12.4
 6045 give two examples from our own research. The key feature is that they
 6046 provide some persistent metadata about how the experiments were con-
 6047 ducted.

```
%%%%%%
Added a simple familiarization slide substitute that presents Bob and
shows that the experiment is about a person talking to you. Before
that, the familiarization slide was simply skipped.
%%%%%
```

```
-----  
November 18 2013  
50 subjects | Betting | No familiarization | Friend  
var participant_response_type = 1;  
var participant_feature_count = 1;  
var linguistic_framing = 0;  
var question_type = 0;  
-----  
November 18 2013  
50 subjects | Likert | No familiarization | Friend  
var participant_response_type = 2;  
var participant_feature_count = 1;  
var linguistic_framing = 0;  
var question_type = 2;  
%%%%%
The experiment now asked the subjects the referent of Bobs statement
at the bottom of the page. The previous experiments always had the
input field just below the stimuli or, in the case of 3fc hoovering
over the images did highlighted possible ones.
%%%%%
```

```
-----  
November 30 2013 ~ 7 pm:  
50 subjects | 3 forced choice condition | No familiarization | Friend  
var participant_response_type = 0;  
var participant_feature_count = 1;  
var linguistic_framing = 0;  
var question_type = 0;
```

Figure 12.4
Excerpt of a log for an iterative run of online experiments.

6048 12.4 Chapter summary: Data collection

6049 In this chapter, we took the perspective of both the participant and the
6050 researcher. Our goal was to discuss how to achieve a good research
6051 outcome for both. On the side of the participant, we highlighted the
6052 responsibility of the experimenter to ensure a robust consent and de-
6053 briefing process. We also discussed the importance of a good experi-
6054 mental experience in the lab and online—ensuring that the experiment
6055 is not only conducted ethically but is also pleasant to participate in. Fi-
6056 nally, we discussed how to address some concerns about data quality
6057 from the researcher perspective, recommending both the extensive use
6058 of non-naive and naive pilot participants and the use of comprehension
6059 and manipulation checks.



DISCUSSION QUESTIONS

1. “Citizen science” is a movement to have a broader base of individuals participate in research because they are interested in discoveries and want to help. In practice, citizen science projects in psychology like Project Implicit (<https://implicit.harvard.edu/implicit/>), Children Helping Science (<https://lookit.mit.edu>), and TheMusicLab.org (<https://themusiclab.org>) have all succeeded by offering participants a compelling experience. Check one of these out, participate in a study, and make a list the features that make it fun and easy to contribute data.

2. Be a Turker! Sign up for an account as an Amazon Mechanical Turk or Prolific Academic worker and complete a couple of tasks. How did you feel about browsing the list of tasks looking for work? What features of tasks attracted your interest? How hard was it to figure out how to participate in each task? And how long did it take to get paid?

6061

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6070 13 PROJECT MANAGEMENT

LEARNING GOALS

- Manage your research projects efficiently and transparently
- Develop strategies for data organization
- Optimize sharing of research products, like data and analysis code, by ensuring they are Findable, Accessible, Interoperable, Reusable (FAIR)
- Discuss potential ethical constraints on sharing research products

6071

6072 Your closest collaborator is you six months ago, but you
6073 don't reply to emails.

6074

— Karl Broman (2016)

6075 Have you ever returned to an old project folder to find a chaotic mess
6076 of files with names like analysis-FINAL, analysis-FINAL-COPY, and
6077 analysis-FINAL-COPY-v2? Which file is actually the final version!?
6078 Or perhaps you've spent hours searching for a data file to send to your

6079 advisor, only to realize with horror that it was *only* stored on your old
6080 laptop—the one that experienced a catastrophic hard drive failure when
6081 you spilled coffee all over it one sleepy Sunday morning. These experi-
6082 ences may make you sympathetic to Karl Broman’s quip above. Good
6083 project management practices not only make it easier to share your re-
6084 search with others, they also make for a more efficient and less error
6085 prone workflow that will avoid giving your future self a headache. This
6086 chapter is about the process of managing all of the products of your re-
6087 search workflow—methodological protocols, materials¹, data, and anal-
6088 ysis scripts. We focus especially on managing projects in ways that max-
6089 imize their value to you and to the broader research community by
6090 aligning with open science practices (maximizing TRANSPARENCY).

6091 When we talk about research products, we typically think of articles
6092 in academic journals, which have been scientists’ main method of com-
6093 munication since the scientific revolution in the 1600s.² But articles
6094 only provide written summaries of research; they are not the original
6095 research products. In recent years, there have been widespread calls
6096 for increased sharing of research products, such as materials, data, and
6097 analysis code (Munafò et al. 2017). When shared appropriately, these
6098 other products can be as valuable as a summary article: Shared stimulus
6099 materials can be reused for new studies in creative ways; shared anal-
6100 ysis scripts can allow for reproduction of reported results and become

¹ We use the term “materials” here to cover a range of things another researcher might need in order to repeat your study, for example, stimuli, survey instruments, and code for computer-based experiments.

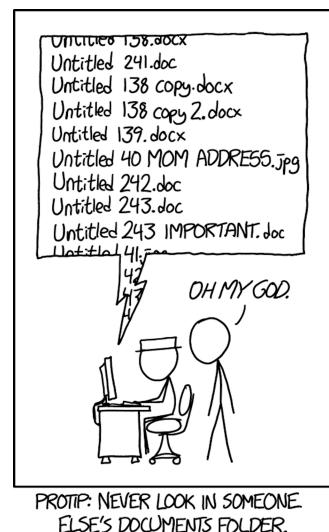


Figure 13.1

Poor file management creates chaos! “Documents” by xkcd (<https://xkcd.com/1459>, licensed under <https://xkcd.com/license.html>).

² The world’s oldest scientific journal is the *Philosophical Transactions of the Royal Society*, first published in 1665.

6101 templates for new analyses; and shared data can enable new analyses or
6102 meta-analyses. Indeed, many funding agencies, and some journals, now
6103 require that research products be shared publicly, except when there
6104 are justified ethical or legal constraints, such as with sensitive medical
6105 data (Nosek et al. 2015).

6106 Data sharing, in particular, has been the focus of intense interest.
6107 Sharing data is associated with benefits in terms of error detection
6108 (Hardwicke et al. 2021), creative re-use that generates new discoveries
6109 (Voytek 2016), increased citations (Piwowar and Vision 2013), and
6110 detection of fraud (Simonsohn 2013). According to surveys, researchers
6111 are usually willing to share data in principle (Houtkoop et al. 2018),
6112 but unfortunately, in practice, they often do not, even if you directly
6113 ask them (Hardwicke and Ioannidis 2018)! Often authors simply
6114 do not respond, but when they do, they frequently report that data
6115 have been lost because they were stored on a misplaced or damaged
6116 computer or drive, or team members with access to the data are no
6117 longer contactable (Tenopir et al. 2020).

6118 As we have discussed in chapter 3, even when data are shared, they are
6119 not always formatted in a way that they can be easily understood and
6120 re-used by other researchers, or even the original authors! This issue
6121 highlights the critical role of **metadata**: information that documents

6122 the data (and other products) that you share, including README files,
 6123 **codebooks** that document datasets themselves, licenses that provide legal
 6124 restrictions on reuse, etc. We will discuss best-practices for metadata
 6125 throughout the chapter.

6126 Sound project management practices and sharing of research projects
 6127 are mutually reinforcing goals that bring benefits for both yourself, the
 6128 broader research community, and scientific progress. One particularly
 6129 important benefit of good project management practices is that they en-
 6130 able reproducibility. As we discussed in chapter 3, computational repro-
 6131 ducibility involves being able to trace the provenance of any reported an-
 6132 alytic result in a research report back to its original source. That means
 6133 being able to recreate the entire analytic chain from data collection to
 6134 data files, though analytic specifications to the research results reported
 6135 in text, tables, and figures. If data collection is documented appropri-
 6136 ately, and if data are stored, organized, and shared, then the provenance
 6137 of a particular result is relatively easy to verify. But once this chain
 6138 is broken it can be hard to reconstruct , figure 13.2. That's why it's
 6139 critical to build good project management practices into your research
 6140 workflow right from the start.

6141 In this chapter, you will learn how to manage your research project both
 6142 efficiently and transparently.³ Working towards these goals can create a

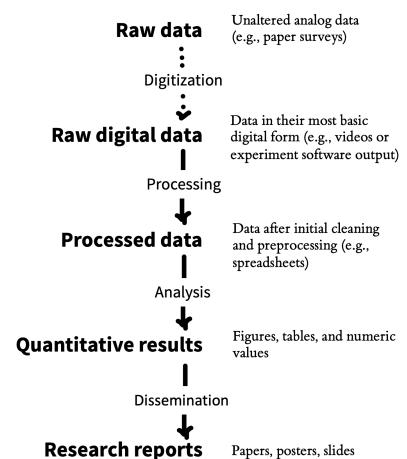


Figure 13.2
 Illustration of the analytic chain from raw data through to research report.

³ This chapter—especially the last section—draws heavily on Klein et al. (2018), an article on research transparency that several of us contributed to.

6143 virtuous cycle: if you organize your research products well, they are eas-
6144 ier to share later, and if you assume that you will be sharing, you will be
6145 motivated to organize your work better! We begin by discussing some
6146 important principles of project management, including folder structure,
6147 file naming, organization, and version control. Then we zoom in specif-
6148 ically on data and discuss best practices for data sharing. We end by
6149 discussing the question of what research products to share and some
6150 of the potential ethical issues that might limit your ability to share in
6151 certain circumstances.



CASE STUDY

ManyBabies, ManySpreadsheetFormats!

The ManyBabies project is an example of “Big Team Science” in psychology. A group of developmental psychology researchers (including some of us) were worried about many of the issues of reproducibility, replicability, and experimental methods that we’ve been discussing throughout this book, so they set up a large-scale collaboration to replicate key effects in developmental science. The first of these studies was ManyBabies 1 (The ManyBabies Consortium et al. 2020), a study of infants’ preference for baby-talk (also known as “infant directed speech”).

The core team expected a handful of labs to contribute, but after a year-long data collection period, they ended up receiving data from 69 labs around the world! The outpouring of interest signaled a lot of enthusi-

asm from the community for this kind of collaborative science. Unfortunately, it also made for a tremendous data management headache. All kinds of complications and hilarity ensued as the idiosyncratic data formatting preferences of the various labs were reorganised to fit into a single standardized analysis pipeline (Byers-Heinlein et al. 2020).

All of the specific formatting changes that individual labs made were reasonable—altering column names for clarity, combining templates into a single Excel file, changing units (e.g., from seconds to milliseconds)—but together they created a very challenging **data validation** problem for the core analysis team, requiring many dozens of hours of coding and hand-checking. The data checking was critical: an error in one lab’s data was flagged during validation and led to the painful decision to drop those data from the final dataset. In future ManyBabies projects, the group has committed to using shared data validation software (<https://manybabies.org/validator/>) to ensure that data files uploaded by individual labs conform to a shared standard.

6153

6154 *13.1 Principles of project management*

6155 A lot of project management problems can be avoided by following a
6156 very simple file organisation system.⁴ For those researchers that “grew
6157 up” managing their files locally on their own computers and email-
6158 ing colleagues versions of data files and manuscripts with names like

6159 manuscript-FINAL-JS-rev1.xlsx, a few aspects of this system may
6160 seem disconcerting. However, with a little practice, this new way of
6161 working will start to feel intuitive and have substantial benefits.

6162 Here are the principles:

6163 1. There should be exactly one definitive copy of each document
6164 in the project, with its name denoting what it is. For example,

6165 fifo_manuscript.Rmd or fifo_manuscript.docx is the write-
6166 up of the “fifo” project as a journal manuscript.

6167 2. The location of each document should be within a folder which
6168 serves to uniquely identify the document’s function within the
6169 project. For example,

6170 analysis/experiment1/eye_tracking_preprocessing.Rmd
6171 is clearly the file that performs pre-processing for the analysis of
6172 eye-tracking data from Experiment 1.

6173 3. The full project should be accessible to all collaborators via the
6174 cloud, either using a version control platform (e.g., GitHub) or
6175 another cloud storage provider (e.g., Dropbox, Google Drive).

6176 4. The revision history of all text and text-based documents
6177 (minimally, data, analysis code, and manuscript files) should be
6178 archived automatically. Automatic versioning is the key feature
6179 of all version control systems and is often included by cloud

6180 storage providers.

6181 Keeping these principles in mind, we discuss best practices for project
6182 organization, version control, and file naming.

6183 *13.1.1 Organizing your project*

6184 To the greatest extent possible, all files related to a project should be
6185 stored in the same project folder (with appropriate sub-folders), and on
6186 the same storage provider. There are cases where this is impractical
6187 due to the limitations of different software packages. For example, in
6188 many cases a team will manage its data and analysis code via github but
6189 decide to write collaboratively using google docs, overleaf, or another
6190 collaborative platform. (It can also be hard to ask all collaborators to use
6191 a version control system they are unfamiliar with.) In that case, the final
6192 paper should still be linked in some way to the project repository.⁵

6193 figure 13.3 shows an example project stored on the Open Science Frame-
6194 work. The top level folder contains sub-folders for analyses, materi-
6195 als, raw and processed data (kept separately). It also contains the paper
6196 manuscript, and, critically, a README file in a text format that de-
6197 scribes the project. A README is a great way to document any other

⁵ The biggest issue that comes up in using a split workflow like this is the need to ensure reproducible written products, a process we cover in chapter 14.

6198 metadata that the authors would like to be associated with the research

6199 products, for example a license, explained below.

Name	Modified
Example project (/rpydu/)	
- OSF Storage (United States)	
+ Analyses	
Heycke, Aust, & Stahl (2017) Subliminal influence on prefer... 2018-01-12 06:29 AM	
+ Material	
+ Processed data	
+ Raw data	
README.md	2018-06-12 07:26 AM
Study protocol (Stage-1 registered report).pdf	2018-01-12 06:33 AM

Figure 13.3

Sample top level folder structure for a project. From Klein et al. (2018). Original visible on the Open Science Framework (<https://osf.io/xf6ug>).

6200 There are many reasonable ways to organize the sub-folders of a re-

6201 search project, but the broad categories of materials, data, analysis, and

6202 writing are typically present.⁶ In some projects—such as those involving

6203 multiple experiments or complex data types—you may have to adopt a

6204 more complex structure. In many of our projects, it's not uncommon to

6205 find paths like /data/raw_data/exp1/demographics. The key prin-

6206 ciple is to create a hierarchical structure in which subfolders uniquely

6207 identify the part of the broader space of research products that are found

6208 inside them—that is, /data/raw_data/exp1 contains all the raw data

6209 from Experiment 1, and /data/raw_data/exp1/demographics con-

6210 tains all the raw *demographics* data from that particular experiment.

⁶ We like the scheme followed by Project TIER (<https://www.projecttier.org>), which provides very clear guidance about file structure and naming conventions. TIER is primarily designed for a copy-and-paste workflow, which is slightly different from the “dynamic documents” workflow that we primarily advocate for (e.g., using R Markdown or Quarto as in appendix C).

6211 13.1.2 Versioning

6212 Probably everyone who has ever collaborated electronically has experi-

6213 enced the frustration of editing a document, only to find out that you

6214 are editing the wrong version—perhaps some of the problems you are
 6215 working on have already been corrected, or perhaps the section you are
 6216 adding has already been written by someone else. A second common
 6217 source of frustration comes when you take a wrong turn in a project,
 6218 perhaps by reorganizing a manuscript in a way that doesn't work or
 6219 refactoring code in a way that turns out to be short-sighted.

6220 These two problems are solved by modern version control systems.
 6221 Here we focus on the use of `git`, which is the most widely used version
 6222 control system. Git is a great general solution for version control, but
 6223 many people—including several of us—don't love it for collaborative
 6224 manuscript writing. We'll introduce `git` and its principles here, while
 6225 noting that online collaboration tools like Google Docs and Overleaf⁷
 6226 can be easier for writing prose (as opposed to code); we cover this topic
 6227 in a bit more depth in chapter 14.

6228 Git is a tool for creating and managing projects, which are called **repositories**. A Git repository is a directory whose revision history is tracked
 6229 via a series of **commits**—snapshots of the state of the project. These
 6230 commits can form a tree with different **branches**, as when two contrib-
 6231 utors to the project are working on two different parts simultaneously
 6232 (figure 13.4). These branches can later be **merged** either automatically
 6233 or via manual intervention in the case of conflicting changes.

⁷ Overleaf is actually supported by git on the backend!

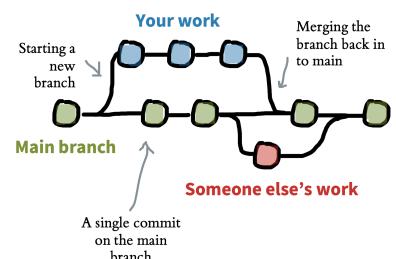


Figure 13.4
 Visualisation of Git version control showing a series of commits (circles) on three different branches: the main branch (green) and two others (blue and red). Branches can be created and then merged back into the main branch.

6235 Commonly, Git repositories are hosted by an online service like Github⁸
6236 to facilitate collaboration. With this workflow, a user makes changes
6237 to a local version of the repository on their own computer and pushes
6238 those changes to the online repository. Another user can then pull those
6239 changes from the online repository to their own local version. The on-
6240 line “origin” copy is always the definitive copy of the project and a
6241 record is kept of all changes. Chapter B provides a practical introduc-
6242 tion to Git and Github, and there are a variety of good tutorials available
6243 online and in print (Blischak, Davenport, and Wilson 2016).

6244 Collaboration using version control tools is designed to solve many of
6245 the problems we’ve been discussing:

- 6246 – A remotely hosted Git repository is a cloud-based backup of your
6247 work, meaning it is less vulnerable to accidental erasure.⁹
- 6248 – By virtue of having versioning history, you have access to previous
6249 drafts in case you find you have been following a blind alley and
6250 want to roll back your changes.
- 6251 – By creating new branches, you can create another, parallel history
6252 for your project, so that you can try out major changes or additions
6253 without disturbing the main branch in the process.
- 6254 – A project’s commit history is labeled with each commit’s author
6255 and date, facilitating record keeping and collaboration.

⁸ <https://github.com>

⁹ In 48BC, Julius Caesar accidentally burned down part of the Great Library of Alexandria where the sole copies of many valuable ancient works were stored. To this day, many scientists have apparently retained the habit of storing single copies of important information in vulnerable locations. Even in the age of cloud computing, hard drive failure is a surprisingly common source of problems!

6256 – Automatic merging can allow synchronous editing of different
6257 parts of a manuscript or codebase.¹⁰

6258 Organizing a project repository for collaboration and hosting on a re-
6259 mote platform is an important first step towards sharing! Many of our
6260 projects (like this book) are actually born open: we do all of our work
6261 on a publicly hosted repository for everyone to see (Rouder 2015). This
6262 philosophy of “working in the open” encourages good organization
6263 practices from the beginning. It can feel uncomfortable at first, but this
6264 discomfort soon vanishes as you realize that basically no one is looking
6265 at your in-progress project.

6266 One concern that many people raise about sharing in-progress research
6267 openly is the possibility of “scooping”—that is, other researchers get-
6268 ting an idea or even data from the repository and writing a paper before
6269 you do. We have two responses to this concern. First, the empirical fre-
6270 quency of this sort of scooping is difficult to determine, but likely very
6271 low—we don’t know of any documented cases. Mostly, the problem is
6272 getting people to care about your experiment at all, not people caring
6273 so much that they would publish using your data or materials! In Gary
6274 King’s words (King and Shieber 2013), “The thing that matters the least
6275 is being scooped. The thing that matters the most is being ignored.”
6276 On the other hand, if you are in an area of research that you perceive

¹⁰ Version control isn’t magic, and if you and a collaborator edit the same paragraph or function, you will likely have to merge your changes by hand. But Git will at least show you where the conflict is!

6277 to be competitive, or where there is some significant risk of this kind
6278 of shenanigans, it's very easy to keep part, or all, of a repository, private
6279 among your collaborators until you are ready to share more widely. All
6280 of the benefits we described still accrue. For an appropriately organized
6281 and hosted project, often the only steps required to share materials, data,
6282 and code are 1) to make the hosted repository public and 2) to link it to
6283 an archival storage platform like the Open Science Framework.

6284 13.1.3 *File names*

6285 As Phil Karlton reportedly said¹¹, “There are only two hard things in
6286 Computer Science: cache invalidation and naming things.” What’s
6287 true for computer science is true for research in general.¹² Naming
6288 files is hard! Some very organized people survive on systems like
6289 INFO-r1-draft-2020-07-13-js.docx – meaning, “the INFO
6290 project revision 1 draft of July 13th, 2020, with edits by JS.” But
6291 this kind of system needs a lot of rules and discipline, and it requires
6292 everyone in a project to buy in completely.

6293 On the other hand, if you are naming a file in a hierarchically organized
6294 version control repository, the naming problem gets dramatically eas-
6295 ier. All of a sudden, you have a context in which names make sense.
6296 data.csv is a terrible name for a data file on its own. But the name

¹¹ <https://www.karlton.org/2017/12/naming-things-hard/>

¹² We won’t talk about cache invalidation; that’s a more technical problem in computer science that is beyond the scope of this book.

6297 is actually perfectly informative—in the context of a project repository
6298 with a README that states that there is only a single experiment, a
6299 repository structure such that the file lives in a folder called `raw_data`,
6300 and a commit history that indicates the file's commit date and author.

6301 As this example shows, naming is hard *out of context*. So here's our rule:
6302 name a file with what it contains. Don't use the name to convey the
6303 context of who edited it, when, or where it should go in a project. That
6304 is metadata that the platform should take care of.¹³

¹³ The platform won't take care of it if you email it to a collaborator—precisely why you should share access to the full *platform*, not just the out-of-context file!

6305 13.2 Data Management

6306 We've just discussed how to manage projects in general; in this section
6307 we zoom in on datasets specifically. Data are often the most valuable
6308 research product because they represent the evidence generated by our
6309 research. We maximize the value of the evidence when other scientists
6310 can reuse it for independent verification or generation of novel discov-
6311 eries. Yet lots of research data are not reusable, even when they are
6312 shared. In chapter 3, we discussed Hardwicke et al. (2018)'s study of
6313 analytic reproducibility. But before we were even able to try and re-
6314 produce the analytic results, we had to look at the data. When we did
6315 that, we found that only 64% of shared datasets were both complete and
6316 understandable.

6317 How can you make sure that your data are managed so as to enable

6318 effective sharing? We make four primary recommendations:

6319 1. save your raw data

6320 2. document your data collection process

6321 3. organize your raw data for later analysis

6322 4. document your data using a codebook or other metadata

6323 Let's look at each in turn.

6324 13.2.1 Save your raw data

6325 Raw data take many forms. For many of us, the raw data are those re-

6326 turned by the experimental software; for others, the raw data are videos

6327 of the experiment being carried out. Regardless of the form of these

6328 data, save them! They are often the only way to check issues in what-

6329 ever processing pipeline brings these data from their initial state to the

6330 form you analyze. They also can be invaluable for addressing critiques

6331 or questions about your methods or results later in the process. If you

6332 need to correct something about your raw data, *do not alter the original*

6333 files. Make a copy, and make a note about how the copy differs from

6334 the original.¹⁴

¹⁴ Future you will thank present you for explaining why there are two copies of subject 19's data after you went back and corrected a typo.

6335 Raw data are often not anonymized—or even anonymizable.
6336 Anonymizing them sometimes means altering them (e.g., in the
6337 case of downloaded logs from a service that might include IDs or IP
6338 addresses). Or in some cases, anonymization is difficult or impossible
6339 without significant effort and loss of some value from the data, e.g. for
6340 video data or MRI data (Bischoff-Grethe et al. 2007). Unless you have
6341 specific permission for broad distribution of these identifiable data,
6342 the raw data may then need to be stored in a different way. In these
6343 cases, we recommend saving your raw data in a separate repository
6344 with the appropriate permissions. For example, in the ManyBabies 1
6345 study we described above, the public repository does not contain the
6346 raw data contributed by participating labs, which the team could not
6347 guarantee was anonymized; these data are instead stored in a private
6348 repository.¹⁵

6349 You can use your repository’s README to describe what is and is
6350 not shared. For example, a README might state that “We provide
6351 anonymized versions of the files originally downloaded from Qualtrics”
6352 or “Participants did not provide permission for public distribution
6353 of raw video recordings, which are retained on a secure university
6354 server.” Critically, if you share the derived tabular data, it should
6355 still be possible to reproduce the analytic results in your paper, even
6356 if checking the provenance of those numbers from the raw data is not

¹⁵ The precise repository you use for this task is likely to vary by the kind of data that you’re trying to store and the local regulatory environment. For example, in the United States, to store de-anonymized data with certain fields requires a server that is certified for HIPAA (the relevant privacy law). Many—but by no means all—universities provide HIPAA-compliant cloud storage.

6357 possible for every reader.¹⁶

6358 One common practice is the use of participant identifiers to link spe-
6359 cific experimental data—which, if they are responses on standardized
6360 measures, rarely pose a significant identifiability risk—to demographic
6361 data sheets that might include more sensitive and potentially identifi-
6362 able data.¹⁷ Depending on the nature of the analyses being reported,
6363 the experimental data can then be shared with limited risk. Then a
6364 selected set of demographic variables—for example, those that do not
6365 increase privacy risks but are necessary for particular analyses—can be
6366 distributed as a separate file and joined back into the data later.

¹⁶ One way we organize the raw data in some of our paper is to have three different subfolders in the `data/` directory: `raw/`, for the original data; `processed/`, for the anonymized or otherwise pre-processed data; and `/scripts`, for the code that does the preprocessing. Since these folders are in a git repository, we can then add `raw/*` to the `.gitignore` file, ensuring that they are never added to the public version of the repository even though they sit within our local file hierarchy in the appropriate place.

6367 13.2.2 Document your data collection process

6368 In order to understand the meaning of the raw data, it's helpful to share
6369 as much as possible about the context in which they were collected.
6370 This practice also helps communicate the experience that participants
6371 had in your experiment. Documentation of this experience can take
6372 many forms.

6373 If the experimental experience was a web-based questionnaire, archiv-
6374 ing this experience can be as simple as downloading the questionnaire
6375 source.¹⁸ For more involved studies, it can be more difficult to recon-
6376 struct what participants went through. This kind of situation is where

video data can shine (Gilmore and Adolph 2017). A video recording of a typical experimental session can provide a valuable tutorial for other experimenters—as well as good context for readers of your paper. This is doubly true if there is a substantial interactive element to your experimental experience, as is often the case for experiments with children. For example, in our ManyBabies case study, the project shared “walk through” videos of experimental sessions¹⁹ for many of the participating labs, creating a repository of standard experiences for infant development studies. If nothing else, a video of an experimental session can sometimes be a very nice archive of a particular context.²⁰

Regardless of what specific documentation you keep, it’s critical to create some record linking your data to the documentation. For a questionnaire study, for example, this documentation might be as simple as a README that says that the data in the data/raw/ directory were collected on a particular date using the file named experiment1.qsf. This kind of “connective tissue” linking data to materials can be very important when you return to a project with questions. If you spot a potential error in your data, you will want to be able to examine the precise version of the materials that you used to gather those data in order to identify the source of the problem.

¹⁷ A word about subject identifiers. These should be anonymous identifiers, like randomly generated numbers, that cannot be linked to participant identities (like data of birth) and are unique. You laugh, but one of us was in a lab where all the subject IDs were the date of test and the initials of the participant. These were neither unique nor anonymous. One common convention is to give your study a code-name and to number participants sequentially, so your first participant in a sequence of experiments on information processing might be INFO-1-01.

¹⁸ If it’s in a proprietary format like a Qualtrics .QSF file, a good practice is to convert it to a simple plain text format as well so it can be opened and re-used by folks who do not have access to Qualtrics (which may include future you!).

¹⁹ <https://nyu.databrary.org/volume/>
²⁰ 896 Videos of experimental sessions also are great demos to show in a presentation about your experiment, provided you have permission from the participant.

6397 13.2.3 Organize your data for later analysis: Spreadsheets

6398 Data come in many forms, but chances are that at some point during
6399 your project you will end up with a spreadsheet full of information.
6400 Well-organized spreadsheets can mean the difference between project
6401 success and failure! A wonderful article by Broman and Woo (2018) lays
6402 out principles of good spreadsheet design. We highlight some of their
6403 principles here (with our own, opinionated ordering):

6404 1. *Make it a rectangle*.²¹ Nearly all data analysis software, like SPSS,
6405 Stata, Jamovi and JASP (and many R packages), require data to be
6406 in a tabular format.²² If you are used to analyzing data exclusively
6407 in a spreadsheet, this kind of tabular data isn't quite as readable,
6408 but readable formatting gets in the way of almost any analysis you
6409 want to do. Figure 13.5 gives some examples of non-rectangular
6410 spreadsheets. All of these will cause any analytic package to choke
6411 because of inconsistencies in how rows and columns are used!

	A	B	C	D	E	F
1						
2		101	102	103	104	105
3	sex	Male	Female	Male	Male	Male
4						
5		101	102	103	104	105
6	glucose	134.1	120.8	124.8	83.1	105.2
7						
8		101	102	103	104	105
9	insulin	0.60	1.18	1.23	1.16	0.73

	A	B	C	D	E	F	G
1		1MIN					
2			Normal			Mutant	
3	B6	146.6	138.6	155.6	166	179.3	186.9
4	BTBR	245.7	240				
5							
6	5MIN						
7			Normal			Mutant	
8	B6	333.6	353.6	408.8	450.6	474.4	423.8
9	BTBR	514.4	610.6	597.9	412.1	447.4	446.5

	A	B	C	D	E	F
1						
2	Date	11/3/14				
3	Days on Diet	126				
4	Mouse #	43				
5	sex	f				
6	experiment	values		mean	SD	
7	control	0.186	0.191	1.081	0.49	0.52
8	treatment A	7.414	1.468	2.254	3.71	3.23
9	treatment B	9.811	9.259	11.296	10.12	1.05
10						
11	fold change	values		mean	SD	
12	treatment A	15.26	3.82	4.64	7.64	6.65
13	treatment B	20.19	19.05	23.24	20.83	2.17

	A	B	C	D	E	F	G
1		GTt date	GTt weight	time	glucose mg/dl	insulin ng/ml	
2	321	2/9/15	24.5	0	99.3	10	off curve
3				6	309.3	0.295	
4				15	284.1	0.129	
5				30	312	0.175	
6				60	99.9	0.122	
7				120	217.9	10	off curve
8	322	2/9/15	18.9	0	185.8	0.251	
9				5	297.4	2.228	
10				15	439	2.078	
11				30	343.3	0.175	
12				40	232.7	0.15	
13				120	249.7	0.523	
14	323	2/9/15	24.7	0	198.5	0.151	
15				5	530.6	off curve 10	

²¹ Think of your data like a well-ordered plate of sushi, neatly packed together without any gaps.

²² Tabular data is a precursor to “tidy” data, which we describe in more detail in appendix D.

Figure 13.5

Examples of non-rectangular spreadsheet formats that are likely to cause problems in analysis. Adapted from Broman and Woo (2018).

6412 2. *Choose good names for your variables.* No one convention for name
 6413 formatting is best, but it's important to be consistent. We tend
 6414 to follow the tidyverse style guide²³ and use lowercase words sep-
 6415 arated by underscores (_). It's also helpful to give units where
 6416 these are available, e.g., are reaction times in seconds or millisec-
 6417 onds. Table 13.1 gives some examples of good and bad variable
 6418 names.

Table 13.1
 Examples of good and bad variable names. Adapted from Broman and Woo (2018).

Good name	Good alternative	Avoid
subject_id	SubID	subject #
sex	female	M/F
rt_msec	reaction_time_ms	reaction time (millisec.)

6419 3. *Be consistent with your cell formatting.* Each column should have one
 6420 kind of thing in it. For example, if you have a column of numeri-
 6421 cal values, don't all of a sudden introduce text data like "missing"
 6422 into one of the cells. This kind of mixing of data types can cause
 6423 havoc down the road. Mixed or multiple entries also don't work,
 6424 so don't write "0 (missing)" as the value of a cell. Leaving cells
 6425 blank is also risky because it is ambiguous. Most software pack-
 6426 ages have a standard value for missing data (e.g. NA is what R uses).
 6427 If you are writing dates, please be sure to use the "global standard"

²³ <https://style.tidyverse.org>

6428 (ISO 8601), which is YYYY-MM-DD. Anything else can be mis-
6429 interpreted easily.²⁴

6430 4. *Decoration isn't data.* Decorating your data with bold headings or
6431 highlighting may seem useful for humans, but it isn't uniformly
6432 interpreted or even recognized by analysis software (e.g., reading
6433 an Excel spreadsheet into R will scrub all your beautiful highlighting
6434 and artistic fonts) so do not rely on it.

6435 5. *Save data in plain text files.* The CSV (comma-delimited) file for-
6436 mat is a common standard for data that is uniformly understood
6437 by most analysis software (it is an “interoperable” file format).²⁵
6438 The advantage of CSVs is that they are not proprietary to Mi-
6439 crossoft or another tech company and can be inspected in a text
6440 editor, but be careful: they do not preserve Excel formulas or for-
6441 matting!

6442 Given the points above, we recommend that you avoid analyzing your
6443 data in Excel. If it is necessary to analyze your data in a spreadsheet
6444 program, we urge you to save the raw data as a separate CSV and then
6445 create a distinct analysis spreadsheet so as to be sure to retain the raw
6446 data unaltered by your (or Excel's) manipulations.

²⁴ Dates in Excel deserve special mention as a source of terribleness. Excel has an unfortunate habit of interpreting information that has nothing to do with dates as dates, destroying the original content in the process. Excel's issue with dates has caused unending horror in the genetics literature, where gene names are automatically converted to dates, sometimes without the researchers noticing (Ziemann, Eren, and El-Osta 2016). In fact, some gene names have had to be changed in order to avoid this issue!

²⁵ Be aware of some interesting differences in how these files are output by European vs. American versions of Microsoft Excel! You might find semi-colons instead of commas in some datasets.

6447 13.2.4 Organize your data for later analysis: Software

6448 Many researchers do not create data by manually entering information
6449 into a spreadsheet. Instead they receive data as the output from a web
6450 platform, software package, or device. These tools typically provide re-
6451 searchers limited control over the format of the resulting tabular data
6452 export. Case in point is the survey platform Qualtrics, which—at least
6453 at the moment—provides data with not one but two header rows, com-
6454 plicating import into almost all analysis software!²⁶

²⁶ The R package qualtrics can help with this.

6455 That said, if your platform *does* allow you to control what comes out,
6456 you can try to use the principles of good tabular data design outlined
6457 above. For example, try to give your variables (e.g., questions in
6458 Qualtrics) sensible names!

 ACCIDENT REPORT

Bad variable naming can lead to analytic errors!

In our methods class, students often try to reproduce the original analyses from a published study before attempting to replicate the results in a new sample of participants. When Kengthsagn Louis looked at the code for the study she was interested in, she noticed that the variables in the analysis code were named horribly (presumably because they were output this way by the survey software). For example, one piece of Stata code looked like this:

```
gen recall1=.  
  
replace recall1=0 if Q21==1  
  
replace recall1=1 if Q21==3 | Q21==5 | Q21==6  
  
replace recall1=2 if Q21==2 | Q21==4 | Q21==7 | Q21==8  
  
replace recall1=0 if Q69==1  
  
replace recall1=1 if Q69==3 | Q69==5 | Q69==6  
  
replace recall1=2 if Q69==2 | Q69==4 | Q69==7 | Q69==8  
  
ta recall1
```

In the process of translating this code into R in order to reproduce the analyses, Kengthsagn and a course teaching assistant, Andrew Lampinen, noticed that some participant responses had been assigned to the wrong variables. Because the variable names were not human-readable, this error was almost impossible to detect. Since the problem affected some of the inferential conclusions of the article, the article's author—to their credit—issued an immediate correction ([Petersen 2019](#)).

The moral of the story: Obscure variable names can hide existing errors and create opportunities for further error! Sometimes you can adjust these within your experimental software, avoiding the issue. If not, make sure to create a “key” and translate the names immediately, double checking after you are done.

6461 13.2.1 Document the format of your data

6462 Even the best-organized tabular data are not always easy to understand
 6463 by other researchers, or even yourself, especially after some time has
 6464 passed. For that reason, you should make a **codebook** (also known as
 6465 a **data dictionary**) that explicitly documents what each variable is. Fig-
 6466 ure 13.7 shows an example codebook for the trial-level data in the bot-
 6467 tom of figure 13.6. Each row represents one variable in the associated
 6468 dataset. Codebooks often describe what type of variable a column is
 6469 (e.g., numeric, string), and what values can appear in that column. A
 6470 human-readable explanation is often given as well, providing provid-
 6471 ing units (e.g., “seconds”) and a translation of numeric codes (e.g., “test
 6472 condition is coded as 1”) where relevant.

	A	B	C	D	E	F	G	H	I
1	lab	subid	method	RA	age_days	trial_order	session_error	session_error_type	notes
2	babylab_nijmegen	ba01_6-9	HPP	KM	245	1	noerror	NA	teeth may be painful
3	babylab_nijmegen	ba02_6-9	HPP	KM	206	4	noerror	NA	NA
4	babylab_nijmegen	ba03_6-9	HPP	KM	257	3	noerror	NA	NA
5	babylab_nijmegen	ba04_6-9	HPP	KM	245	2	error	baby cried	teeth may be painful
6	babylab_nijmegen	ba05_6-9	HPP	KM	288	2	noerror	NA	baby was sick 2 months ago

	A	B	C	D	E	F
1	lab	subid	trial_type	stimulus	trial_num	looking_time
2	babylab_nijmegen	ba01_6-9	training	train1	-2	18.02
3	babylab_nijmegen	ba01_6-9	training	train2	-1	9.05
4	babylab_nijmegen	ba01_6-9	IDS	IDS1	1	17.48
5	babylab_nijmegen	ba01_6-9	ADS	ADS1	2	5.51
6	babylab_nijmegen	ba01_6-9	IDS	IDS2	3	16.34
7	babylab_nijmegen	ba01_6-9	ADS	ADS2	4	13.9

	A	B	C	D
1	Variable Name	Type	Possible Values	Explanation
2	lab	string	<your lab ID>	your unique lab ID
3	subid	string	<participant ID codes>	unique (within lab) ID for the participant
4	trial_type	string	'IDS', 'ADS', and 'training'	stimulus type on this trial
5	stimulus	string	'IDS-x', 'ADS-x', 'training'	the actual sound file that was playing
6	trial_num	integer	-2, -1, 1-8	trial number, from 1 -- 8 (with -2 and -1 denoting training trials)
7	looking_time	double	range 0-20	looking time in seconds

Figure 13.6

Example participant (top) and trial (bottom) level data from the ManyBabies (2020) case study.

Figure 13.7

Codebook for trial-level data (see above) from the ManyBabies (2020) case study.

6473 Creating a codebook need not require a lot of work. Almost any docu-
 6474 mentation is better than nothing! There are also several R packages that
 6475 can automatically generate a codebook for you, for example codebook,

6476 `dataspice`, and `dataMaid` (Arslan 2019). Adding a codebook can sub-
6477 stantially increase the reuse value of the data and prevent hours of frus-
6478 tration as future you and others try to decode your variable names and
6479 assumptions.

6480 *13.3 Sharing Research Products*

6481 As we've been discussing throughout this chapter, if you've managed
6482 your research products effectively, sharing them with others is a far less
6483 daunting prospect, and usually just requires uploading them to an online
6484 repository like the Open Science Framework. This section addresses
6485 some potential limitations on sharing that you should bear in mind and
6486 discusses where and how to share research products.

6487 *13.3.1 What you can and can't share*

6488 We've been advocating that you share all of your research products, es-
6489 pecially your data. In practice, however, **participant privacy** (as well as
6490 a few other constraints) limits what you can share. Luckily, there are
6491 some concrete steps you can take to make sure that you protect partici-
6492 pants and comply with your obligations while still realizing the benefits
6493 of data sharing.

6494 Unless they explicitly waive their rights, participants in psychology ex-
6495 periments have the expectation of privacy—that is, no one should be
6496 able to identify them from the data they have provided. Protecting par-
6497 ticipant privacy is an important part of researchers' ethical responsibili-
6498 ties (Ross, Iguchi, and Panicker 2018), and needs to be balanced against
6499 the ethical imperatives to share (see chapter 4).²⁷

6500 Furthermore, there are legal regulations that protect participants' data,
6501 though these vary from country to country. In the US, the relevant reg-
6502 ulation is **HIPAA**, the Health Insurance Portability and Accountability
6503 Act, which limits disclosures of private health information (**PHI**). In the
6504 European Union, the relevant regulation is the European **GDPR** (Gen-
6505 eral Data Protection Regulation). It's beyond the scope of this book to
6506 give a full treatment of these regulatory frameworks; you should con-
6507 sult with your local ethics board regarding compliance, but here is the
6508 way we have navigated this situation while still sharing data.

6509 Under both frameworks, **anonymization** (or equivalently de-
6510 **identification**) of data is a key concept, such that data sharing is
6511 generally just fine if the data meet the relevant standard. Under US
6512 guidelines, researchers can follow the “safe harbor” standard²⁸ under
6513 which data are considered to be anonymized if they do not contain
6514 identifiers like names, telephone numbers, email addresses, social

²⁷ Meyer (2018) gives an excellent overview of how to navigate various legal and ethical issues around data sharing in the US context.

²⁸ As described on the relevant DHHS page (<https://www.hhs.gov/hipaa/for-professionals/privacy/special-topics/de-identification/index.html>).

6515 security numbers, dates of birth, faces, etc. Thus, data that only contain
6516 participant IDs and nothing from this list can typically be shared
6517 without participant consent without a problem.²⁹

6518 The EU's GDPR also allows fully anonymized data sharing, with one
6519 big complication. Putting anonymous identifiers in a data file and re-
6520 moving identifiable fields does not itself suffice for GDPR anonymiza-
6521 tion if the data are still **in-principle re-identifiable** because you have
6522 maintained documentation linking IDs to identifiable data like names
6523 or email addresses. Only when the key linking identifiers to data has
6524 been destroyed are the data truly de-identified according to this stan-
6525 dard.

²⁹ US IRBs are a very de-centralized bunch and their interpretations often vary considerably. For reasons of liability or ethics, they may not allow data sharing even though it is permitted by US law. If you feel like arguing with an IRB that takes this kind of stand, you could mention that the DHHS rule actually doesn't consider de-identified data to be "human subjects" data at all, and thus the IRB may not have regulatory authority over it. We're not lawyers, and we're not sure if you'll succeed but it could be worth a try.

☞ ACCIDENT REPORT

Really anonymous?

When we first began teaching Psych 251, our experimental methods course at Stanford, one of the biggest contributions of the course was simply showing students how to do experiments online. Amazon's Mechanical Turk crowdsourcing service was relatively new, and our IRB did not have a good sense of what this service really was. We proposed that we would share data from the class and received approval for this practice. Our datasets were downloaded directly from Mechanical Turk and included participants' MTurk IDs (long alphanumeric strings that seemed

completely anonymous). Several experiences caused us to reconsider this practice!

First, we discovered that MTurk IDs were in some cases linked to study participants' public Amazon "wish lists," which could both inadvertently provide information about the participant and also even potentially provide a basis for reidentification (in rare cases). This discovery led us to consult with our IRB and provide more explicit consent language in our class experiments, linking to instructions for making Amazon profiles private.

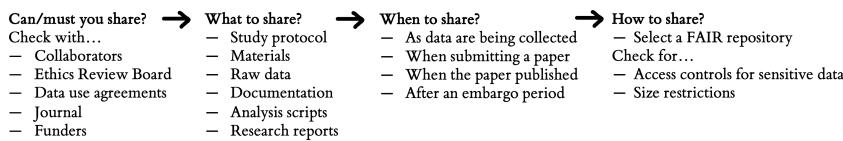
Then, a little later we received an irate email from an MTurk participant who had discovered their data on github via a search for their MTurk ID. Although they were not identified in this dataset, it convinced us that at least some participants would not like this ID shared. After another consultation with the IRB, we apologized to this individual and removed their and others' IDs from our github commit histories across that and other repositories. Prior to posting data, we now take care to anonymize IDs by creating a secret mapping between the IDs we post and the actual MTurk IDs.

6527

6528 De-identification is not always enough. As datasets get richer, **statistical**
6529 **reidentification risks** go up substantially such that, with a little bit of out-
6530 side information, data can be matched with a unique individual. These
6531 risks are especially high with linguistic, physiological, and geospatial
6532 data, but they can be present even for simple behavioral experiments.

6533 In one influential demonstration, knowing a person's location on two
 6534 occasions was often enough to identify their data uniquely in a huge
 6535 database of credit card transactions (De Montjoye et al. 2015).³⁰ Thus,
 6536 simply removing fields from the data is a good starting point—but if you
 6537 are collecting richer data about participants' behavior you may need to
 6538 consult an expert.

6539 Privacy issues are ubiquitous in data sharing, and almost every experi-
 6540 mental research project will need to solve them before sharing data. For
 6541 simple projects, often these are the only issues that preclude data sharing.
 6542 However, in more complex projects, other concerns can arise. Funders
 6543 may have specific mandates regarding where your data should be shared.
 6544 Data use agreements or collaborator preferences may restrict where and
 6545 when you can share. And certain data types require much more sensi-
 6546 tivity since they are more consequential than, say, the reaction times on
 6547 a Stroop task. We include here a set of questions to walk through to plan
 6548 your sharing (figure 13.8). When in doubt, it's often a good idea to con-
 6549 sult with the relevant local authority, e.g. your ethics board for ethical
 6550 issues or your research management office for regulatory issues.



³⁰ For an example closer to home, many of the contributing labs in the ManyBabies project logged the date of test for each participant. This useful and seemingly innocuous piece of information is unlikely to identify any particular participant—but alongside a social media post about a lab visit or a dataset about travel records, it could easily reveal a particular participant's identity.

Figure 13.8
 A decision chart for thinking about sharing research products. Adapted from Klein et al. (2018).

6551 13.3.1 *Where and how to share: the FAIR principles*

6552 For shared research products³¹ to be usable by others, they should meet
6553 the FAIR standard by being Findable, Accessible, Interoperable, and
6554 Reusable (Wilkinson et al. 2016).

- 6555 – **Findable** products are easily discoverable to both humans and
6556 machines. That means linking to them in research reports
6557 using unique persistent identifiers (e.g. a digital object identifier
6558 [DOI]).³² and attaching them with metadata describing what
6559 they are so they can be indexed by search engines.
- 6560 – **Accessibility** means that research products need to be preserved
6561 across the long-term and are retrievable via their standardized
6562 identifier.
- 6563 – **Interoperability** means that the research products needs to be in a
6564 format that people and machines (e.g., search engines and analysis
6565 software) can understand.
- 6566 – **Reusable** means that the research products need to be well orga-
6567 nized, documented, and licensed so that others know how to use
6568 them.

31 Most of this discussion is about data, because that's where the community has focused its efforts. That said, almost everything here applies to other research products as well!

32 DOIs are those long URL-like things that are often used to link to papers. Turns out they can also be associated with datasets and other research products. Critically, they are guaranteed to work to find stuff, whereas standard web URLs often go stale after several years when people refactor their website. Most online repositories, like the Open Science Framework, will issue DOIs for the research products you store there.

6569 If you've followed the guidance in the rest of this chapter, then you will
6570 already be well on your way to making your research products FAIR.

6571 There are a few final steps to consider. An important decision is where
6572 you are going to share the research products. We recommend upload-
6573 ing the files to a repository that's designed according to support FAIR
6574 principles. Personal websites don't cut it, since these sites tend to go out
6575 of date and disappear. There's also no easy way to find research products
6576 on personal sites unless you know who created them. Github, though
6577 it's a great platform for collaboration, isn't a FAIR repository—for one
6578 thing, products there don't have DOIs³³—and there are no archival guar-
6579 antees on files that are shared there. Perhaps surprisingly for some re-
6580 searchers, journal supplementary materials are also not a great place to
6581 put research products. Often supplementary materials are assigned no
6582 unique DOI or metadata, have limited supported formats, and have no
6583 persistence guarantees (Evangelou, Trikalinos, and Ioannidis 2005).

6584 Fortunately, there are many repositories that help you conform to FAIR
6585 standards. Zenodo, Figshare, the Open Science Framework (OSF), and
6586 the various Dataverse sites are designed for this purpose, though there
6587 are many other domain-specific repositories that are particularly rele-
6588 vant for different research fields. We often use the OSF as it makes it
6589 easy to share all research products connected to a project in one place.
6590 OSF is FAIR compatible and allows users to assign DOIs to their data
6591 and provide appropriate metadata.

³³ You can get a DOI for github soft-
ware through a partnership with Zenodo
(zenodo.org), a FAIR-compliant reposi-
tory.

6592 We recommend you attach a license to your research products. Academic culture is (usually) unburdened by discussion of intellectual property and attribution. The basic expectation is that if you rely on someone else's research, you explicitly acknowledge the relevant journal article through a citation. Although norms are still evolving, using research products created by others generally adheres to the same scholarly principle. Research products can also be useful in non-academic contexts, however. Perhaps you created software that a company would like to use. Maybe a pediatrician would like to use a research instrument you've been working on to assess their patients. These applications (and many other reuses of the data) require a legal license. In practice, there are a number of simple, open source licenses that permit reuse. We tend to favor Creative Commons licenses³⁴, which come in a variety of flavors such as CC0³⁵ (which allows all reuse), CC-BY³⁶ (which allows reuse as long as there is attribution), and CC-BY-NC³⁷ (which only allows attributed, non-commercial reuse).³⁸ Regardless of what license you choose, having a license means that your products won't be in a "not sure what I'm allowed to do with this" limbo for others who are interested in reusing them.

6612 As we have discussed, you may want to consider storing your work in a public repository from the outset of the project. If you are using Github

³⁴ <https://creativecommons.org>

³⁵ <https://creativecommons.org/share-your-work/public-domain/cc0/>

³⁶ <https://creativecommons.org/licenses/by/4.0/>

³⁷ <https://creativecommons.org/licenses/by/4.0/>

³⁸ Klein et al. (2018) recommend the CC0 license, which puts no limits on what can be done with your data. At first blush it may seem like a license that requires attribution is useful. But academic norms, rather than the threat of litigation, lead to good citation practices.

In addition, more restrictive licenses can mean that some legitimate uses of your data or research can be blocked.

6614 to manage your project, you can link the Git repository to the Open
6615 Science Framework so it automatically syncs. This provides a valuable
6616 incentive to organize your work properly throughout your project and
6617 makes sharing super easy, because you've already done it! On the other
6618 hand, this way of working can feel exposed for some researchers, and it
6619 does carry some risks, however small, of "scooping" or pre-emption by
6620 other groups working in the same space. Fortunately you can set up the
6621 same Git-OSF workflow and keep it private until you're ready to make
6622 it public later on.

6623 The next stage at which you should consider sharing your research prod-
6624 ucts is when you submit your study to a journal. If you're still hesitant
6625 to make the project entirely public, many repositories (including OSF)
6626 will allow you to create special links that facilitate limited access to, for
6627 example, reviewers and editors. In general, the earlier you share your
6628 research products the better because there are more opportunities for
6629 others to learn from, build on, and verify your research.³⁹ But if neither
6630 of these options seem appealing, please do share your research products
6631 once your paper is accepted. Doing so will increase the value (and the
6632 impact) of your publication.

³⁹ If there are errors in our work, we'd certainly love to hear about it *before* the article is published in a journal rather than after!

6633 13.4 Chapter summary

6634 All of the hard work you put into your experiments—not to mention
6635 the contributions of your participants—can be undermined by bad data
6636 and project management. As our accident reports and case study show,
6637 bad organizational practices can at a minimum cause huge headaches.
6638 Sometimes the consequences can be even worse. On the flip side, start-
6639 ing with a firm organizational foundation sets your experiment up for
6640 success. These practices also make it easier to share all of the products
6641 of your research, not just your findings. Such sharing is both useful for
6642 individual researchers and for the field as a whole.



DISCUSSION QUESTIONS

1. Find an Open Science Framework repository that corresponds to a published paper. What is their strategy for documenting what is shared? How easy is it to figure out where everything is and if the data and materials sharing is complete?
2. Open up the US Department of Health and Human Services “safe harbor” standards (<https://www.hhs.gov/hipaa/for-professionals/privacy/special-topics/de-identification/index.html>) and navigate to the section called “The De-identification Standard.” Go through the list of identifiers that must be removed. Are there any on this list that you would need to include in your dataset in order to conduct your own research? Can you think of any others that do not

fall on this list?

6644

READINGS

- A more in-depth tutorial on various aspects of scientific openness:

Klein, O., Hardwicke, T. E., Aust, F., Breuer, J., Danielsson, H., Hofe-
lich Mohr, A., Ijzerman, H., Nilsonne, G., Vanpaemel, W., & Frank,
M. C. (2018). A practical guide for transparency in psychological sci-
ence. *Collabra: Psychology*, 4, 20. <https://doi.org/10.1525/collabra.158>.

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REPORTING

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6653 14 WRITING

LEARNING GOALS

- Write clearly by being concise, using structure, and adjusting to your audience
- Write reproducibly by interleaving writing and analysis code
- Write responsibly by acknowledging limitations, correcting errors, and calibrating your conclusions

6654

6655 You've designed and run your experiment, and you have even analyzed
6656 your data. This final section of Experimentology discusses reporting
6657 your results. We begin by thinking through how to write clearly, re-
6658 producibility, and responsibly (this chapter); then we turn to the ques-
6659 tion of designing informative and pretty data visualizations (chapter 15).
6660 Our final chapter in the section introduces meta-analysis as a tool for
6661 research synthesis, allowing us to contextualize research results. These
6662 chapters focus on themes of TRANSPARENCY as well as (especially for
6663 meta-analysis) BIAS REDUCTION and MEASUREMENT PRECISION.

6664 All of the effort you put into designing and running an effective ex-
6665 periment may be wasted if you cannot clearly communicate what you
6666 did. Writing is a powerful tool—though you contribute to the conver-
6667 sation only once, it enables you to speak to a potentially infinite num-
6668 ber of readers. So it's important to get it right! In this chapter, we'll
6669 provide some guidance on how to write scientific papers—the primary
6670 method for reporting on experiments—clearly, reproducibly, and re-
6671 sponsibly.¹

6672 *14.1 Writing clearly*

6673 What is the purpose of writing? “Telepathy, of course” says Stephen
6674 King ([King 2000](#)). The goal of writing is to transfer information from
6675 your mind to the reader’s as effectively as possible. Unfortunately, for
6676 most of us, writing clearly does not come naturally; it is a craft we need
6677 to work at.

6678 One of the most effective ways to learn to write clearly is to read and to
6679 imitate the writing you admire. Many scientific articles are not clearly
6680 written, so you will need to be selective in which models you imitate.
6681 Fortunately, as a reader, you will know good writing when you see it—
6682 you will feel like the writer is sending ideas directly from their mind to
6683 yours. When you come across writing like that, try to find more work

¹ Clarity of communication was a founding principle of modern science. Early proto-scientists conducting alchemical experiments often made their work deliberately obscure – even writing in cryptic codes – so that others could not discover the “powerful secrets of nature.” Pioneers of scientific methodology, like Francis Bacon and Robert Boyle, pushed instead for transparency and clarity. Notoriously, Isaac Newton (originally an alchemist and later a scientist), continued to write in a deliberately obscure fashion in order to “protect” his work ([Heard 2016](#)).

6684 by the same author. The more good scientific writing you are exposed
6685 to, the more you will develop a sense of what works and what does not.
6686 You may pick up bad habits as well as good ones (we sure have!), but
6687 over time, your writing will improve if you make a conscious effort to
6688 weed out the bad, and keep the good.

6689 There are no strict rules of clear writing, but there are some generally
6690 accepted conventions that we will share with you here, drawing from
6691 both general style guides and those specific to scientific writing ([Zinsser](#)
6692 [2006; Heard 2016; Gernsbacher 2018; Savage and Yeh 2019](#)).

6693 14.1.1 *The structure of a scientific paper*

6694 A scientific paper is not a novel. Rather than reading from beginning
6695 to end, readers typically jump between sections to extract information
6696 efficiently ([Doumont 2009](#)). This “random access” is possible because
6697 research articles typically follow the same conventional structure (see
6698 figure 14.1). The main body of the article includes four main sections:
6699 Introduction, Methods, Results, and Discussion (IMRaD).² This struc-
6700 ture has a narrative logic: what’s the knowledge gap? (introduction);
6701 how did you address it? (methods); what did you find? (results); what
6702 do the results mean? (discussion).

² In the old old days, there were few conventions—scientists would share their latest findings by writing letters to each other. But as the number of scientists and studies increased, this approach became unsustainable. The IMRaD structure gained traction in the 1800s and became dominant in the mid-1900s as scientific productivity rapidly expanded in the post-war era. We think IMRaD style articles are a big improvement, even if it is nice to receive a letter every now and again.

6703 Structure helps writers as well as readers. Try starting the writing pro-
 6704 cess with section headings as a structure, then flesh it out, layer by layer.
 6705 In each section, start by making a list of the key points you want to con-
 6706 vey, each representing the first sentence of a new paragraph. Then add
 6707 the content of each paragraph and you'll be well on your way to having
 6708 a full first draft of your article.

6709 Imagine that the breadth of focus in the body of your article has an
 6710 “hourglass” structure (figure 14.1). The start of the introduction should
 6711 have a broad focus, providing the reader with the general context of
 6712 your study. From there, the focus of the introduction should get in-
 6713 creasingly narrow until you are describing the specific knowledge gap
 6714 or problem you will address and (briefly how you are going to address
 6715 it. The methods and results sections are at the center of the hourglass
 6716 because they are tightly focused on your study alone. In the discussion
 6717 section, the focus shifts in the opposite direction, from narrow to broad.
 6718 Begin by summarizing the results of your study, discuss limitations, then
 6719 integrate the findings with existing literature and describe practical and
 6720 theoretical implications.

6721 Research articles are often packed with complex information; it is easy
 6722 for readers to get lost. A “cross reference” is a helpful signpost that tells
 6723 readers where they can find relevant additional information without dis-

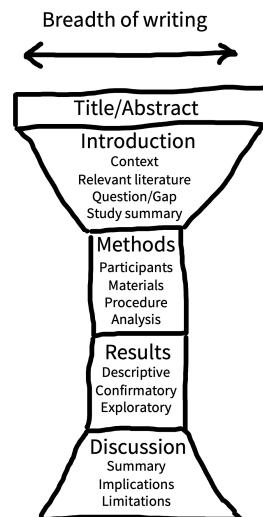


Figure 14.1
 Conventional structure of a research article. The main body of the article consists of Introduction, Methods, Results, and Discussion (IMRaD) sections.

6724 rupting the flow of your writing. For example, you can refer the reader
6725 to data visualizations by cross referencing to figures or tables (e.g., “see
6726 Figure 1”), or additional methodological information in the supplemen-
6727 tary information (e.g., “see Supplementary Information A”).

6728 One useful trick for structuring complex arguments is to cross refer-
6729 ence your research aims/hypotheses with your results. For example,
6730 you could introduce numbered hypotheses in the introduction of an
6731 article and then refer to them directly when reporting the relevant anal-
6732 yses and results. These cross references can serve to remind readers how
6733 different results or analyses relate back to your research goals.

6734 *14.1.2 Paragraphs, sentences, and words*

6735 Writing an article is like drawing a human form. If you begin by sketch-
6736 ing the clothes, you risk adding beautiful textures onto an impossible
6737 shape. Instead, you have to start by understanding the underlying skele-
6738 ton and then gradually adding layers until you can visualize how cloth
6739 hangs on the body. The structure of an article is the “skeleton” and
6740 the paragraphs and sentences are the “flesh”. Only start thinking about
6741 paragraphs and sentences once you have a solid outline in place.

6742 Ideally, each paragraph should correspond to a single point in the ar-
6743 ticle’s outline, with the specifics necessary to convince the reader em-

6744 bedded within. “P-E-E-L” (Point – Explain – Evidence – Link) is a
6745 useful paragraph structure, particularly in the introduction and discus-
6746 sion sections. First, state the paragraph’s message succinctly in the first
6747 sentence (P). The core of the paragraph is dedicated to further explain-
6748 ing the point and providing evidence (E-E; you can also include a third
6749 “E”—an example). At the end of the paragraph, take a couple of sen-
6750 tences to remind the reader of your point and set up a link to the next
6751 paragraph.

6752 Since each sentence in a paragraph has a purpose, you can compose and
6753 edit the sentence by asking how its form serves that purpose. For ex-
6754 ample, short sentences are great for making strong initial points. On
6755 the other hand, if you only use short sentences your writing may come
6756 across as monotonous and robotic. Try varying sentence lengths to give
6757 your writing a more natural rhythm. Just avoid cramming too much in-
6758 formation into the same sentence; very long sentences can be confusing
6759 and difficult to process.

6760 You can also use sentence structure as a scaffold to support the reader’s
6761 thinking. Start sentences with something the reader already knows. For
6762 example, rather than writing “We performed a between-subjects *t*-test
6763 comparing performance in the experimental and control groups to ad-
6764 dress the cognitive dissonance hypothesis”, write “To address the cog-

6765 nitive dissonance hypothesis, we compared performance in the experi-
6766 mental group and control group using a between-subjects t-test.”

6767 Human readers are good at processing narratives about people. Yet of-
6768 ten scientists compromise the research narrative by removing themselves
6769 from the process, sometimes even using awkward grammatical construc-
6770 tions to do so. For example, scientists sometimes write “the data were
6771 analysed” or, worse, “an analysis of the data was carried out.” Many of
6772 us were taught to write sentences like these, but it’s much clearer to say
6773 “we analyzed the data.”

6774 Similarly, many of us tend to hide our views with frames and caveats:
6775 “[It is believed that/Research indicates that/Studies show that] money
6776 leads to increased happiness (Frog & Toad, 1963).” If you truly do be-
6777 lieve that money causes happiness, simply assert it—with a citation if
6778 necessary. Save caveats for cases where *someone* believes that money
6779 causes happiness, but it’s *not* you. Emphasize uncertainty where you in
6780 fact feel that uncertainty is warranted and readers will take your doubts
6781 more seriously.

6782 14.2 Advice

6783 Scientific writing has a reputation for being dry, dull, and soulless.

6784 While it's true that writing research articles is more constrained than

6785 writing fiction, there are still ways to surprise and entertain your reader

6786 with metaphor, alliteration, and even humor. As long as your writing

6787 is clear and accurate, we see no reason why you cannot also make

6788 it enjoyable. Enjoyable articles are easier to read and more fun to

6789 write.³

6790 Here are a few more pieces of advice about expressing yourself

6791 clearly.

6792 **Be explicit.** Avoid vagueness and ambiguity. The more you leave the

6793 meaning of your writing to your reader's imagination the greater the

6794 danger that different readers will imagine different things! So be direct

6795 and specific.

6796 **Be concise.** Maximize the signal to noise ratio in your writing by omit-

6797 ting needless words and removing clutter ([Zinsser 2006](#)). For example,

6798 say *we investigated* rather than *we performed an investigation of* and say *if*

6799 *rather than in the event that.* Don't try to convey everything you know

6800 about a topic—a research report is not an essay. Include only what you

6801 need to achieve the purpose of the article and exclude everything else.

³ One of our favorite examples of an enjoyable article is Cutler ([1994](#)), a delightful piece that uses the form of the article to make a point about human language processing. Read it: you'll see!

6802 **Be concrete.** Concrete examples make abstract ideas easier to grasp. But
6803 some ideas are just hard to express in prose, and diagrams can be very
6804 helpful in these cases. For example, it may be clearer to illustrate a com-
6805 plex series of exclusion criteria using a flow chart rather than text. You
6806 can even use photos, videos, and screenshots to illustrate experimental
6807 tasks (Heycke and Spitzer 2019).

6808 **Be consistent.** Referring to the same concept using different words can
6809 be confusing because it may not be clear if you are referring to a different
6810 concept or just using a synonym. For example, in everyday conversation,
6811 “replication” and “reproducibility” may sound like two different ways
6812 to refer to the same thing, but in scientific writing, these two concepts
6813 have different technical definitions, so we should not use them inter-
6814 changeably. Define each technical term once and then use the same
6815 term throughout the manuscript.

6816 **Adjust to your audience.** Most of us adjust our conversation style de-
6817 pending on who we’re talking to; the same principle applies to good
6818 writing. Knowing your audience is more difficult with writing, because
6819 we cannot see the reader’s reactions and adjust accordingly. Neverthe-
6820 less, we can make some educated guesses about who our readers might
6821 be. For example, if you are writing an introductory review article, you
6822 may need to pay more attention to explaining technical termsn than if

6823 you are writing a research article for a specialty journal.

6824 **Check your understanding.** Unclear writing can be a symptom of un-
6825 clear thinking. If an idea doesn't make sense in your head, how will it
6826 ever make sense on the page? In fact, trying to communicate something
6827 in writing is an excellent way to probe your understanding and expose
6828 logical gaps in your arguments. So if you are finding it difficult to write
6829 clearly, stop and ask yourself *do I know what I want to say?* If the problem
6830 is unclear thinking, then it might be worth talking out the ideas with a
6831 colleague or advisor before you try to write them down.

6832 **Use acronyms sparingly.** It's tempting to replace lengthy terminology
6833 with short acronyms — why say “cognitive dissonance theory” when
6834 you can say “CDT”? Unfortunately, acronyms can increase the reader’s
6835 cognitive burden and cause misunderstandings.⁴ For example, if you
6836 shorten “odds ratio” to “OR”, the reader has to take the extra step of
6837 translating “OR” back to “odds ratio” every time they encounter it. The
6838 problem multiplies as you introduce more acronyms into your article.
6839 Worse, for some readers, “OR” tends to mean “operating room”, not
6840 “odds ratio.” Acronyms can be useful, but usually only when they are
6841 widely used and understood.

⁴ Barnett and Doubleday (2020) found that acronyms are widely used in research articles and argued that they undermine clear communication. Here is one example of text Barnett and Doubleday extracted from a 2019 publication to illustrate the point: “Applying PROBAST showed that ADO, B-AE-D, B-AE-D-C, extended ADO, updated ADO, updated BODE, and a model developed by Bertens et al. were derived in studies assessed as being at low risk of bias.”

6842 14.2.1 Drafting and revision

6843 The clearest and most effortless-seeming scientific writing has proba-
6844 bly gone through extensive revision to appear that way. It can sur-
6845 prise many students to know the amount of revision that has gone into
6846 many “breezy” articles. For example, Tversky and Kahneman repeat-
6847 edly drafted and re-drafted each word of their famous (and highly read-
6848 able) articles on judgment and decision-making, hunched over the type-
6849 writer together (Lewis 2016).

6850 Think of the article you are writing as a garden. Your first draft may
6851 be an unruly mess of intertwined fronds and branches. Several rounds
6852 of pruning and sculpting will be needed before your writing reaches its
6853 most effective form. You’ll be amazed how often you find words you
6854 can omit or elaborate sentences you can simplify.

6855 It can be difficult to judge if your own writing has achieved its tele-
6856 pathic goal, especially after several rounds of revision. Try to get feed-
6857 back from somebody in your target audience. Their comments—even
6858 if not wholly positive—will give you a good sense of how much of your
6859 argument they understood (and agreed with).⁵

⁵ Seek out people who are willing to tell you that your writing is not good! They may not make you feel good, but they will help you improve.

6860 14.3 Writing reproducibly

6861 Many research results are not reproducible — that is, the numbers
6862 and graphs that they report can't be recreated by repeating the origi-
6863 nal analyses—even on the original data. As we discussed in chapter 3,
6864 a lack of reproducibility is a big problem for the scientific literature; if
6865 you can't trust the numbers in the articles you read, it's much harder to
6866 build on the literature.

6867 Fortunately, there are number of tools and techniques available that you
6868 can use to write fully reproducible research reports. The basic idea is to
6869 create an unbroken chain that links every single part of the data analysis
6870 pipeline, from the raw data through to the final numbers reported in
6871 your research article. This linkage enables you—and hopefully others as
6872 well—to trace the provenance of every number and recreate (reproduce)
6873 it from scratch.

6874 14.3.1 Why write reproducible reports?

6875 There are (at least) three reasons to write reproducible reports. First,
6876 data analysis is an error-prone activity. Without safeguards in place, it
6877 can be easy to accidentally overwrite data, mislabel experimental con-
6878 ditions, or copy and paste the wrong statistics. As we discussed in chap-
6879 ter 3, one study found that nearly half of a sample of psychology papers

6880 contained obvious statistical reporting errors (Nuijten et al. 2016). You
6881 can reduce opportunities for error by adopting a reproducible analysis
6882 workflow that avoids error-prone manual actions, like copying and past-
6883 ing.

6884 Second, technical information about data analysis can be difficult to
6885 communicate in writing. Prose is often ambiguous and authors can in-
6886 advertently leave out important details (Hardwicke et al. 2018). By con-
6887 trast, a reproducible workflow documents the entire analysis pipeline
6888 from raw data to research report exactly as it was implemented, describ-
6889 ing the origin of any reported values and allowing readers to assess, ver-
6890 ify, and repeat the analysis process.

6891 Finally, reproducible workflows are typically more efficient workflows.
6892 For example, you may realize you forgot to perform data exclusions and
6893 need to rerun the analysis. You may produce a graph and then decide
6894 you'd prefer a different color scheme. Or perhaps you want to output
6895 the same results table in a PDF document and in a PowerPoint slide. In
6896 a reproducible workflow, all of the analysis steps are scripted, and can
6897 be easily re-run at the click of a button. You (and others) can also reuse
6898 parts of your code in other projects, rather than having to write from
6899 scratch.

6900 14.3.2 Principles of reproducible writing

6901 Below we outline some general principles of reproducible writing.
6902 These can be put in practice in a number of different software ecosys-
6903 tems. We recommend RMarkdown and its successor, Quarto, which
6904 are ways of writing data analysis code in R so that it compiles into
6905 spiffy documents or even websites. (This book was written in Quarto).
6906 Chapter C gives an introduction to the nuts and bolts of using these
6907 tools to create scientific papers.

6908 – **Never break the chain.** Every part of the analysis pipeline—from
6909 raw data⁶ to final product—should be present in the project
6910 repository. By consulting the repository documentation, a reader
6911 should be able to follow the steps to go from the raw data to the
6912 final manuscript, including tables and figures.

⁶ Modulo the privacy concerns discussed in chapter 13, of course.

6913 – **Script everything.** Try to ensure that each step of the analysis
6914 pipeline is executed by computer code rather than manual ac-
6915 tions such as copying and pasting or directly editing spreadsheets.

6916 This practice ensures that every step is documented via executable
6917 code rather than ambiguous description, ensuring it can be re-
6918 produced. Imagine, for example, that you decided to re-code
6919 a variable in your dataset. You could use the “find and replace”
6920 function in Excel, but this action would not be documented—you

6921 might even forget that you did it! A better option would be to
6922 write an R script. While a scripted pipeline can be a pain to set
6923 up the first time, by the third time you rerun it, it will save you
6924 time.

- 6925 – **Use literate programming.** The meaning of a chunk of computer
6926 code is not always obvious to another user, especially if they’re
6927 not an expert. Indeed, we frequently look at our own code and
6928 scratch our heads, wondering what on earth it’s doing. To avoid
6929 this problem, try to structure your code around plain language
6930 comments that explain what it should be doing, a technique
6931 known as “literate programming” ([Knuth 1992](#)).

- 6932 – **Use defensive programming.** Errors can still occur in scripted
6933 analyses. Defensive programming is a series of strategies to help
6934 anticipate, detect, and avoid errors in advance. A typical defensive
6935 programming tool is the inclusion of **tests** in your code, snippets
6936 that check if the code or data meet some assumptions. For exam-
6937 ple, you might test if a variable storing reaction times has taken on
6938 values below zero (which should be impossible). If the test passes,
6939 the analysis pipeline continues; if the test fails, the pipeline halts
6940 and an error message appears to alert you to the problem.

- 6941 – **Use free/open-source software and programming languages.** If

possible, avoid using commercial software, like SPSS or Matlab, and instead use free, open-source software and programming languages, like JASP, Jamovi, R, or Python. This practice will make it easier for others to access, reuse, and verify your work—including yourself!⁷

- **Use version control.** In chapter 13, we introduced the benefits of version control—a great way to save your analysis pipeline incrementally as you build it, allowing you to roll back to a previous version if you accidentally introduce errors.
- **Preserve the computational environment.** Even if your analysis pipeline is entirely reproducible on your own computer, you still need to consider whether it will run on somebody else’s computer, or even your own computer after software updates. You can address this issue by documenting and preserving the computational environment in which the analysis pipeline runs successfully. Various tools are available to help with this, including Docker, Code Ocean, renv (for R), and pip (for Python).⁸

6959 14.3.3 *The reproducibility-collaboration trade-off*

6960 We would love to leave it there and watch you walk off into the sunset
6961 with a spring in your step and a reproducible report under your arm.

⁷ Several of us have libraries of old Matlab code. While discounted licenses are available to students, a full-price software license can be a major barrier to researchers with limited resources. If you move away from Matlab, it’s also terrible to have to ask yourself whether it’s worth the price of another year’s license just to rerun one old analysis.

⁸ If you are interested in going in this direction, we recommend Peikert and Brandmaier (2021), which gives an advanced tutorial for complete computational reproducibility using Docker and make as tools to supplement git and R Markdown.

6962 Unfortunately, we have to admit that writing reproducibly can create a
6963 few practical difficulties when it comes to collaboration.

6964 A major aspect of collaboration is exchanging comments and inline text
6965 edits with co-authors. You can do this exchange with R Markdown files
6966 and Git, but these tools are not as user-friendly as, say, Word or Google
6967 Docs, and some collaborators will be completely unfamiliar with them.
6968 Most journals also expect articles to be submitted as Word documents.
6969 Outputting R Markdown files to Word can often introduce formatting
6970 issues, especially for moderately complex tables. So until more user-
6971 friendly tools are introduced, some compromise between reproducibil-
6972 ity and collaboration may be necessary. Here are two workflow styles
6973 for you to consider.

6974 First, the **maximal reproducibility** approach. If your collaborators are
6975 familiar with R Markdown and you don't mind exchanging comments
6976 and edits via Git—or if they don't mind giving you lists of comments and
6977 changes that you implement in the R Markdown document—then you
6978 can maintain a fully reproducible workflow for your project. The jour-
6979 nal submission and publication process may still introduce some issues
6980 such as incorporating changes made by the copy editor, but at least your
6981 submitted manuscript (and the preprint you have hopefully posted) will
6982 be fully reproducible.

6983 Second, the **two worlds** approach. This workflow is a bit clunky, but it
6984 facilitates collaboration and maintains reproducibility. First, write your
6985 results section in R Markdown and generate a Word document (see
6986 appendix C). Then, write the remainder of the manuscript in Word,
6987 including incorporating comments and changes from collaborators.
6988 When you have a final version, copy and paste the abstract, introduction,
6989 methods, and discussion into the R Markdown document.⁹ Integrating
6990 any changes made to the results section back into the R Markdown
6991 requires a bit more effort, either using manual checking or Word's
6992 "compare documents" feature.¹⁰ The advantage of this approach is
6993 that you have a reproducible document and your collaborators have
6994 not had to deviate from their preferred workflow. Unfortunately, it
6995 requires more effort from you and is slightly more error-prone than
6996 the maximal reproducibility approach.

⁹ You can also incorporate Google Docs into this workflow—we find that cloud platforms like Docs are especially useful when gathering comments from multiple collaborators on the same document. Unfortunately, you cannot generate a Google Doc from R Markdown, so you will need to import and convert or else copy and paste.

¹⁰ New packages such as "trackdown" could help as well: <https://claudiozandonella.github.io/trackdown/>.

6997 14.4 Writing responsibly

6998 As a scientific writer, you have both professional and ethical responsi-
6999 bilities. You must communicate all relevant information about your
7000 research so as to enable proper evaluation and verification by other sci-
7001 entists. It is also important not to overstate your findings and calibrate
7002 your conclusions to the available evidence (Hoekstra and Vazire 2021).

7003 If errors are found in your work, you must respond and correct them
7004 when possible (Bishop 2018). Finally, you must meet scholarly obliga-
7005 tions with regards to authorship and citation practices.

7006 14.4.1 Responsible disclosure and interpretation

7007 Back in school, we all learned that getting the right answer is not
7008 enough—you need to demonstrate how you arrived at that answer
7009 in order to get full marks. The same expectation applies to research
7010 reports. Don’t just tell the reader what you found, tell them how you
7011 found it.¹¹ That means describing the methods in full detail, as well as
7012 sharing data, materials, and analysis scripts.

7013 In a journal article, you typically have some flexibility in terms of how
7014 much detail you provide in the main body of the article and how much
7015 you relegate to the supplementary information. Readers have different
7016 needs; some may just want to know the highlights, and some will need
7017 detailed methodological information in order to replicate your study.

7018 As a rule of thumb, try to make sure there is nothing relegated to the sup-
7019 plementary information that might surprise the reader. You certainty
7020 should not use the supplementary information to hide important details
7021 deliberately or use it as a disorganized dumping ground—the principles
7022 of clear writing still apply!

¹¹ It can be easy to overlook important details, especially when you reach the end of a project. Looking back at your study preregistration can be a helpful reminder. Reporting guidelines for different research designs can also provide useful checklists (Appelbaum et al. 2018).

7023 Here are a few more guidelines for responsible writing:

- 7024 – **Don't overclaim.** Scientists often feel they are (and unfortunately,
- 7025 often are) evaluated based on the *results* of their research, rather
- 7026 than the *quality* of their research. Consequently, it can be tempt-
- 7027 ing to make bigger and bolder claims than are really justified by
- 7028 the evidence. Think carefully about the limitations of your re-
- 7029 search and calibrate your conclusions to the evidence, rather than
- 7030 what you wish you were able to claim. Ensure that your con-
- 7031 clusions are appropriately stated throughout the manuscript, es-
- 7032 pecially in the title and abstract.
- 7033 – **Acknowledge limitations on interpretation and generalizability.**
- 7034 Even if you calibrate your claims appropriately throughout, there
- 7035 are likely specific limitations that are worth discussing, either as
- 7036 you introduce the design of the study in the introduction or as you
- 7037 interpret it in the discussion section. For example, if your exper-
- 7038 iment used one particular manipulation to instantiate a construct
- 7039 of interest, you might discuss this limitation and how it might be
- 7040 addressed by future work. Think carefully about the limitations
- 7041 of your study, state them clearly, and consider how they impact
- 7042 your conclusions (Clarke et al. 2023).¹² Discussions of limitations
- 7043 are a great point to make an explicit statement about the *generaliz-*

¹² Should you just make your claims more modest, and avoid writing about your study's limitations? The balance between claims and limitations is tricky. One way to navigate this issue is to ask yourself, "is it OK to say X in the abstract of my article, if I later go on to say state a limitation relevant to that claim, or will the reader feel tricked?"

ability of your findings (see Simons, Shoda, and Lindsay 2017 for guidance about these kinds of “Constraints on Generality” statements).

- **Discuss, don’t debate.** The purpose of the discussion section is to help the reader interpret your research. Importantly, a journal article is not a debate—don’t feel the need to argue dogmatically for a particular position or interpretation. You should discuss the strengths and weaknesses of the evidence, and the relative merits of different interpretations. For example, perhaps there is a potential confounding variable that you were unable to eliminate with your research design. The reader might be able to spot this themselves, but regardless, it’s your responsibility to highlight it. Perhaps on balance you think the confound is unlikely to explain the results—that’s fine, but you need to explain your reasoning to the reader.

- **Disclose conflicts of interest and funding.** Researchers are usually personally invested in the outcomes of their research and this investment can lead to bias (for example, overclaiming or selective reporting). But sometimes your potential personal gains from a piece of research rise above a threshold and are considered **conflicts of interest**. Where this threshold lies is not always com-

7065 pletely clear. The most obvious conflicts of interest occur when
7066 you stand to benefit financially from the outcomes of your re-
7067 search (for example a drug developer evaluating their own drug).
7068 If you are in doubt about whether you have a potential conflict of
7069 interest, then you should disclose it. You should also disclose any
7070 funding you received for the research, partly because this is often
7071 a requirement of the funder, and partly because it may represent
7072 a conflict of interest, for example if the funder has a particular
7073 stake in the outcome of the research. To avoid ambiguity, you
7074 should also disclose when you do *not* have a conflict of interest or
7075 funding to declare.

- 7076 – **Report transparently.** In chapter 11, you learned about the prob-
7077 lem of selective reporting and how this practice can bias the re-
7078 search literature. There are several ways to avoid this issue in your
7079 own work. First, assuming you *have* reported everything, include
7080 a statement in the methods section that explicitly says so. A state-
7081 ment suggested by Simmons, Nelson, and Simonsohn (2012) is
7082 “We report how we determined our sample size, all data exclu-
7083 sions (if any), all manipulations, and all measures in the study.” If
7084 you have preregistered your study, clearly link to the preregistra-
7085 tion and state whether you deviated from your original plan. You
7086 can include a detailed preregistration disclosure table in the sup-

7087 plementary information and highlight any major deviations in the
7088 methods section. In the results section, clearly identify (e.g., with
7089 sub-headings) which analyses were pre-planned and included in
7090 the preregistration (confirmatory) and which were not planned
7091 (exploratory).

7092 14.4.2 Responsible handling of errors

7093 It is not your responsibility to never make mistakes. But it *is* your re-
7094 sponsibility to respond to errors in a timely, transparent, and professional
7095 manner (Bishop 2018).¹³ Regardless of how the error was identified
7096 (e.g., by yourself or by a reader), we recommend contacting the jour-
7097 nal and requesting that they publish a correction statement (sometimes
7098 called an **erratum**). Several of us have corrected papers in the past. If
7099 the error is serious and cannot be fixed, you should consider retracting
7100 the article.

7101 A correction/retraction statement should include the following infor-
7102 mation:

- 7103 1. **Acknowledge the error.** Be clear that an error has occurred.
- 7104 2. **Describe the error.** Readers need to know the exact nature of the
7105 error.

¹³ As jazz musician Miles Davis once said, “If you hit a wrong note, it’s the next note that you play that determines if it’s good or bad.”

- 7106 **3. Describe the implications of the error.** Readers need to know how
7107 the error might affect their interpretation of the results.
- 7108 **4. Describe how the error occurred.** Knowing how the error hap-
7109 pened may help others avoid the same error.
- 7110 **5. Describe what you have done to address the error.** Others may
7111 learn from solutions you've implemented.
- 7112 **6. Acknowledge the person who identified the error.** Identifying er-
7113 rors can take a lot of work; if the person is willing to be identified,
7114 give credit where credit is due.

ACCIDENT REPORT

In 2018, at a crucial stage of her career, Julia Strand published an important study in the prestigious journal *Psychonomic Bulletin & Review*. She presented the work at conferences and received additional funding to do follow-up studies. But several months later, her team found that they could not replicate the result.

Puzzled, she began searching for the cause of the discrepant results. Eventually, she found the culprit—a programming error. As she sat staring at her computer in horror, she realized that it was unlikely anyone else would ever find the bug. Hiding the error must have seemed like the easiest thing to do.

But she did the right thing. She spent the next day informing her students, her co-authors, the funding officer, the department chair oversee-

ing her tenure review, and the journal—to initiate a retraction of the article. And... it didn't ruin her career. Everybody was understanding and appreciated that she was doing the right thing. The journal corrected the article. She didn't lose her grant. She got tenure. And a lot of scientists, including us, admire her for what she did.

Honest mistakes happen—it's how you respond to them that matters (Strand 2021). In fact, survey research with both scientists and the general public suggests that scientists' reputations are built on the perception that they try to "get it right," not just to "be right" (Ebersole, Axt, and Nosek 2016).

7116

7117 14.4.3 Responsible citation

7118 Citing prior work that your study builds upon ensures that researchers
7119 receive credit for their contributions and helps readers to verify the basis
7120 of your claims. You should certainly avoid copying the work of others
7121 and presenting it as your own (see chapter 4 for more on plagiarism).
7122 Try to be explicit about why you are citing a source. For example, does
7123 it provide evidence to support your point? Is it a review paper that gives
7124 the reader useful background? Or is it a description of a theory you are
7125 testing?

7126 Make sure you read articles before you cite them. Stang, Jonas, and

7127 Poole (2018) reports a cautionary tale in which a commentary criticizing
7128 a methodological tool was frequently cited as *supporting* the use of
7129 that tool! It seems that many authors had not read the paper they were
7130 citing, which is both misleading and embarrassing.

7131 Try to avoid selective or uncritical citation. It is misleading to cite only
7132 research that supports your argument and ignoring research that doesn't.
7133 You should provide a balanced account of prior work, including contra-
7134 dictory evidence. Make sure to evaluate and integrate evidence from
7135 prior studies, rather than simply describing them. Remember—every
7136 study has limitations.

7137 14.4.4 Responsible authorship practices

7138 It is an ethical responsibility to credit the individuals who worked on a
7139 research project—both so that they can reap the benefits if the work is
7140 influential, but also so that they can take responsibility for errors.¹⁴

7141 Currently in academia, the *authorship model* is dominant. Under this
7142 model, authorship and authorship order are important signals about re-
7143 searchers contributions to a project. It is generally expected that to qual-
7144 ify for authorship, an individual should have made a substantial contri-
7145 bution to the research (e.g., design, data collection, analysis), assisted
7146 with writing the research report, and takes joint responsibility for the

¹⁴ In 1975, physicist and mathematician Jack H. Hetherington wrote a paper he intended to submit to the journal *Physical Review Letters*. We're not sure why, but Hetherington wrote the paper in first person plural (i.e., referring to himself as "we" rather than "I"). He subsequently discovered that the journal would not accept the use of "we" for single-authored articles. Hetherington had painstakingly tapped out the article on his typewriter, an exercise he was not keen to repeat. Instead, he opted for a less taxing solution and named his cat—a feline by the name of F. D. C. Willard—as a coauthor. The paper was accepted and published (Hetherington and Willard 1975).

7147 research along with the other co-authors. Individuals who worked on
7148 the project who do not reach this threshold are instead mentioned in a
7149 separate acknowledgements section and not considered authors.

7150 **Authorship order** is often understood to signal the nature and extent
7151 of an author's contribution. In psychology (and neighboring disci-
7152 plines), the first author and last author are typically the project leaders.
7153 Typically—though certainly not always!—the first author is a junior
7154 colleague who implements the project and the last author is a senior
7155 colleague who supervises the project.

7156 It has been argued that the authorship model should be replaced with
7157 a more inclusive *contributorship* model in which all individuals who
7158 worked on the project are acknowledged as 'contributors'. Unlike the
7159 authorship model, there is no arbitrary threshold for contributorship.
7160 The actual contributions of each individual are explicitly described,
7161 rather than relying on the implicit conventions of authorship order.
7162 The contributorship model may facilitate collaboration and ensure
7163 student assistants are properly credited.

7164 You will probably find that most journals still expect you to use the
7165 authorship model. Nevertheless, it is usually possible—and sometimes
7166 required—to include a contributorship statement in your article that
7167 describes what everybody did. For example, the CREDIT taxonomy

7168 provides a structured taxonomy of research tasks, making for uniform
7169 contributorship reporting.¹⁵

7170 Because authorship is such an important signal in academia, it's impor-
7171 tant to agree on an authorship plan with your collaborators (particularly
7172 who will be the first and last authors) as early as possible.¹⁶

7173 14.5 *Chapter summary: Writing*

7174 Writing a scientific article can be a rewarding endpoint for the process
7175 of doing experimental research. But writing is a craft, and writing
7176 clearly—especially about complex and technical topics—can require
7177 substantial practice and many drafts. Further, writing about research
7178 comes with ethical and professional responsibilities that are different
7179 than the burdens of other kinds of writing. A scientific author must
7180 work to ensure the reproducibility of their findings and report on
7181 those findings responsibly, noting limitations and weaknesses as well as
7182 strengths.

¹⁵ For larger projects, the tool Tenzing allows for CREDIT statements to be generated automatically from standardized forms (Holcombe et al. 2020).

¹⁶ If you have find yourself in a situation where all authors have contributed equally, you may have to draw inspiration from historical examples and determine authorship order based on a 25 game croquet series (Hassell and May 1974), rock, paper, scissors (Kupfer, Webbeking, and Franklin 2004), or a brownie bake-off (Young and Young 1992). Alternatively, you can adopt the method of Lakens, Scheel, and Isager (2018) and randomize the authorship order in R!



DISCUSSION QUESTIONS

1. Find a writing buddy and exchange feedback on a short piece of writing (the abstract of a paper in progress, a conference abstract, or even a class project proposal would be good examples). Think about how to

improve each other's writing using the advice offered in this chapter.

2. Identify a published research article with openly available data and see if you can reproduce an analysis in their paper by recovering the exact numerical values they report. You can find support for this exercise at the Social Science Reproduction Platform (<https://www.socialescience-reproduction.org>) or ReproHack (<https://www.reprohack.org>). Discuss with a friend what challenges you faced in this exercise and how they might be avoided in your own work.

7184

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⁷¹⁹² 15 VISUALIZATION

LEARNING GOALS

- Analyze the principles behind informative visualizations
- Incorporate visualization into an analysis workflow
- Learn to make “the design plot”: a standard visualization of experimental data
- Select different visualizations of variability and distribution
- Connect visualization concepts to measurement principles

⁷¹⁹³

⁷¹⁹⁴ What makes visualizations so useful, and what role do they play in
⁷¹⁹⁵ the experimenter’s toolkit? Simply put, data visualization is the act of
⁷¹⁹⁶ “making the invisible visible.” Our visual systems are remarkably pow-
⁷¹⁹⁷ erful pattern detectors, and relationships that aren’t at all clear when
⁷¹⁹⁸ scanning through rows of raw data can immediately jump out at us when
⁷¹⁹⁹ presented in an appropriate graphical form (Zacks and Franconeri 2020).
⁷²⁰⁰ Good visualizations aim to deliberately harness this power and put it to
⁷²⁰¹ work at every stage of the research process, from the quick sanity checks

7202 we run when first reading in our data to the publication-quality figures

7203 we design when we are ready to communicate our findings.

7204 Yet our powerful pattern detectors can also be a liability; if we're not

7205 careful, we can easily be fooled into seeing patterns that are unreliable

7206 or even misleading. As psychology moves into an era of bigger data and

7207 more complex behaviors, we become increasingly reliant on **data visu-**

7208 **alization literacy** (Börner, Bueckle, and Ginda 2019) to make sense of

7209 what is going on. Further, as a researcher reporting about your data, cre-

7210 ating appropriate visualizations that are aligned with your analyses (as

7211 well as your design and preregistration) is an important part of TRANS-

7212 PARENCEY and BIAS REDUCTION in your reporting.



CASE STUDY

Mapping a pandemic

In 1854, a deadly outbreak of cholera was sweeping through London.

The scientific consensus at the time was that diseases like cholera spread through breathing poisonous and foul-smelling vapors, an idea known as the “miasma theory” (Halliday 2001). An obstetrician and anesthesiologist named John Snow, however, had proposed an alternative theory: rather than spreading through foul air, he thought that cholera was spreading through a polluted water supply (Snow 1855). To make a public case for this idea, he started counting cholera deaths. He marked each case

on a map of the area, and indicated the locations of the water pumps for reference. Furthermore, a line could be drawn representing the region that was closest to each water pump, a technique which is now known as a Voronoi diagram (https://en.wikipedia.org/wiki/Voronoi_diagram). The resulting illustration clearly reveals that cases clustered around an area called Golden Square, which received water from a pump on Broad Street (figure 15.1). Although the precise causal role of these maps in Snow's own thinking is disputed, and it is likely that he produced them well after the incident (Brody et al. 2000), they nonetheless played a significant role in the history of data visualization (Friendly and Wainer 2021).

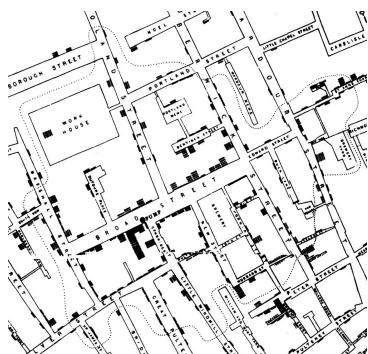


Figure 15.1
Mapping out a cholera epidemic (Snow 1854). Dotted line shows region for which Broad Street pump is nearest.

Nearly two centuries later, as the COVID-19 pandemic swept through the world, governmental agencies like the CDC produced maps of the outbreak that became much more familiar (figure 15.2).

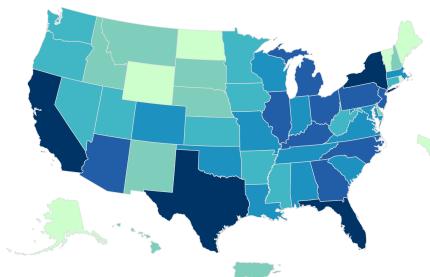


Figure 15.2

Map showing the counts of COVID hospitalizations by state since August 2020 as of January 2024 (from the CDC COVID Data Tracker, <https://covid.cdc.gov/covid-data-tracker>). Usage does not constitute endorsement or recommendation by the U.S. Government, Department of Health and Human Services, or Centers for Disease Control and Prevention.

These maps make abstract statistics visible: By assigning higher cumulative case rates to darker colors, we can see at a glance which areas have been most affected. And we're not limited by the spatial layout of a map. We're now also used to seeing the horizontal axis correspond to *time* and the vertical axis correspond to some value at that time. Curves like the following, showing the weekly counts of new cases, allow us to see other patterns, like the *rate of change*. Even though more and more cases accumulate every day, we can see at a glance the different “waves” of cases, and when they peaked (figure 15.3).

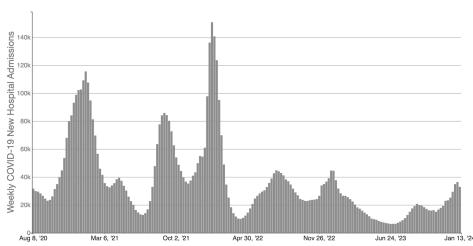


Figure 15.3

Weekly counts of new reported COVID hospital admissions in the US between August 2020 and January 2024 (from the CDC COVID Data Tracker, <https://covid.cdc.gov/covid-data-tracker>). Usage does not constitute endorsement or recommendation by the U.S. Government, Department of Health and Human Services, or Centers for Disease Control and Prevention.

While these visualizations capture purely descriptive statistics, we often want our visualizations to answer more specific questions. For example, we may ask about the effectiveness of vaccinations: how do case rates differ across vaccinated and unvaccinated populations? In this case, we may talk about “breaking out” a curve by some other variable, like vaccination status (figure 15.4).

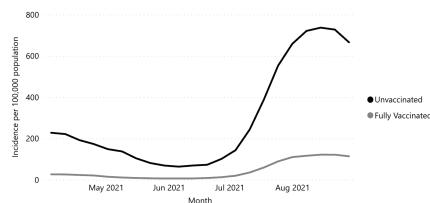


Figure 15.4

Rates of COVID cases by vaccination status (from the CDC COVID Data Tracker, <https://covid.cdc.gov/covid-data-tracker>). Usage does not constitute endorsement or recommendation by the U.S. Government, Department of Health and Human Services, or Centers for Disease Control and Prevention.

From this visualization, we can see that unvaccinated individuals are about 6x more likely to test positive. At the same time, these visualizations were produced using *observational* data, which makes it challenging to draw causal inferences. For example, people were not randomly assigned to vaccination conditions, and those who have avoided vaccinations may differ in other ways than those who sought out vaccinations. Additionally, you may have noticed that these visualizations typically do not give a sense of the raw data, the sample sizes of each group, or uncertainty about the estimates. In this chapter, we will explore how to use visualizations to communicate the results of carefully controlled psychology experiments, which license stronger causal inferences.

7217 15.1 Basic principles of (confirmatory) visualization

7218 In this section, we begin by introducing a few simple guidelines to keep
7219 in mind when making informative visualizations in the context of ex-
7220 perimental psychology.¹ Remember that our needs may be distinct from
7221 other fields, such as journalism or public policy. You may have seen
7222 beautiful and engaging full-page graphics with small print and a wealth
7223 of information. The art of designing and producing these graphics is
7224 typically known as **infoviz** and should be distinguished from what we
7225 call **statistical visualization** (Gelman and Unwin 2013).

7226 Roughly, infoviz aims to construct rich and immersive worlds to visu-
7227 ally explore: a reader can spend hours pouring over the most intricate
7228 graphics and continue to find new and intriguing patterns. **Statistical**
7229 **visualization**, on the other hand, aims to crisply convey the logic of a
7230 specific inference at a glance. These visualizations are the produc-
7231 tions ready figures that anchor the results section of a paper and accompany
7232 the key, pre-registered analyses of interest. In this section, we review
7233 several basic principles of making statistical visualizations. We then re-
7234 turn below to the role of visualization in more exploratory analyses.

¹ For the purposes of understanding the examples in this chapter, it should be sufficient to work through the tutorials on data manipulation and visualization in appendix D and appendix E.

7235 15.1.1 Principle 1: Show the design

7236 There are so many different kinds of graphs (bar graphs, line graphs,
7237 scatter plots, and pie charts) and so many different possible attributes of
7238 those graphs (colors, sizes, line types). How do we begin to decide how
7239 to navigate these decisions? The first principle guiding good statistical
7240 visualizations is to *show the design* of your experiment.

7241 The first confirmatory plot you should have in mind for your exper-
7242 iment is the **design plot**. Analogous to the “default” or “saturated”
7243 model in chapter 7, the design plot should show the key dependent
7244 variable of the experiment, broken down by all of the key manipu-
7245 lations. Critically, design plots should neither omit particular manipu-
7246 lations because they didn’t yield an effect or include extra covariates
7247 because they seemed interesting after looking at the data. Both of these
7248 steps are the visual analogue of p-hacking! Instead, the design plot is the
7249 “preregistered analysis” of your visualization: it illustrates a first look at
7250 the estimated causal effects from your experimental manipulations. In
7251 the words of Coppock (2019), “visualize as you randomize”!

7252 It can sometimes be a challenge to represent the full pattern of manipula-
7253 tions from an experiment in a single plot. Below we give some tricks for
7254 maximizing the legible information in your plot. But if you have tried
7255 these and your design plot still looks crowded and messy, that could be

7256 an indication that your experiment is manipulating too many things at
7257 once!

7258 There are strong (unwritten) conventions about how your confirmatory
7259 analysis is expected to map onto graphical elements, and following these
7260 conventions can minimize confusion. Start with the variables you ma-
7261 nipulate, and make sure they are clearly visible. Conventionally, the
7262 primary manipulation of interest (e.g. condition) goes on the x-axis, and
7263 the primary measurement of interest (e.g. responses) goes on the y-axis.
7264 Other critical variables of interest (e.g. secondary manipulations, demo-
7265 graphics) are then assigned to “visual variables” (e.g. color, shape, or
7266 size).

CODE

The visualization library `ggplot` (see appendix E) makes the mapping of variables in the data to visual data. Part of a `ggplot` call is an `aes` (short for aesthetics) mapping:

```
aes(  
  x = ...,  
  y = ...,  
  color = ...,  
  linetype = ...,  
)
```

The aesthetics argument serves as a statement of how data are mapped to “marks” on the plot. This transparent mapping makes it very easy to explore different plot types by changing that `aes()` statement, as we’ll see below.

7268

7269 As an example, we will consider the data from Stiller, Goodman, and
7270 Frank (2015) that we explored back in chapter 7. Because this experi-
7271 ment was a developmental study, the primary independent variable of
7272 interest was the age group of participants (ages 2, 3, or 4). So age gets
7273 assigned to the horizontal (x) axis. The dependent variable is accuracy:
7274 the proportion of trials that a participant made the correct response (out
7275 of 4 trials). So accuracy goes on the vertical (y) axis. Now, we have two
7276 other variables that we might want to show: the condition (experi-
7277 mental vs. control) and the type of stimuli (houses, beds, and plates of pasta).
7278 When we think about it, though, only condition is central to expos-
7279 ing the design. While we might be interested in whether some types of
7280 stimuli are systematically easier or harder than others, condition is more
7281 central for understanding the *logic* of the study.

CODE

As a reminder, here’s our code for loading the Stiller, Goodman, and
Frank (2015) data:

7282

```

repo <- "https://raw.githubusercontent.com/langcog/experimentology/main/"

sgf <- read_csv(file.path(repo, "data/tidyverse/stiller_scales_data.csv")) |>

  mutate(age_group = cut(age, 2:5, include.lowest = TRUE),
         condition = condition |>

    fct_recode("Experimental" = "Label", "Control" = "No Label"))

sgf_cond_means <- sgf |>

  group_by(condition, age_group) |>

  summarise(rating = mean(correct))

```

7283

7284 15.1.2 Principle 2: Facilitate comparison

7285 Now that you've mapped elements of your design to the figure's axes,
 7286 how do you decide which graphical elements to display? You might
 7287 think: well, in principle, these assignments are all arbitrary anyway. As
 7288 long as we clearly label our choices, it shouldn't matter whether we
 7289 use lines, points, bars, colors, textures, or shapes. It's true that there
 7290 are many ways to show the same data. But being thoughtful about our
 7291 choices can make it much easier for readers to interpret our findings.
 7292 The second principle of statistical visualizations is to *facilitate comparison*
 7293 along the dimensions relevant to our scientific questions. It is easier
 7294 for our visual system to accurately compare the location of elements

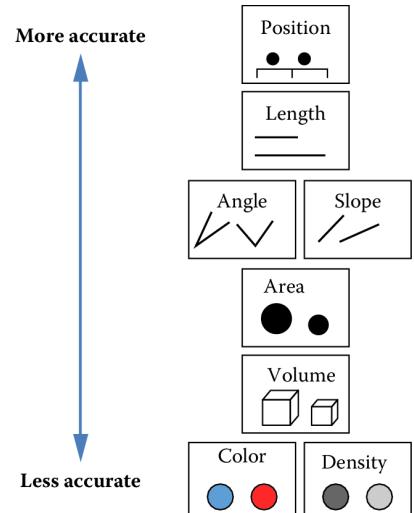


Figure 15.5
 Principles of visual perception can help guide visualization choices. Based on Mackinlay (1986; see also Cleveland and McGill 1984).

7295 (e.g. noticing that one point is a certain distance away from another) than
7296 to compare their areas or colors (e.g. noticing that one point is bigger or
7297 brighter than another). figure 15.5 shows an ordering of visual variables
7298 based on how accurate our visual system is in making comparisons.

7299 For example, we *could* start by plotting the accuracy of each age group
7300 as colors (figure 15.6).

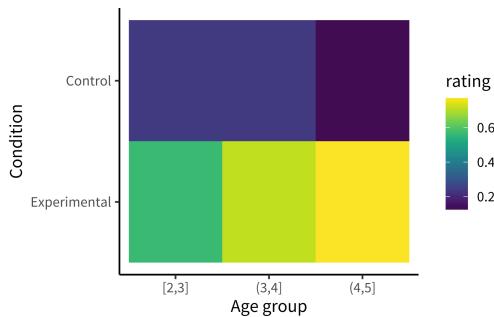


Figure 15.6
A first visualization of the Stiller, Goodman, and Frank (2015) data.

 CODE

To make this (bad) visualization, we used a `ggplot` function called `geom_tile()`.

```
ggplot(sgf_cond_means, aes(x = age_group, y = condition, fill = rating)) +  
  geom_tile() +  
  labs(x = "Age group", y = "Condition")
```

`geom_tile()` is commonly used to make heat maps (https://en.wikipedia.org/wiki/Heat_map): for each value of some pair of variables (x, y), it shows a color representing the magnitude of a third variable (z).

While a heat map is a silly way to visualize the Stiller, Goodman, and Frank (2015) data, consider using `geom_tile()` when you have a pair of continuous variables, each taking a large range of values. In these cases, bar plots and line plots tend to get extremely cluttered, making it hard to see the relationship between the variables. Heat maps help these relationships to pop out as clear “hot” and “cold” regions. For example, in Barnett, Griffiths, and Hawkins (2022), a heatmap was used to show a specific range of parameters where an effect of interest emerged (see figure 15.7).

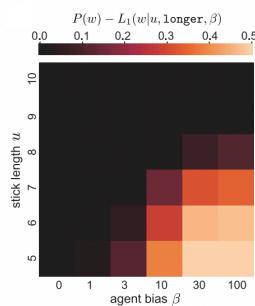


Figure 15.7

Heatmap showing a specific range of continuous parameters where an effect emerged. Barnett, Griffiths, and Hawkins (2022), Figure 3 (licensed under CC BY 4.0).

7302

7303 Or we could plot the accuracy of each age group as sizes/areas (fig-

7304 ure 15.8).

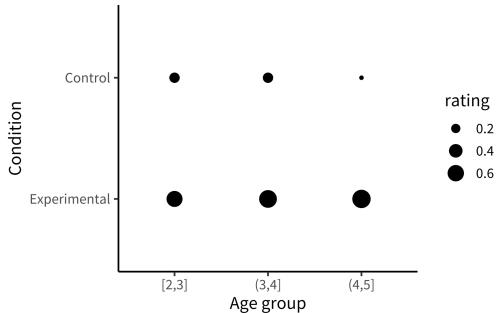


Figure 15.8
Iterating on the Stiller data using size.

CODE

To make this (bad) visualization, we mapped the rating DV to the `size` element in our `aes()` call.

```
ggplot(sgf_cond_means, aes(x = age_group, y = condition, size = rating)) +
  geom_point() +
  labs(x = "Age group", y = "Condition")
```

7305

7306 These plots allow us to see that one condition is (qualitatively) bigger
 7307 than others, but it's hard to tell how much bigger. Additionally, this
 7308 way of plotting the data places equal emphasis on age and condition, but
 7309 we may instead have in mind particular contrasts, like the *change* across
 7310 ages and how that change differs across conditions. An alternative is to
 7311 show six bars: three on the left showing the ‘experimental’ phase and
 7312 three on the right showing the ‘control’ phase. Maybe the age groups
 7313 then are represented as different colors, as in figure 15.9.

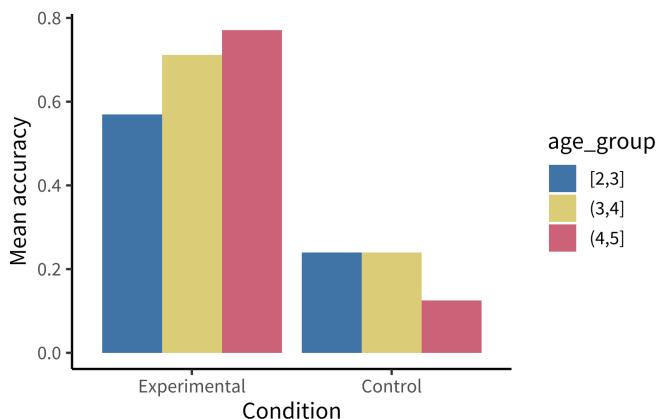


Figure 15.9
 A bar graph of the Stiller data.

 CODE

We make bar plots using the `ggplot` function `geom_col()`. By default, it creates “stacked” bar plots, where all values associated with the same x value (here, `condition`) get stacked up on top of one another. Stacked bar plots can be useful if, for example, you’re plotting proportions that sum up to 1, or want to show how some big count is broken down into subcategories. It’s also common to use `geom_area()` for this purpose, which connects adjacent regions. But the more common bar plot used in psychology puts the bars next to one another, or “dodges” them. To accomplish this, we use the `position = "dodge"` argument:

```
ggplot(sgf_cond_means, aes(x = condition, y = rating, fill = age_group)) +  
  geom_col(position = "dodge") +  
  labs(x = "Condition", y = "Mean accuracy")
```

7314

7315 This plot is slightly better: it’s easier to compare the heights of bars than
7316 the ‘blueness’ of squares, and mapping age to color draws our eye to
7317 those contrasts. However, we can do even better by noticing that our
7318 experiment was designed to test an *interaction*. That statistic of interest
7319 is a difference of differences. To what extent does the developmental
7320 change in performance on the experimental condition different from
7321 developmental change in performance on the control condition? Some
7322 researchers have gotten proficient at reading off interactions from bar
7323 plots, but they also require a complex set of eye movements. We have

7324 to look at the pattern across the bars on the left, and then jump over
 7325 to the bars on the right, and implicitly judge one difference against the
 7326 other: the actual statistic isn't explicitly shown anywhere! What could
 7327 help facilitate this comparison? Consider the line plot in figure 15.10.

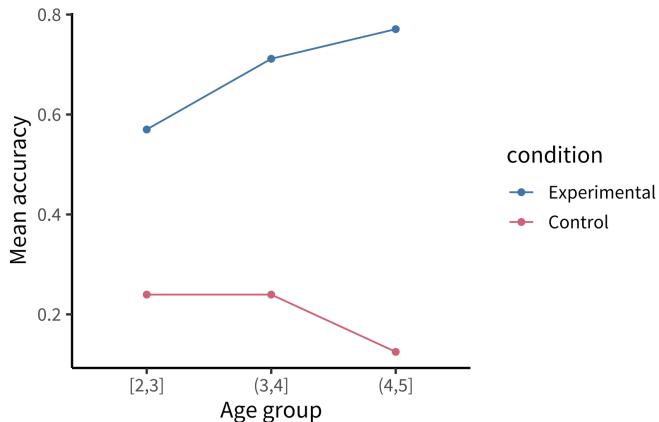


Figure 15.10
 A line graph of the Stiller data promotes comparison.

UserCode

Using a combination of `geom_point()` and `geom_line()`:

```
ggplot(sgf_cond_means, aes(x = age_group, y = rating, color = condition)) +  

  geom_point() +  

  geom_line(aes(group = condition)) +  

  labs(x = "Age group", y = "Mean accuracy")
```

7328
 7329 The interaction contrast we want to interpret is highlighted visually in
 7330 this plot. It is much easier to compare slopes of lines than mentally com-
 7331 pute a difference of differences between bars. Here are a few corollaries
 7332 of this principle (adapted from a presentation by Karl Broman²).

² https://www.biostat.wisc.edu/~kbroman/presentations/IowaState2013/graphs_combined.pdf

- 7333 – It is easier to compare values that are *adjacent* to one another. This
7334 is especially important when there are many different conditions
7335 included on the same plot. If particular sets of conditions are of
7336 theoretical interest, place them close to one another. Otherwise,
7337 sort conditions by a meaningful value (rather than alphabetically,
7338 which is usually the default for plotting software).
- 7339 – When possible, color-code labels and place them directly next to
7340 data rather than in a separate legend. Legends force readers to
7341 glance back and forth to remember what different colors or lines
7342 mean.
- 7343 – When making histograms or density plots, it is challenging to
7344 compare distributions when they are placed side-by-side. Instead,
7345 facilitate comparison of distributions by vertically aligning them,
7346 or making them transparent and placed on the same axes.
- 7347 – If the scale makes it hard to see important differences, consider
7348 transforming the data (e.g. taking the logarithm).
- 7349 – When making bar plots, be very careful about the vertical y-axis.
7350 A classic “misleading visualization” mistake is to cut off the bot-
7351 tom of the bars by placing the endpoint of the y-axis at some
7352 arbitrary value near the smallest data point. This is misleading

7353 because people interpret bar plots in terms of the relative *area* of
7354 the bars (i.e. the amount of ink taken up by the bar), not just their
7355 absolute y-values.

- 7356 – If a key variable from your design is mapped to color, choose
7357 the color scale carefully. For example, if the variable is binary or
7358 categorical, choose visually distinct colors to maximize contrast
7359 (e.g. black, blue, and orange). If the variable is ordinal or contin-
7360 uous, use a color gradient. If there is a natural midpoint (e.g. if
7361 some values are negative and some are positive), consider using a
7362 diverging scale (e.g. different colors at each extreme). Remember
7363 also that a portion of your audience may be color-blind.³

³ Palettes like *viridis* have been de-
signed to be colorblind-friendly and also
perceptually uniform (i.e. the perceived
difference between 0.1 and 0.2 is approx-
imately the same as the difference be-
tween 0.8 and 0.9).

7364 15.1.3 Principle 3: Show the data

7365 Looking at older papers, you may be alarmed to notice how little infor-
7366 mation is contained in the graphs. The worst offenders might show just
7367 two bars, representing average values for two conditions. This kind of
7368 plot adds very little beyond a sentence in the text reporting the means,
7369 but it can also be seriously misleading. It hides real variation in the data,
7370 making a noisy effect based on a few data points look the same as a more
7371 systematic one based on a larger sample. Additionally, it collapses the *dis-*
7372 *tribution* of the data, making a multi-modal distribution look the same as

7373 a unimodal one. The third principle of modern statistical visualization

7374 is to *show the data* and visualize variability in some form.

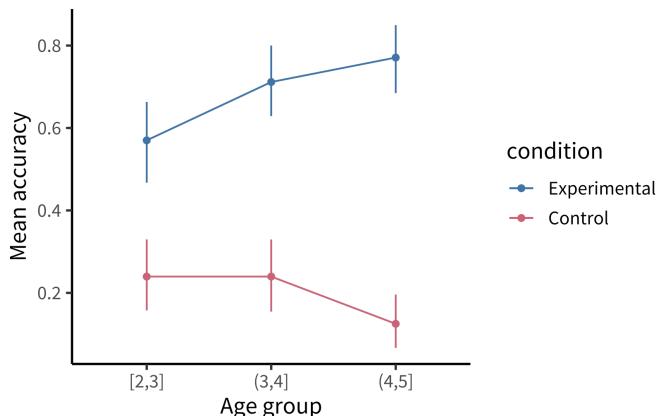
7375 The most minimal form of this principle is to *always include error bars*.⁴

7376 Error bars turn a purely descriptive visualization into an inferential one.

7377 They represent a minimal form of uncertainty about the possible statistics

7378 that might have been observed, not just the one that was actually

7379 observed. figure 15.11 shows the data with (bootstrapped) error bars.



4 And be sure to tell the reader what the error bars represent—a 95% confidence interval? A standard error of the mean?—without this information, error bars are hard to interpret (see Depth box below).

Figure 15.11
Error bars (95% CIs) added to the Stiller data line graph.

CODE

A common problem arises when we want to add error bars to a dodged bar plot. Naively, we'd expect we could just dodge the error bars in the same way we dodged the bars themselves:

```
geom_col(position = "dodge") +
  geom_errorbar(aes(ymin = ci_lower, ymax = ci_upper), position = "dodge")
```

But this doesn't work! The rationale is kind of technical, but the width

of the error bars is much narrower than the width of the bars, so we need to manually specify how much to dodge the error bars with the `position_dodge()` function:

```
geom_col(position = position_dodge()) +  
  geom_errorbar(aes(ymin = ci_lower, ymax = ci_upper),  
    position = position_dodge(width = 0.9))
```

This does the trick!

7381

7382 But we can do even better. By overlaying the distribution of the actual
7383 data points on the same plot, we can give the reader information not just
7384 about the statistical inferences but the underlying data supporting those
7385 inferences. In the case of the Stiller, Goodman, and Frank (2015) study,
7386 data points for individual trials are binary (correct or incorrect). It's
7387 technically possible to show individual responses as dots at 0s and 1s, but
7388 this doesn't tell us much (we'll just get a big clump of 0s and a big clump
7389 of 1s). The question to ask yourself when 'showing the data' is: what are
7390 the theoretically meaningful *units* of variation in the data? This question
7391 is closely related to our discussion of mixed-effects models in chapter 7,
7392 when we considered which random effects we should include. Here, a
7393 reader is likely to wonder how much variance was found across *different*
7394 *children* in a given age group. To show such variation, we aggregate to
7395 calculate an accuracy score for each participant.⁵

7396 There are many ways of showing the resulting distribution of
7397 participant-level data. For example, a **boxplot** shows the median
7398 (a horizontal line) in the center of a box extending from the lower
7399 quartile (25%) to the upper quartile (75%). Lines then extend out to
7400 the biggest and smallest values (excluding outliers, which are shown as
7401 dots). Figure 15.12 gives the boxplots for the Stiller data, which don't
7402 look that informative—perhaps because of the coarseness of individual
7403 participant averages due to the small number of trials.

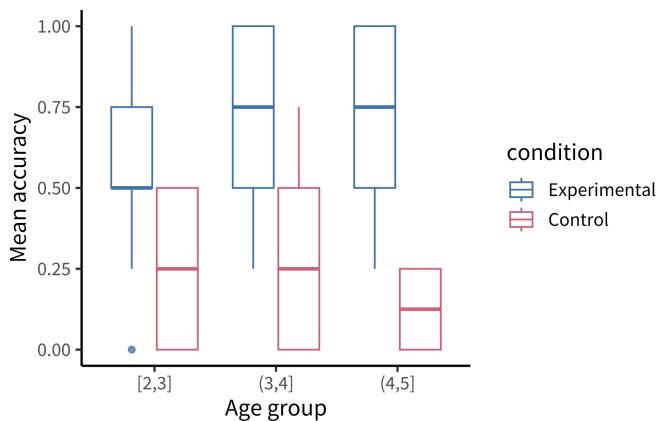


Figure 15.12
Boxplot of the Stiller data.

CODE

In `ggplot`, we can make box plots using `geom_boxplot()`:

```
geom_boxplot(alpha = 0.8)
```

A common problem to run into is that `geom_boxplot()` requires the variable assigned to `x` to discrete. If you have discrete levels of a numeric

variable (e.g. age groups), make sure you've actually converted that variable to a `factor`. Otherwise, if it's still coded as `numeric`, `ggplot` will collapse all of the levels together!

7406 It is also common to show the raw data as jittered values with low trans-
 7407 parency. In figure 15.13, we jitter the points because many participants
 7408 have the same numbers (e.g. 50% and if they overlap it is hard to see
 7409 how many points there are.

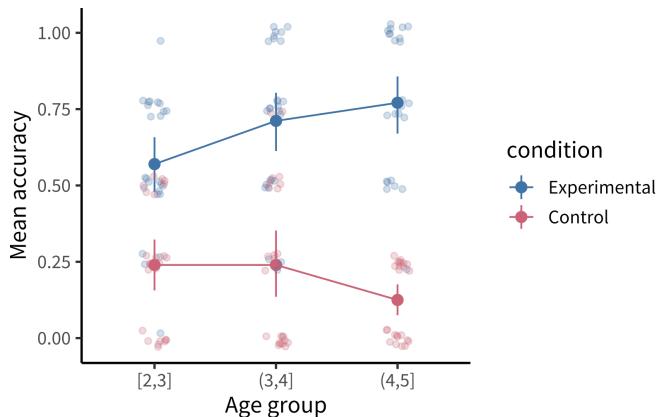


Figure 15.13
 Jittered points representing the data distribution of the Stiller data.

CODE

Adding the jittered points is simple using `geom_jitter()`, but we are starting to have a fairly complex plot so maybe it's worth taking stock of how we get there.

To plot both *condition* means and *participant* means, we need to create two different data frames. Here `sgf_subj_means` is a data frame of means for each participant; `sgf_subj_ci` is a data frame with means and confidence intervals *across* participants. For this purpose, we use the `tidyboot` package and the `tidyboot_mean()` function, which gives us bootstrapped 95% confidence intervals for the means.

```
sgf_subj_means <- sgf |>  
  group_by(condition, age_group, subid) |>  
  summarize(rating = mean(correct))  
  
sgf_subj_ci <- sgf_subj_means |>  
  group_by(condition, age_group) |>  
  tidyboot::tidyboot_mean(rating) |>  
  rename(rating = empirical_stat)  
  
ggplot(sgf_subj_ci, aes(x = age_group, y = rating, color = condition)) +  
  geom_pointrange(aes(ymin = ci_lower, ymax = ci_upper)) +  
  geom_line(aes(group = condition)) +  
  geom_jitter(data = sgf_subj_means, alpha = 0.25, width = 0.1, height = .03) +  
  labs(x = "Age group", y = "Mean accuracy")
```

The most noteworthy aspect of this code is that the `geom_jitter()` function doesn't just take a different aesthetic, it also takes a different dataframe altogether! Mixing dataframes can be an important tool for creating complex plots.

7411

7412 Perhaps the format that takes this principle the furthest is the so-called
7413 “raincloud plot” (Allen et al. 2019) shown in figure 15.14. A raincloud
7414 plot combines the raw data (“rain”) with a smoothed density (“cloud”)
7415 and a boxplot giving the median and quartiles of the distribution.

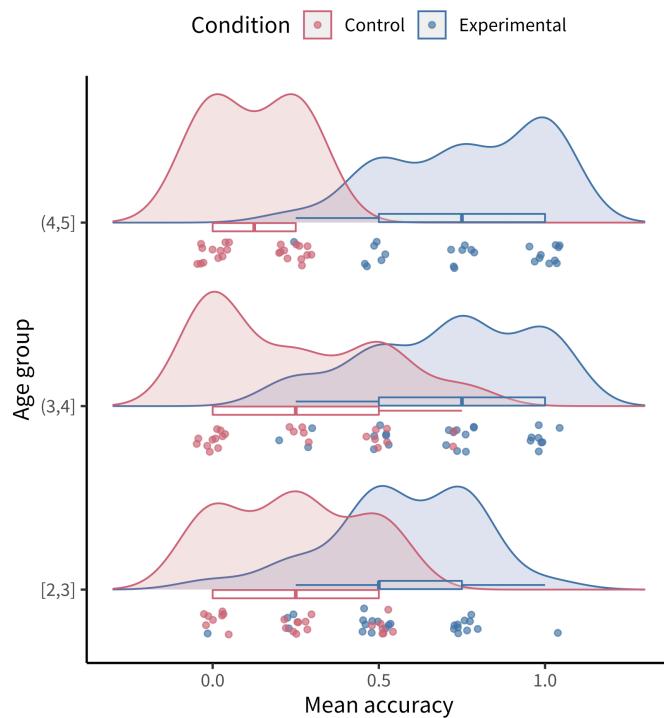


Figure 15.14
Raincloud plot of the Stiller data.

CODE

This raincloud plot requires two additional plotting packages: `ggridges` for the densities and `ggstance` for the horizontal boxplots.

```
library(gggridges)
library(ggstance)

ggplot(sgf_subj_means, aes(y = age_group, x = rating, color = condition)) +
  geom_density_ridges(aes(fill = condition), alpha = 0.2, scale = 0.7,
    jittered_points = TRUE, point_alpha = 0.7,
    position = position_raincloud(width = 0.05, height = 0.15,
      ygap = 0.1)) +
  geom_boxplot(width = 0.1, alpha = 0.2, outlier.shape = NA, show.legend = FALSE) +
  scale_y_discrete(expand = expansion(mult = c(0.2, 0.4))) +
  guides(fill = "none", color = guide_legend(reverse = TRUE)) +
  labs(x = "Mean accuracy", y = "Age group", color = "Condition") +
  theme(legend.position = "top")
```

7417

DEPTH

Visualizing uncertainty with error bars

One common misconception is that error bars are a measure of variance *in the data*, like the standard deviation of the response variable. Instead, they typically represent a measure of precision extracted from the statistical model. In older papers, for example, it was common to use the standard error of the mean (SEM; see chapter 6). Remember that this is not the standard deviation of the data distribution but of the *sampling distribution* of the mean that is being estimated. Given the central limit theorem, which tells us that this sampling distribution is asymptotically normal, it

7418

was straightforward to estimate the standard error analytically using the empirical standard deviation of the data divided by the square root of the sample size: `sd(x) / sqrt(length(x))`. Error bars based on the SEM often looked misleadingly small, as they only represent a 68% interval of the sampling distribution and go to zero quickly as a function of sample size. As a result, it became more common to show the 95% confidence interval instead: $[-1.96 \times \text{SEM}, 1.96 \times \text{SEM}]$.

While these analytic equations remain common, an increasingly popular alternative is to *bootstrap* confidence intervals (see Depth box in chapter 6 for more on bootstrapping). The bootstrap is a powerfully generic technique, especially when you want to show error bars for summary statistics that are more complex than means, where we do not have such convenient asymptotic guarantees and “closed-form” equations. For example, if you’re working with a skewed response variable or a dataset with clear outliers, and you want to estimate medians and quartiles.

Or suppose you want to estimate proportions from categorical data, or a more *ad hoc* statistic like the AUC (area underneath the curve) in a hierarchical design where it is not clear how to aggregate across items or participants in a mixed-effects model. Analytic estimators of confidence intervals can in principle be derived for these statistics, subject to different assumptions, but it is often more transparent and reliable in practice to use the bootstrap. As long as you can write a code snippet to compute a value from a dataset, you can use the bootstrap.

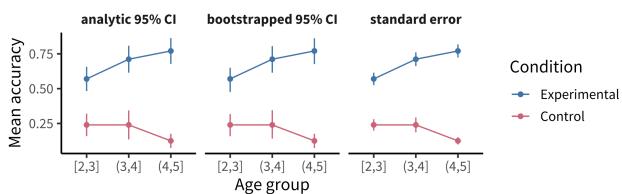


Figure 15.15

Three different error bars for the Stiller data: bootstrapped 95% confidence intervals (left), standard error of the mean (middle), and analytically computed confidence intervals (right).

As we can see, the bootstrapped 95% CI looks similar to the analytic 95% CI derived from the standard error, except the upper and lower limits are slightly asymmetric (reflecting outliers in one direction or another). Of course, the bootstrap is not a silver bullet and can be abused in particularly small samples. This is because the bootstrap is fundamentally limited to the sample we run it on. It can be expected to be reasonably accurate if the sample is reasonably representative of the population. But at the end of the day, as they say, “there’s no such thing as a free lunch.” In other words, we cannot magically pull more information out of a small sample without making additional assumptions about the data generating process.

7420

7421 15.1.1 Principle 4: Maximize information, minimize ink

7422 Now that we have the basic graphical elements in place to show our
7423 design and data, it might seem like the rest is purely a matter of aesthetic
7424 preference, like choosing a pretty color scheme or font. Not so.

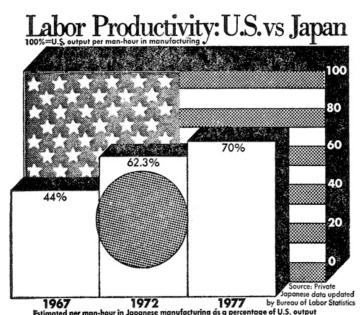


Figure 15.16

This figure uses a lot of ink to show three numbers, for a “ddi” of 0.2 (from the Washington Post, 1978; see Wainer (1984) for other examples).

7425 There are well-founded principles to make the difference between an
 7426 effective visualization and a confusing or obfuscating one. Simply put,
 7427 we should try to use the simplest possible presentation of the maximal
 7428 amount of information: we should maximize the “data-ink ratio”. To
 7429 calculate the amount of information shown, Tufte (1983) suggested
 7430 a measure called the “data density index,” the “numbers plotted per
 7431 square inch”. The worst offenders have a very low density while also
 7432 using a lot of excess ink (e.g., figure 15.16 and figure 15.17)

7433 The defaults in modern visualization libraries like ggplot prevent
 7434 some of the worst offenses, but are still often suboptimal. For example:
 7435 consider whether the visual complexity introduced by the default grey
 7436 background and grid lines in figure 15.18) is justified, or whether a
 7437 more minimal theme would be sufficient (see the ggthemes⁶ package
 7438 for a good collection of themes).

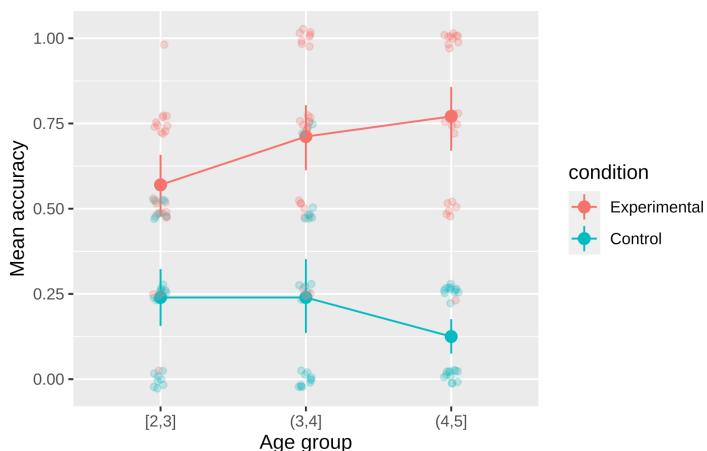


Figure 15.18
 Standard “gray” themed Stiller figure.

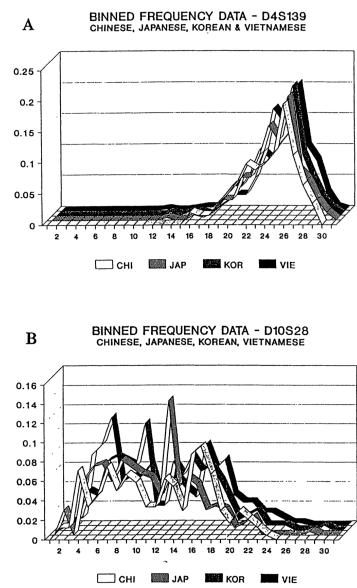


Figure 15.17
 This figure uses complicated 3D ribbons to compare distributions across four countries (from Roeder 1994). How could the same data have been presented more legibly?

⁶ <https://yutannihilation.github.io/allYourFigureAreBelongToUs/ggthemes/>

7439 figure 15.19 shows a slightly more “styled” version of the same plot with

7440 labels directly on the plot and a lighter-weight theme.

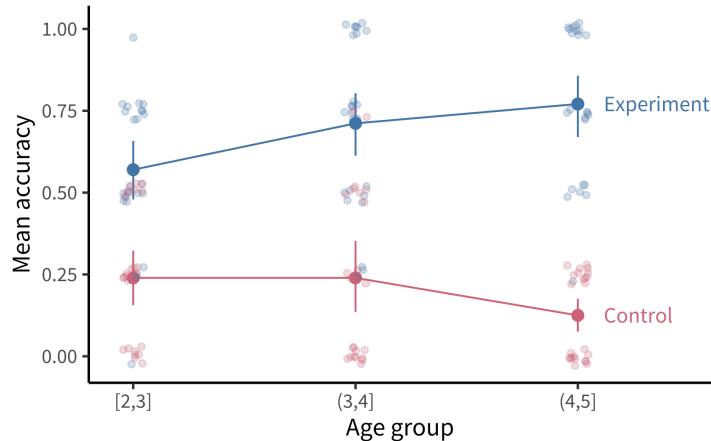


Figure 15.19
Custom themed Stiller figure with direct labels.

CODE

To produce the plot above, we’ve added a few styling elements including:

- The nice and minimal custom theme, with a larger font size.
- A more accessible color palette (`scale_colour_pt01()`) from the `ggthemes` package.
- Direct labels using `geom_dl()` from the `directlabels` package.

```
geom_dl(aes(label = condition), method = list("last.points", dl.trans(x = x + 0.5)))
```

7441

7442 Here are a few final tips for making good confirmatory visualizations:

- 7443 – Make sure the font size of all text in your figures is legible and 7444 no smaller than other text in your paper (e.g. 10pt). This change 7445 may require, for example, making the axis breaks sparser, rotating

7446 text, or changing the aspect ratio of the figure.

- 7447 – Another important tool to keep in your visualization arsenal is the
7448 **facet plot**. When your experimental design becomes more com-
7449 plex, consider breaking variables out into a *grid* of facets instead
7450 of packing more and more colors and line-styles onto the same
7451 axis. In other words, while higher information density is typi-
7452 cally a good thing, you want to aim for the sweet spot before it
7453 becomes too dense and confusing. Remember Principle 2. When
7454 there is too much going on in every square inch, it is difficult to
7455 guide your reader’s eye to the comparisons that actually matter,
7456 and spreading it out across facets gives you additional control over
7457 the salient patterns.

- 7458 – Sometimes these principles come into conflict, and you may need
7459 to prioritize legibility over, for example, showing all of the data.
7460 For example, suppose there is an outlier orders of magnitude away
7461 from the summary statistics. If the axis limits are zoomed out to
7462 show that point, then most of the plot will be blank space! It is
7463 reasonable to decide that it is not worth compressing the key sta-
7464 tistical question of your visualization into the bottom centimeter
7465 just to show one point. It may suffice to truncate the axes and
7466 note in the caption that a single point was excluded.

- 7467 – Fix the axis labels! A common mistake is to keep the default
7468 shorthand you used to name variables in your plotting software
7469 instead of more descriptive labels (e.g., “RT” instead of “Reaction
7470 Time”). Use consistent terminology for different manipulations
7471 and measures in the main text and figures. If anything might be
7472 unclear in the figure, explain it in the caption.
- 7473 – Different audiences may require different levels of detail. Some-
7474 times it is better to collapse over secondary variables (even if they
7475 are included in your statistical models) in order to control the den-
7476 sity of the figure and draw attention to the key question of inter-
7477 est.

7478 15.2 Exploratory visualization

7479 So far in this chapter we have focused on principles of *confirmatory* data
7480 visualization: how to make production-quality figures that convey the
7481 key pre-registered analyses without hiding sources of variability or mis-
7482 leading readers about the reliability of the results. Yet this is only one
7483 role that data visualization plays when doing science. An equally im-
7484 portant role is called *exploratory visualization*: the more routine practice
7485 of understanding one’s own data by visualizing it. This role is analo-
7486 gous to the sense of exploratory data analyses discussed in chapter 11.

7487 We typically do not pre-register exploratory visualizations, and when
7488 we decide to include them in a paper they are typically in the service
7489 of a secondary argument (e.g., checking the robustness of an effect or
7490 validating that some assumption is satisfied).

7491 This kind of visualization plays a ubiquitous role in a researcher's day-to-
7492 day activities. While confirmatory visualization is primarily audience-
7493 driven and concerned with visual communication, exploratory visual-
7494 ization is first and foremost a "cognitive tool" for the researcher. The
7495 first time we load in a new dataset, we start up a new feedback loop —
7496 we ask ourselves questions and answer them by making visualizations.
7497 These visualizations then raise further questions and are often our best
7498 tool for debugging our code. In this section, we consider some best
7499 practices for exploratory visualization.

7500 15.2.1 Examining distributional information

7501 The primary advantage of exploratory visualization—the reason it is
7502 uniquely important for data science—is that it gives us access to holistic
7503 information about the distribution of the data, that cannot be captured
7504 in any single summary statistic. The most famous example is known
7505 as "Anscombe's quartet," a set of four datasets with identical statistics
7506 (figure 15.20). They have the same means, the same variances, the same

correlation, the same regression line, and the same R^2 value. Yet when they are plotted, they reveal striking structural differences. The first looks like a noisy linear relationship—the kind of idealized relationship we imagine when we imagine a regression line. But the second is a perfect quadratic arc, the third is a perfectly noiseless line with a single outlier, and the fourth is nearly categorical: every observation except one shares exactly the same x-value.

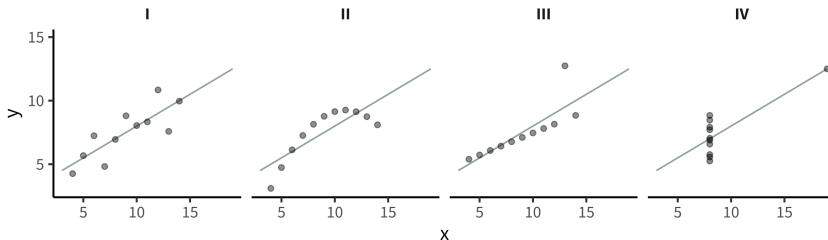


Figure 15.20
Anscombe's quartet (Anscombe 1973).

If our analyses are supposed to help us distinguish between different data-generating processes, corresponding to different psychological theories, it is clear that these four datasets would correspond to dramatically different theories even though they share the same statistics. Of course, there are arbitrarily many datasets with the same statistics, and most of these differences don't matter (this is why they are called "summary" statistics, after all!). figure 15.21 and table 15.1 show just how bad things can get when we rely on summary statistics. When we operationalize a theory's predictions in terms of a single statistic (e.g., a difference between groups or a regression coefficient) we can lose track of everything else that may be going on. Good visualizations force us to zoom out and

7525 take in the bigger picture.

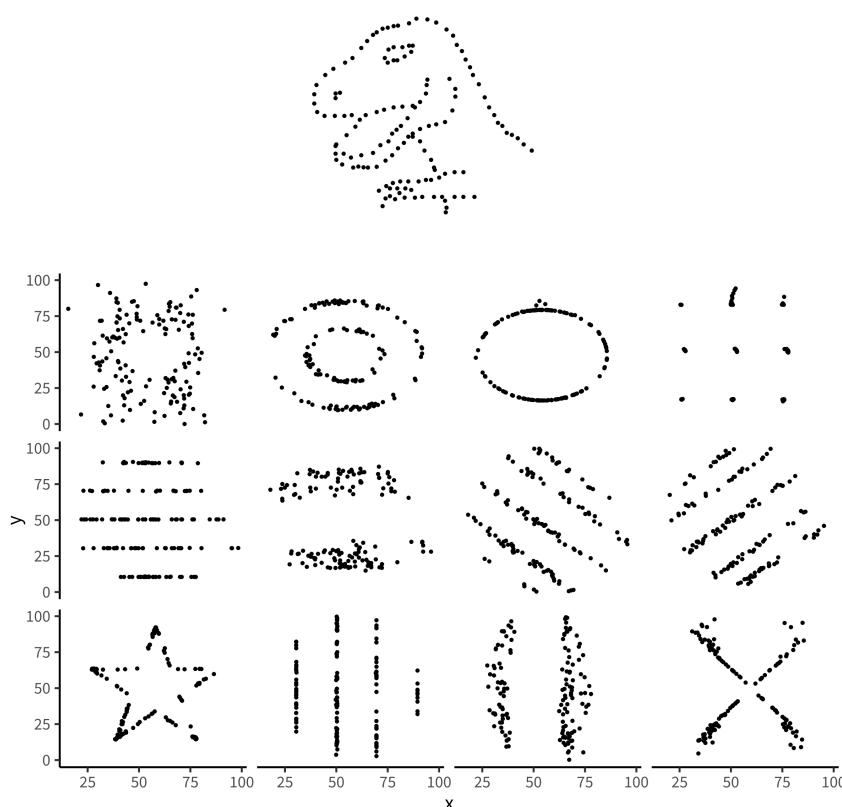


Figure 15.21

Originally inspired by the Datasaurus figure constructed by @albertocairo on Twitter (Cairo 2016) using the DrawMyData tool (<http://robertgrantstats.co.uk/drawmydata.html>), we can construct an arbitrary number of different graphs with exactly the same statistics (Matejka and Fitzmaurice 2017; Murray and Wilson 2021), such as the Datasaurus Dozen (Matejka and Fitzmaurice 2017).

Table 15.1
Summary statistics for each dataset in the Datasaurus Dozen (Matejka 2017).

dataset	mean_x	mean_y	sd_x	sd_y	cor_xy
away	54.3	47.8	16.8	26.9	-0.064
bullseye	54.3	47.8	16.8	26.9	-0.069
circle	54.3	47.8	16.8	26.9	-0.068
dino	54.3	47.8	16.8	26.9	-0.064
dots	54.3	47.8	16.8	26.9	-0.060
h_lines	54.3	47.8	16.8	26.9	-0.062
high_lines	54.3	47.8	16.8	26.9	-0.069

Table 15.1
Summary statistics for each dataset in the Datasaurus Dozen (Matejka 2017).

dataset	mean_x	mean_y	sd_x	sd_y	cor_xy
slant_down	54.3	47.8	16.8	26.9	-0.069
slant_up	54.3	47.8	16.8	26.9	-0.069
star	54.3	47.8	16.8	26.9	-0.063
v_lines	54.3	47.8	16.8	26.9	-0.069
wide_lines	54.3	47.8	16.8	26.9	-0.067
x_shape	54.3	47.8	16.8	26.9	-0.066

⚠️ ACCIDENT REPORT

[Distributional] gorillas in our midst.

Many data scientists don't bother checking what their data looks like before proceeding to test specific hypotheses. Yanai and Lercher (2020) cleverly designed an artificial dataset for their students to test for such oversight. Each row of the dataset contained an individual's body mass index (BMI) and the number of steps they walked on a given day. While the spreadsheet looked innocuous, the data was constructed such that simply plotting the raw data revealed a picture of a gorilla. One group of 19 students was given an explicit set of hypotheses to test (e.g. about the relationship between BMI and steps). Fourteen of these students failed to notice a gorilla, suggesting that they evaluated these hypotheses without ever visualizing their data. Another group of 14 students were simply asked what, if anything, they could conclude (without being given explicit hypotheses). More of these students apparently made the visualization, but five of them still failed to notice the gorilla (figure 15.22)!

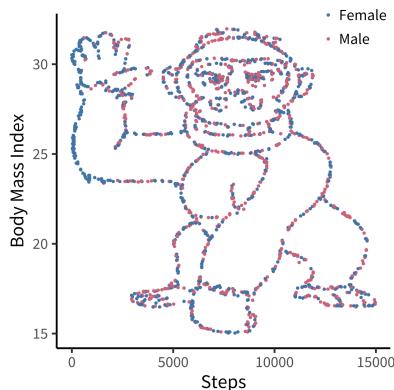


Figure 15.22

A dataset constructed by Yanai and Lercher (2020) which revealed a picture of a gorilla when the raw data were plotted.

While it may not be surprising that a group of students would take the shortest path to completing their assignment, similar concerns have been raised in much more serious cases concerning how experienced researchers could fail to notice obviously fraudulent data. For example, when the Datacolada bloggers -Datacolada (2021) made a simple histogram of the car mileage data reported in Shu et al. (2012; released publicly by Kristal et al. 2020), they were immediately able to observe that it followed a perfectly uniform distribution, truncated at exactly 50,000 miles (figure 15.23). Given a little thought, this pattern should be extremely puzzling. Over a given period of time, we would typically expect something more bell-shaped: a small number of people will drive very little (e.g., 1000 miles), a small number of people will drive a lot (e.g., 50,000 miles), and most people will fall between these tails. So it is highly surprising to find exactly the same number of drivers in every mileage bin. While further specialized analyses revealed additional evidence of fraud (e.g. based on patterns of rounding and pairs of duplicated data points), this humble histogram was already enough to set off alarm bells. A recurring regret raised by the co-authors of this paper is that they never thought to make this visualization before reporting their statistical tests.

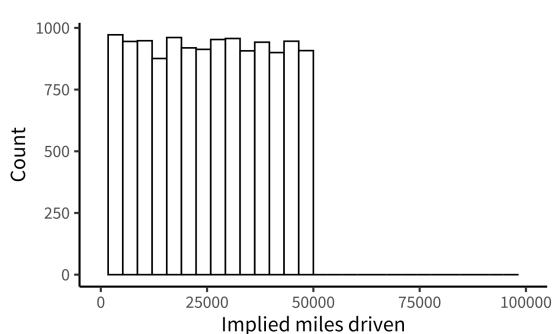


Figure 15.23

A suspiciously uniform distribution abruptly cutting off at 50k miles. Ring the alarm!

Our data are always messier than we expect. There might be a bug in our coding scheme, a column might be mislabeled, or might contain a range of values that we didn't expect. Maybe our design wasn't perfectly balanced, or something went wrong with a particular participant's keyboard presses. Most of the time, it's not tractable to manually scroll through our raw data looking for such problems. Visualization is our first line of defense for the all-important process of running "data diagnostics." If there is a weird artifact in our data, it will pop out if we just make the right visualizations.

7528

7529 15.2.1 Data diagnostics

7530 So which visualizations should we start with? The best practice is to
7531 always start by making histograms of the raw data. As an example, let's
7532 consider the rich and interesting dataset shared by Blake, McAuliffe,
7533 and colleagues (2015) in their article "Ontogeny of fairness in seven
7534 societies." This article studies the emergence of children's reasoning

7535 about fairness—both when it benefits them and when it harms them—

7536 across cultures.

 CODE

If you want to follow along with this example at home, you can load the data from our repository!

```
repo <- "https://raw.githubusercontent.com/langcog/experimentology/main/"  
  
fairness_raw <- read_csv(file.path(repo, "data/viz/ontogeny_of_fairness.csv"))  
  
  
fairness <- fairness_raw |>  
  
  mutate(trial_num = trial |> str_remove("t") |> as.numeric(),  
  
         trial_type = eq.uneq |> fct_recode("Equal" = "E", "Unequal" = "U"),  
  
         condition = condition |> fct_recode("Advantageous" = "AI",  
  
                                         "Disadvantageous" = "DI"),  
  
         age = floor(actor.age.years),  
  
         reject = decision == "reject") |>  
  
  select(subj_id = actor.id, age, country, condition, trial_num, trial_type, reject) |>  
  arrange(country, condition, subj_id, trial_num)
```

7537

7538 In this study, pairs of children played the “inequity game”: they sat
7539 across from one another and were given a particular allocation of snacks.
7540 On some trials, each participant was allocated the same amount (Equal
7541 trials) and on some trials they were allocated different amounts (Un-
7542 equal trials). One participant was chosen to be the “actor” and got to
7543 choose whether to accept or reject the allocation: in the case of rejec-
7544 tion, neither participant got anything. The critical manipulation was

7545 between two forms of inequity. Some pairs were assigned to the Dis-
7546 advantageous condition, where the actor was allocated less than their
7547 partner on Unequal trials (e.g. 1 vs. 4). Others were assigned to the Ad-
7548 vantageous condition, where they were allocated more (e.g. 4 vs. 1).

7549 The confirmatory design plot for this study would focus on contrast-
7550 ing developmental trajectories for Advantageous vs. Disadvantageous
7551 inequality. However, this is a complex, multivariate dataset, including
7552 866 pairs from different age groups and different testing sites across the
7553 world which used subtly different protocols. How might we go about
7554 the process of exploratory visualization for this dataset?

7555 15.2.2 Plot data collection details

7556 Let's start by getting a handle on some of the basic sample character-
7557 istics. For example, how many participants were in each age bin (fig-
7558 ure 15.24)?

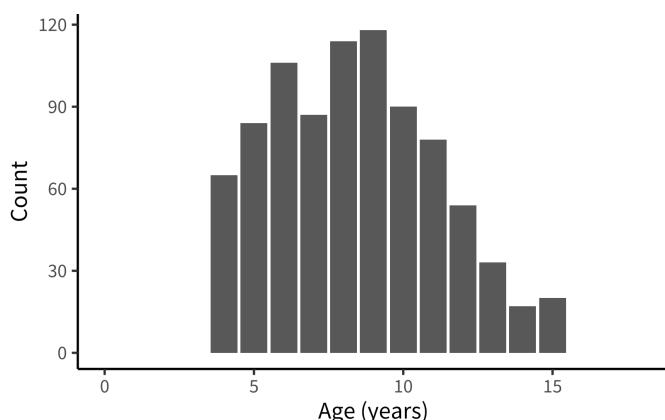


Figure 15.24
Participants by age in the Blake data.

 CODE

Exploratory histograms are often a combination of an aggregation step and a plotting step. In the aggregation step, we make use of the convenience `count()` function, which gives the number (`n`) of rows in a particular grouping. Here we `count()` twice in order to get first one row per participant and then count the number of participants within each age group.

```
fairness_by_age <- fairness |>  
  count(age, subj_id) |>  
  count(age)
```

And then we plot using `ggplot()`:

```
ggplot(fairness_by_age, aes(x = age, y = n)) +  
  geom_col() +  
  xlim(0, 18) +  
  labs(x = "Age (years)", y = "Count")
```

An alternative (perhaps more elegant) workflow here would be to use a histogram:

```
fairness_by_age <- fairness |>  
  count(age, subj_id)  
  
ggplot(fairness_by_age, aes(x = age)) +  
  geom_histogram(binwidth = 1) +  
  labs(x = "Age (years)", y = "Count")
```

Histograms are intended by ggplot to be for continuous data, however, and so they don't give the discrete bars that our earlier workflow did.

7561 How many participants were included from each country (fig-
7562 ure 15.25)?

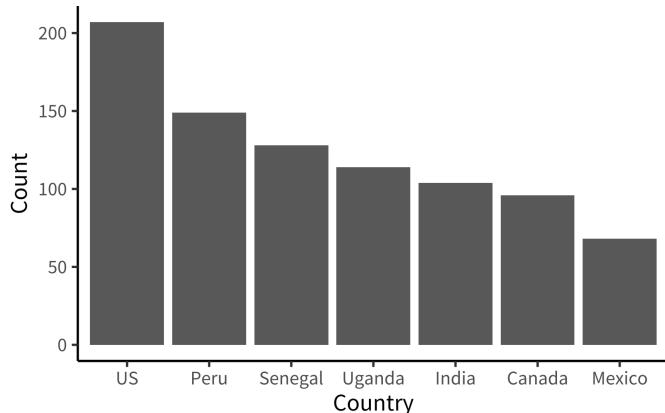


Figure 15.25
Participants by country in the Blake data.

CODE

Here we are going to make things even terser and use a pipe chain that *includes* the `ggplot()` call, just so we are writing only a single call to produce our plot. It's up to you whether you think this enhances the readability of your code or decreases it. We find that it's sometimes useful when you don't plan on keeping the intermediate data frame for any other use than plotting.

```
fairness |>  
  
  count(country, subj_id) |>  
  
  count(country) |>  
  
  mutate(country = fct_reorder(country, -n)) |>  
  
  ggplot(aes(x = country, y = n)) +  
  
    geom_col() +  
  
    labs(x = "Country", y = "Count")
```

If you use this technique, be careful to use pipe (`|>` or `%>%`) between function calls but use `(+)` between `ggplot` layers!

The only other trick to point out here is that we use the `fct_reorder()` call to order the levels of the `country` factor in descending order. This function is found in the very useful `forcats` package of the `tidyverse`, which contains all sorts of functions for working with factors.

7565 Are ages roughly similar across each country (figure 15.26)?

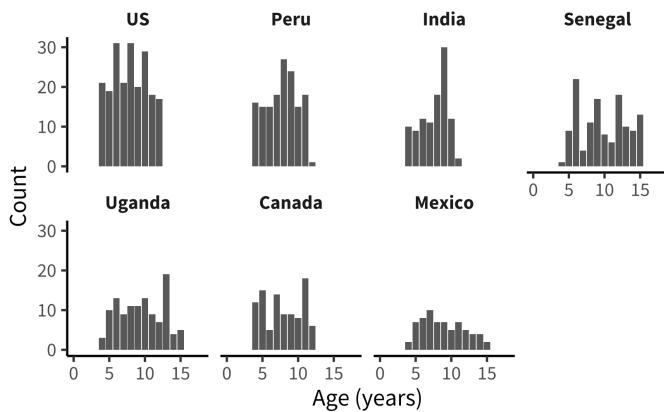


Figure 15.26
Age distribution across countries in the Blake data.

CODE

This next plot simply combines the grouping factors of each of the last two plots, and uses `facet_wrap()` to show a separate histogram by country:

```
fairness |>

  count(country, age, subj_id) |>

  count(country, age) |>

  mutate(country = fct_reorder(country, -n)) |>

  ggplot(aes(x = age, y = n)) +

    facet_wrap(vars(country), ncol = 4) +

    geom_col() +

    xlim(0, 18) +

    labs(x = "Age (years)", y = "Count")
```

7566

7567 These exploratory visualizations help us read off some descriptive prop-

7568 erties of the sample. For example, we can see that age ranges differ
7569 somewhat across sites: the maximum age is 11 in India but 15 in Mex-
7570 ico. We can also see that age groups are fairly imbalanced: in Canada,
7571 there are 18 11-year-olds but only 5 6-year-olds.

7572 None of these properties are problematic, but seeing them gives us a
7573 degree of awareness that could shape our downstream analytic decisions.

7574 For example, if we did not appropriately model random effects, our
7575 estimates would be dominated by the countries with larger sample sizes.

7576 And if we were planning to compare specific groups of 6-year-olds (for
7577 some reason), this analysis would be underpowered.

7578 *15.2.3 Explorating distributions*

7579 Now that we have a handle on the sample, let's get a sense of the depen-
7580 dent variable: the participant's decision to accept or reject the allocation.

7581 Before we start taking means, let's look at how the "rejection rate" vari-
7582 able is distributed. We'll aggregate at the participant level, and check
7583 the frequency of different rejection rates, overall (figure 15.27).

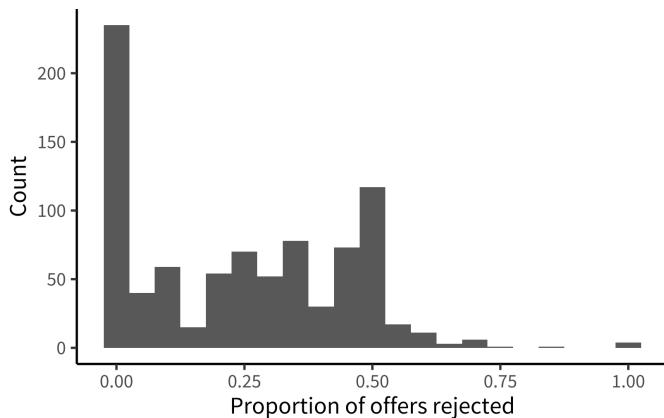


Figure 15.27
Rejection rates in the Blake data.

CODE

Rejection rate is a continuous variable, so we switch to using a histogram in this case, choosing .05 as a reasonable bin width to see the distribution.

```

fairness_by_subj <- fairness |>

filter(!is.na(trial_type)) |>

group_by(subj_id) |>

summarise(mean_reject = mean(reject, na.rm = TRUE))

ggplot(fairness_by_subj, aes(x = mean_reject)) +
  geom_histogram(binwidth = .05) +
  labs(x = "Proportion of offers rejected", y = "Count")

```

7584

7585 We notice that many participants (27%) never reject in the entire experiment. This kind of “zero-inflated” distribution is not uncommon in
 7586 psychology, and may warrant special consideration when designing the
 7587 statistical model. We also notice that there is clumping around certain

7589 values. This clumping leads us to check how many trials each partici-

7590 pant is completing (figure 15.28).

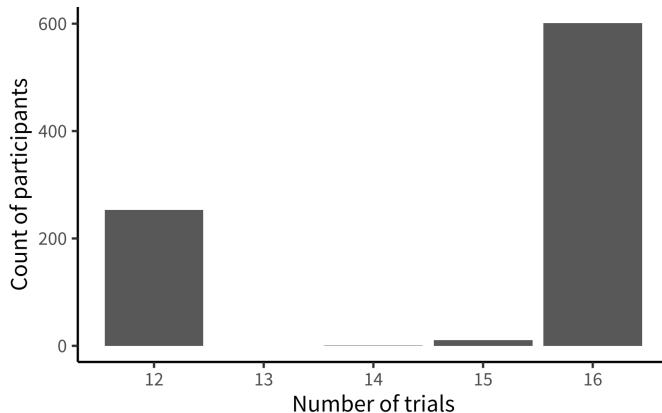


Figure 15.28
Trials per participant in the Blake data.

CODE

This histogram is very similar to the ones above; however, we now use `count()` twice, first getting the trial counts for each participant and then counting how many times each count occurs overall!

```
fairness |>

  filter(!is.na(trial_type)) |>

  count(subj_id) |>

  count(n) |>

  ggplot(aes(x = n, y = nn)) +

  geom_col() +

  labs(x = "Number of trials", y = "Count of participants")
```

7591

7592 There's some variation here: most participants completed 17 trials, but

7593 some participants completed 8 trials, and a small number of participants

7594 have 14 or 15. Given the logistical complexity of large multi-site stud-
7595 ies, it is common to have some changes in experimental protocol across
7596 data collection. Indeed, looking at the supplement for the study, we
7597 see that while India and Peru had 12 trials, additional trials were added
7598 at the other sites. In a design where the number of trials was carefully
7599 controlled, seeing unexpected numbers here (like the 14 or 15 trial bins)
7600 are clues that something else may be going on in the data. In this case, it
7601 was a small number of trials with missing data. More generally, seeing
7602 this kind of signal in a visualization of our own data typically leads us
7603 to look up the participant IDs in these bins and manually inspect their
7604 data to see what might be going on.

7605 15.2.4 *Hypothesis-driven exploration*

7606 Finally, we can make a few versions of the design plot that are broken
7607 out by different variables. Let's start by just looking at the data from the
7608 largest site (figure 15.29).

7609 figure 15.29 is not a figure we'd put in a paper, but it helps us get a sense
7610 of the pattern in the data. There appears to be an age trend that's specific
7611 to the Unequal trials, with rejection rates rising over time (compared to
7612 roughly even or decreasing rates in the Equal trials). Meanwhile, rejec-
7613 tion rates for the Disadvantageous group also seem slightly higher than

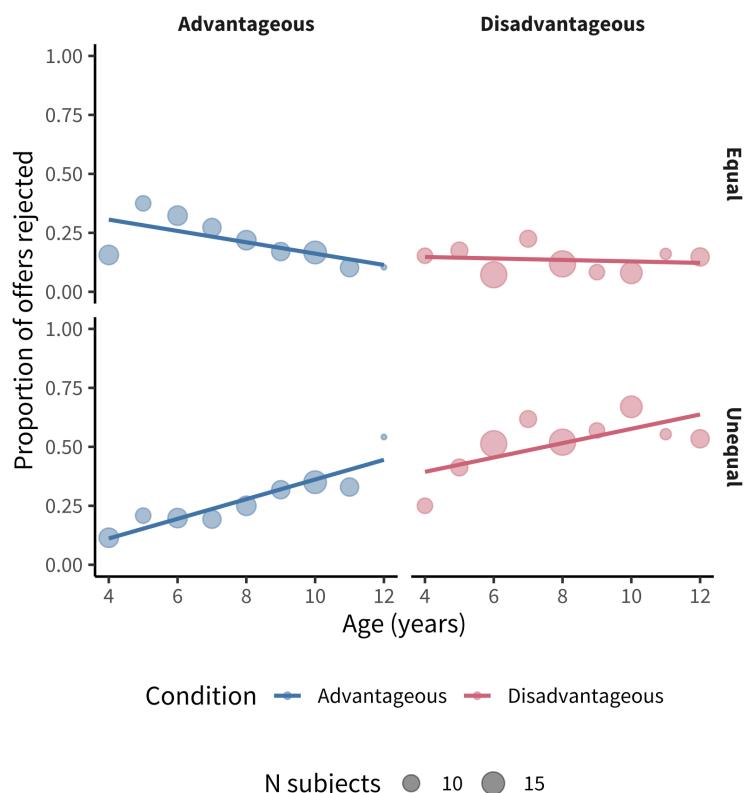


Figure 15.29
Rejection rates in the US data from Blake, plotted by age.

7614 those in the Advantageous group.

 CODE

Here, we are using `geom_smooth()` to overlay regression trends over the raw data. `geom_smooth()` takes a number of different options corresponding to different smoothing techniques. Non-parametric smoothing can be a good choice for exploratory visualizations if you have a lot of data and want to make minimal assumptions about the form of the trend.

Here, however, we show the linear regression trend, `geom_smooth(method = "lm")`, which better corresponds to the predictions of the study and the statistical model being used (see chapter 7). Other regression forms can be specified with the `formula` argument. For example, we could show quadratic smoothing with `geom_smooth(method = "lm", formula = y ~ poly(x, 2))`. The form of smoothing you use may differ across exploratory and confirmatory visualizations. In a confirmatory visualization — if you are going to include a smoothing curve — it is typically best to use the one specified by your statistical model, as the slopes will correspond to the inferences being tested.

We begin by making a summary dataset:

```

fairness_by_age <- fairness |>
  filter(!is.na(reject)) |>
  group_by(country, trial_type, condition, age, subj_id) |>
  summarise(mean_reject_subj = mean(reject, na.rm = TRUE)) |>
  group_by(country, trial_type, condition, age) |>
  summarise(mean_reject_age = mean(mean_reject_subj, na.rm = TRUE),
            n_subj = n()) |>
  ungroup()

```

Then we can create the visualization:

```

fairness_by_age |> filter(country == "US") |>
  ggplot(aes(x = age, y = mean_reject_age, color = condition)) +
  facet_grid(vars(trial_type), vars(condition)) +
  geom_smooth(method = "lm", se = FALSE) +
  geom_point(aes(size = n_subj), alpha = .5) +
  ylim(c(0, 1)) +
  labs(x = "Age (years)", y = "Proportion of offers rejected",
       color = "Condition", size = "N subjects") +
  theme(legend.position = "bottom", legend.box = "vertical")

```

We often find it convenient to filter the summary dataset in the plotting call, so that we can reuse it again.

7616

⁷⁶¹⁷ Now let's re-bin the data into two-year age groups so that individual

⁷⁶¹⁸ point estimates are a bit more reliable, and add the other countries back

7619 in.⁷

⁷ Binning data is a trick that we often use for reducing complexity in a plot when data are noisy. It should be used with care, however, since different binning decisions can sometimes lead to different conclusions. Here we tried several binning intervals and decided that two-year age bins showed the underlying trends pretty well.

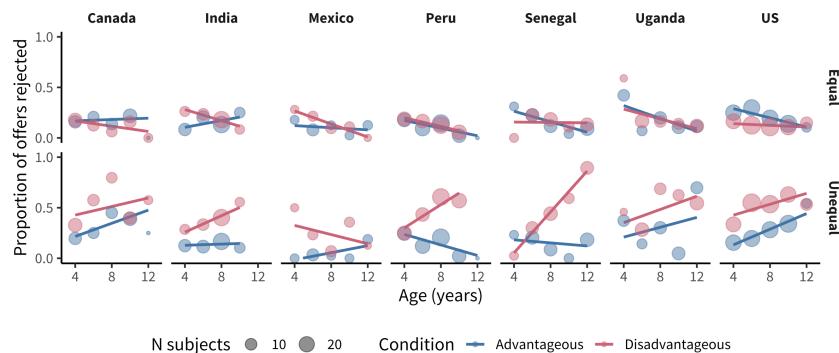


Figure 15.30
Rejection rates by age for all data in the
Blake dataset.

figure 15.30 is now looking much closer to a quick-and-dirty version
of a “design plot” we might include in a paper. The DV (rejection rate)
is on the y-axis, and the primary variable of interest (age) is on the x-
axis. Other elements of the design (country and trial type) are mapped
to color and facets, respectively.

CODE

Despite the difference between the plot above and this one, the code to produce them is actually very similar. The only difference is the creation of the binned variable and a slight shift of aesthetic and faceting variables.

```
fairness_by_age_binned <- fairness |>  
  filter(!is.na(reject)) |>  
  mutate(age_binned = floor(age / 2) * 2) |>  
  group_by(country, trial_type, condition, age_binned, subj_id) |>  
  summarise(mean_reject_subj = mean(reject, na.rm = TRUE)) |>  
  group_by(country, trial_type, condition, age_binned) |>  
  summarise(mean_reject_age = mean(mean_reject_subj, na.rm = TRUE),  
            n = n()) |>  
  ungroup()  
  
ggplot(fairness_by_age_binned,  
       aes(x = age_binned, y = mean_reject_age, color = condition)) +  
  facet_grid(vars(trial_type), vars(country)) +  
  geom_smooth(method = "lm", se = FALSE, aes(weight=n)) +  
  geom_point(alpha = .5, aes(size = n)) +  
  scale_x_continuous(breaks = seq(4, 12, 4), limits = c(3,13)) +  
  scale_y_continuous(limits = c(0, 1), breaks = c(0, .5, 1)) +  
  labs(x = "Age (years)", y = "Proportion of offers rejected",  
        color = "Condition", size = "N subjects") +  
  theme(legend.position = "bottom")
```

7627 *15.2.5 Visualization as debugging*

7628 The point of exploratory visualization is to converge toward a better
7629 understanding of what's going on in your data. As you iterate through
7630 different exploratory visualizations, *stay vigilant!* Think about what you
7631 expect to see before making the plot, then ask yourself whether you
7632 got what you expected. You can think of this workflow as a form of
7633 "visual debugging". You might notice a data point with an impossible
7634 value, such as a proportion greater than 1 or a reaction time less than 0.
7635 Or you might notice weird clusters or striations, which might indicate
7636 heterogeneity in data entry (perhaps different coders used slightly dif-
7637 ferent rubrics or rounded in different ways). You might notice that an
7638 attribute is missing for some values, and trace it back to a bug reading in
7639 the data or merging data frames (maybe there was a missing comma in
7640 our csv file). If you see anything that looks weird, track it down until
7641 you understand why it's happening. Bugs that are subtle and invisible
7642 in other parts of the analysis pipeline will often pop out as red flags in
7643 visualizations.

7644 *15.3 Chapter summary: Visualization*

7645 This chapter has given a short review of the principles of data visual-
7646 ization, especially focusing on the needs of experimental psychology,

7647 which are often quite different than those of other fields. We partic-
7648 ularly focused on the need to make visualization part of the experi-
7649 menter’s analytic workflow. Picking up the idea of a “default model”
7650 from chapter 7, we discussed a default “design plot” that reflects the
7651 key choices made in the experimental design. Within this framework,
7652 we then discussed different visualizations of distribution and variability
7653 that better align our graphics with the principles of measurement and
7654 attention to raw data that we have been advocating throughout.



DISCUSSION QUESTIONS

1. Choose a recent piece of research that you’ve heard about and try to sketch the “design plot” with pencil and paper. What does and doesn’t work? How does your sketch differ from the visualizations in the paper?
2. The “design plot” idea that we’ve discussed here can run into problems when an experimental design is too complex to show on a single plot. Imagine you had data from a trial of attention deficit hyperactivity disorder (ADHD) treatment that manipulated both whether a medication was given and whether patients received therapy in a crossed design. The researchers measured two different outcomes: parent report symptom severity and teacher report symptom severity in four different time-points (baseline, 3 months, 6 months, and 9 months). How could you show the data from such an experiment in a transpar-

ent way?

7656

READINGS

There are many good introductions to data visualization. Here are two social-science focused books whose advice we agree with and that also contain a lot of practical information and helpful R code for the same packages we use here.

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- Wilke, C. O. (2019). *Fundamentals of Data Visualization*. O'Reilly Media. Available free online at <https://clauswilke.com/dataviz/>.

For a more classical treatment, see:

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7657

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16 META-ANALYSIS

7663

LEARNING GOALS

- Discuss the benefits of synthesizing evidence across studies
- Conduct a simple fixed- or random-effects meta analysis
- Reason about the role of within- and across-study biases in meta-analysis

7664

7665 Throughout this book, we have focused on how to design individual
7666 experiments that maximize measurement precision and minimize bias.

7667 But even when we do our best to get a precise, unbiased estimate in an
7668 individual experiment, one study can never be definitive. Variability in
7669 participant demographics, stimuli, and experimental methods may limit

7670 the generalizability of our findings. Additionally, even well-powered
7671 individual studies have some amount of statistical error, limiting their
7672 precision. Synthesizing evidence across studies is critical for developing
7673 a balanced and appropriately evolving view of the overall evidence on

7674 an effect of interest and for understanding sources of variation in the
7675 effect.

7676 Synthesizing evidence rigorously takes more than putting a search term
7677 into Google Scholar, downloading articles that look topical or inter-
7678 esting, and qualitatively summarizing your impressions of those stud-
7679 ies. While this ad-hoc method can be an essential first step in perform-
7680 ing a literature review (Grant and Booth 2009), it is not systematic and
7681 doesn't provide a *quantitative* summary of a particular effect. Further,
7682 it doesn't tell you anything about potential biases in the literature—for
7683 example, a bias for the publication of positive effects.

7684 To address these issues, a more systematic, quantitative review of the
7685 literature is often more informative. This chapter focuses on a specific
7686 type of quantitative review called **meta-analysis**: a method for combin-
7687 ing effect sizes across different studies. (If you need a refresher on effect
7688 size, see chapter 5, where we introduce the concept).¹ We include a
7689 chapter on meta-analysis in Experimentology because we believe it's an
7690 important tool that can focus experimental researchers on issues of MEA-
7691 SUREMENT PRECISION and BIAS REDUCTION, two of our key themes.

7692 By combining information from multiple studies, meta-analysis often
7693 provides more precise estimates of an effect size than any single study.
7694 In addition, meta-analysis also allows the researcher to look at the extent

¹ We'll primarily be using Cohen's d , the standardized difference between means, which we introduced in chapter 5. There are many more varieties of effect size available, but we focus here on d because it's common and easy to reason about in the context of the statistical tools we introduced in the earlier sections of the book.

7695 to which an effect varies across studies. If an effect does vary across stud-
7696 ies, meta-analysis also can be used to test whether certain study charac-
7697 teristics systematically produce different results (e.g., whether an effect
7698 is larger in certain populations).



CASE STUDY

Towel reuse by hotel guests

Imagine you are staying in a hotel and you have just taken a shower. Do you throw the towels on the floor or hang them back up again? In a widely-cited study on the power of social norms, Goldstein, Cialdini, and Griskevicius (2008) manipulated whether a sign encouraging guests to reuse towels focused on environmental impacts (e.g., “help reduce water use”) or social norms (e.g., “most guests re-use their towels”). Across two studies, they found that guests were significantly more likely to reuse their towels after receiving the social norm message (Study 1: odds ratio [OR] = 1.46, 95% CI [1.00, 2.16], $p = .05$; Study 2: OR = 1.35, 95% CI [1.04, 1.77], $p = .03$).

However, five subsequent studies by other researchers did not find significant evidence that social norm messaging increased towel reuse. (ORs ranged from 0.22 to 1.34, and no hypothesis-consistent p -value was less than .05). This caused many researchers to wonder if there is any effect at all. To examine this question, Scheibehenne, Jamil, and Wagenmakers (2016) statistically combined evidence across the studies via meta-analysis. This meta-analysis indicated that using social norm messages did signifi-

cantly increase hotel towel reuse, on average ($OR = 1.26$, 95% CI [1.07, 1.46], $p < .005$). This case study demonstrates an important strength of meta-analysis: by pooling evidence from multiple studies, meta-analysis can generate more powerful insights than any one study alone. We will also see how meta-analysis can be used to assess variability in effects across studies.

7700

7701 Meta-analysis often teaches us something about a body of evidence that
7702 we do not intuitively grasp when we casually read through a bunch of
7703 articles. In the above case study, merely reading the individual studies
7704 might give the impression that social norm messages do not increase
7705 hotel towel re-use. But meta-analysis indicated that the average effect
7706 is beneficial, although there might be substantial variation in effect sizes
7707 across studies.²

7708 *16.1 The basics of evidence synthesis*

7709 As we explore the details of conducting a meta-analysis, we'll turn to
7710 another running example: a meta-analysis of studies investigating the
7711 "contact hypothesis" on intergroup relations.

7712 According to the contact hypothesis, prejudice towards members of mi-
7713 nority groups can be reduced through intergroup contact interventions,

7714 in which members of majority and minority groups work together to
 7715 pursue a common goal (Allport, Clark, and Pettigrew 1954). To ag-
 7716 gregate the evidence on the contact hypothesis, Paluck, Green, and
 7717 Green (2019) meta-analyzed studies that tested the effects of random-
 7718 ized intergroup contact interventions on long-term prejudice-related
 7719 outcomes.

7720 Using a systematic literature search, Paluck, Green, and Green (2019)
 7721 searched for all papers that tested these effects and then extracted effect
 7722 size estimates from each paper.³ Because not every paper reports stan-
 7723 dardized effect sizes—or even means and standard deviations for every
 7724 group—this process can often involve scraping information from plots,
 7725 tables, and statistical tests to try to reconstruct effect sizes.⁴

7726 Following best practices for meta-analysis (where there are almost never
 7727 privacy concerns to worry about), Paluck, Green, and Green (2019)
 7728 shared their data openly. The first few lines are shown in table 16.1.
 7729 We'll use these data as our running example throughout.

Table 16.1

First few lines of extracted effect sizes (d) and their variances (var_d) in the Paluck, Green, and Green (2019) meta-analysis.

name	pub_date	target	n_total	d	var_d
Boisjoly 06 B	2006	race	1243	0.030	0.006
Sorensen 10	2010	race	597	0.302	0.007

³ This book will not cover the process of conducting a systematic literature search and extracting effect sizes, but these topics are critical to understand if you plan to conduct a meta-analysis or other evidence synthesis. Our experience is that extracting effect sizes from papers with inconsistent reporting standards can be especially tricky, so it can be helpful to talk to someone with experience in meta-analysis to get advice about this.

⁴ For example, if the outcome variable is continuous, we could estimate Cohen's d from group means and standard deviations reported in the paper, even without having access to raw data.

Table 16.1

First few lines of extracted effect sizes (d) and their variances (var_d) in the Paluck, Green, and Green (2019) meta-analysis.

name	pub_date	target	n_total	d	var_d
Scacco 18	2018	religion	474	0.000	0.010
Finseraas 2017	2017	foreigners	577	0.000	0.011
Sheare 74	1974	disability	400	1.059	0.011
Barnhardt 09	2009	religion	312	0.395	0.015

⁷⁷³⁰ As we've seen throughout this book, visualizing data before and after
⁷⁷³¹ analysis helps benchmark and check our intuitions about the formal sta-
⁷⁷³² tistical results. In a meta-analysis, a common way to plot effect sizes
⁷⁷³³ is the **forest plot**, which depicts individual studies' estimates and con-
⁷⁷³⁴ fidence intervals.⁵ In the forest plot in figure 16.1, the larger squares
⁷⁷³⁵ correspond to more precise studies; notice how much narrower their
⁷⁷³⁶ confidence intervals are than the confidence intervals of less precise stud-
⁷⁷³⁷ ies.

⁵ You can ignore for now the column of percentages and the final line, "RE Model"; we will return to these later.

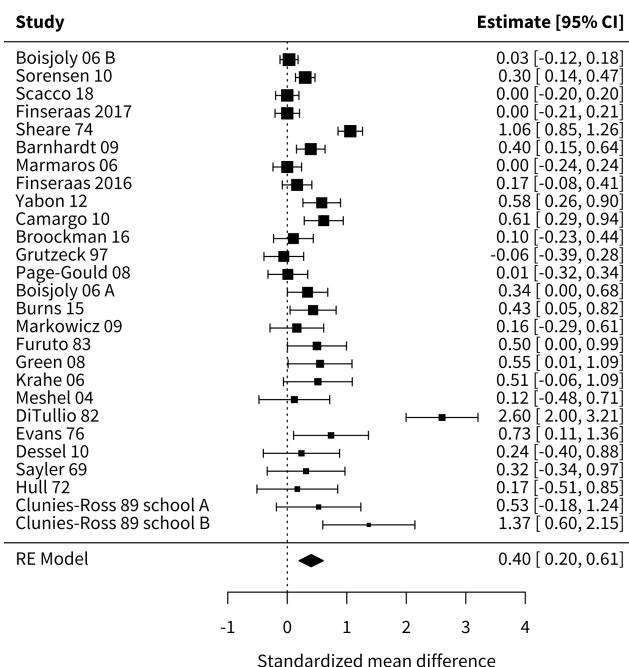


Figure 16.1

Forest plot for Paluck, Green, and Green (2019) meta-analysis. Studies are ordered from smallest to largest standard error.

CODE

In this chapter, we use the wonderful `metafor` package (Viechtbauer 2010). With this package, you must first fit your meta-analytic model. But once you've fit your model `mod`, you can simply call `forest(mod)` to create a plot like the one above.

7738

16.1.1 How not to synthesize evidence

7740 Many people's first instinct in evidence synthesis is to count how
 7741 many studies supported versus did not support the hypothesis under
 7742 investigation. This technique usually amounts to counting the num-

ber of studies with “significant” p -values, since—for better or for worse—“significance” is largely what drives the take-home conclusions researchers report (McShane and Gal 2017; Nelson, Rosenthal, and Rosnow 1986). In meta-analysis, we call this practice of counting the number of significant p -values **vote-counting** (Borenstein et al. 2021). For example, in the Paluck, Green, and Green (2019) meta-analysis, almost all studies had a positive effect size, but only 12 of 27 were significant. So, based on this vote-count, we would have the impression that most studies do not support the contact hypothesis.

Many qualitative literature reviews use this vote-counting approach, although often not explicitly. Despite its intuitive appeal, vote-counting can be very misleading because it characterizes evidence solely in terms of dichotomized p -values, while entirely ignoring effect sizes. In chapter 3, we saw how fetishizing statistical significance can mislead us when we consider individual studies. These problems also apply when considering multiple studies.

For example, small studies may consistently produce non-significant effects due to their limited power. But when many such studies are combined in a meta-analysis, the meta-analysis may provide strong evidence of a positive average effect. Inversely, many studies might have statistically significant effects, but if their effect sizes are small, then a meta-

7764 analysis might indicate that the average effect size is too small to be
7765 practically meaningful. In these cases, vote-counting based on statistical
7766 significance can lead us badly astray (Borenstein et al. 2021). To avoid
7767 these pitfalls, meta-analysis combines the effect size estimates from each
7768 study (not just their p -values), weighting them in a principled way.

7769 16.1.2 Fixed-effects meta-analysis

7770 If vote-counting is a bad idea, how should we combine results across
7771 studies? Another intuitive approach might be to average effect sizes
7772 from each study. For example, in Paluck et al.’s meta-analysis, the mean
7773 of the studies’ effect size estimates is 0.44. This averaging approach is a
7774 step in the right direction, but it has an important limitation: averaging
7775 effect size estimates gives equal weight to each study. A small study
7776 (e.g., Clunies-Ross and O’Meara 1989 with $N=30$) contributes as much
7777 to the mean effect size as a large study (e.g., Boisjoly et al. 2006 with
7778 $N=1243$). Larger studies provide more precise estimates of effect sizes
7779 than small studies, so weighting all studies equally is not ideal. Instead,
7780 larger studies should carry more weight in the analysis.

7781 To address this issue, **fixed-effects meta-analysis** uses a **weighted aver-**
7782 **age** approach. Larger, more precise studies are given more weight in the
7783 calculation of the overall effect size. Specifically, each study is weighted

⁷⁷⁸⁴ by the inverse of its variance (i.e., the inverse of its squared standard er-
⁷⁷⁸⁵ ror). This makes sense because larger, more precise studies have smaller
⁷⁷⁸⁶ variances, and thus get more weight in the analysis.

⁷⁷⁸⁷ In general terms, the fixed-effect pooled estimate is:

$$\hat{\mu} = \frac{\sum_{i=1}^k w_i \hat{\theta}_i}{\sum_{i=1}^k w_i}$$

⁷⁷⁸⁸ where k is the number of studies, $\hat{\theta}_i$ is the point estimate of the i^{th} study,
⁷⁷⁸⁹ and $w_i = 1/\hat{\sigma}_i^2$ is study i 's weight in the analysis (i.e., the inverse of its
⁷⁷⁹⁰ variance).⁶

⁷⁷⁹¹ Using the fixed-effects formula, we can estimate that the overall effect
⁷⁷⁹² size in Paluck et al.'s meta-analysis is a standardized mean difference of $\hat{\mu}$
⁷⁷⁹³ $= 0.28$; 95% confidence interval $[0.23, 0.34]$; $p < .001$. Because Cohen's
⁷⁷⁹⁴ d is our effect size index, this estimate would suggest that intergroup
⁷⁷⁹⁵ contact decreased prejudice by 0.28 standard deviations.

⁶ If you are curious, the standard error of the fixed-effect $\hat{\mu}$ is $\frac{1}{\sum_{i=1}^k w_i}$. This standard error can be used to construct a confidence interval or p -value, as described in chapter 6.

CODE

Fitting meta-analytic models in `metafor` is quite simple. For example, for the fixed effects model above, we simply ran the `rma()` function and specified that we wanted a fixed effects analysis.

```
fe_model <- rma(yi = d, vi = var_d, data = paluck, method = "FE")
```

Then `summary(fe_model)` gives us the relevant information about the

fitted model.

7797

7798 16.1.3 Limitations of fixed-effects meta-analysis

7799 One of the limitations of fixed-effect meta-analysis is that it assumes
7800 that the true effect size is, well, *fixed*! In other words, fixed-effect meta-
7801 analysis assumes that there is a single effect size that all studies are es-
7802 timating. This is a stringent assumption. It's easy to imagine that it
7803 could be violated. Imagine, for example, that intergroup contact de-
7804 creased prejudice when the group succeeded at its joint goal, but *in-*
7805 *creased* prejudice when the group failed. If we meta-analyzed two stud-
7806 ies under these conditions—one in which intergroup contact substan-
7807 tially increased prejudice, and one in which intergroup contact substan-
7808 tially decreased prejudice—it might appear that the true effect of inter-
7809 group contact was close to zero, when in fact both of the meta-analyzed
7810 studies had large effects.

7811 In Paluck et al.'s meta-analysis, studies differed in several ways that
7812 could lead to different true effects. For example, some studies recruited
7813 adult participants while others recruited children. If intergroup contact
7814 is more or less effective for adults versus children, then it is misleading
7815 to talk about a single (i.e., "fixed") intergroup contact effect. Instead,

7816 we would say that the effects of intergroup contact vary across studies,
7817 an idea called **heterogeneity**.

7818 Does the concept of heterogeneity remind you of anything from when
7819 we analyzed repeated-measures data in chapter 7 on models? Recall
7820 that, with repeated-measures data, we had to deal with the possibility
7821 of heterogeneity across participants—and of the ways we did so was by
7822 introducing participant-level random intercepts to our regression model.
7823 It turns out that we can do a similar thing in meta-analysis to deal with
7824 heterogeneity across studies.

7825 16.1.4 Random-effects meta-analysis

7826 While fixed-effect meta-analysis essentially assumes that all studies
7827 in the meta-analysis have the same population effect size, μ , random-
7828 effects meta-analysis instead assumes that study effects come from
7829 a normal distribution with mean μ and standard deviation τ .⁷ The
7830 larger the standard deviation, τ , the more heterogeneous the effects are
7831 across studies. A random-effects model then estimates both μ and τ ,
7832 for example by maximum likelihood (DerSimonian and Laird 1986;
7833 Brockwell and Gordon 2001).

7834 Like fixed-effect meta-analysis, the random-effects estimate of $\hat{\mu}$ is still

⁷ Technically, other specifications of random-effects meta-analysis are possible. For example, robust variance estimation does not require making assumptions about the distribution of effects across studies (Hedges, Tipton, and Johnson 2010). These approaches also have other substantial advantages, like their ability to handle effects that are clustered [e.g., because some papers contribute multiple estimates; Hedges, Tipton, and Johnson (2010); Pustejovsky and Tipton (2021)] and their ability to provide better inference in meta-analyses with relatively few studies (Tipton 2015). For these reasons, we often use these robust methods.

7835 a weighted average of studies' effect size estimates:

$$\hat{\mu} = \frac{\sum_{i=1}^k w_i \hat{\theta}_i}{\sum_{i=1}^k w_i}$$

7836 However, in random-effects meta-analysis, the inverse-variance

7837 weights now incorporate heterogeneity: $w_i = 1 / (\hat{\tau}^2 + \hat{\sigma}_i^2)$. Where

7838 before we had one term in our weights, now we have two. That

7839 is because these weights represent the inverse of studies' *marginal*

7840 variances, taking into account both statistical error due to their finite

7841 sample sizes ($\hat{\sigma}_i^2$ as before) and also genuine effect heterogeneity ($\hat{\tau}^2$).

7842 Conducting a random-effects meta-analysis of Paluck et al.'s dataset

7843 yields $\hat{\mu} = 0.4$; 95% confidence interval [0.2, 0.61]; $p < .001$. That

7844 is, *on average across studies*, intergroup contact was associated with a de-

7845 crease in prejudice of 0.4 standard deviations, substantially larger than

7846 the estimate from the fixed effects model. This meta-analytic estimate

7847 is shown as the bottom line of figure 16.1.

CODE

Fitting a random effects model requires only a small change to the methods argument of `rma()`. (We also include the `knha` flag that adds a correction to the computation of standard errors and p-values).

```
re_model <- rma(yi = d, vi = var_d, data = paluck, method = "REML", knha = TRUE)
```

7849 Based on the random effects model, intergroup contact effects appear
 7850 to differ across studies. Paluck et al. estimated that the standard devi-
 7851 ation of effects across studies was $\hat{\tau} = 0.44$; 95% confidence interval
 7852 [0.25, 0.57]. This estimate indicates a substantial amount of heterogene-
 7853 ity! To visualize these results, we can plot the estimated density of the
 7854 population effects, which is just a normal distribution with mean $\hat{\mu}$ and
 7855 standard deviation $\hat{\tau}$ (figure 16.2).

7856 This meta-analysis highlights an important point: that the overall effect
 7857 size estimate $\hat{\mu}$ represents only the *mean* population effect across studies.
 7858 It tells us nothing about how much the effects *vary* across studies. Thus,
 7859 we recommend always reporting the heterogeneity estimate $\hat{\tau}$, prefer-
 7860 ably along with other related metrics that help summarize the distribu-
 7861 tion of effect sizes across studies (Riley, Higgins, and Deeks 2011; Wang
 7862 and Lee 2019; Mathur and VanderWeele 2019, 2020a). Reporting the
 7863 heterogeneity helps readers know how consistent or inconsistent the ef-
 7864 fects are across studies, which may point to the need to investigate *mod-
 7865 erators* of the effect (i.e., factors that are associated with larger or smaller
 7866 effects, such as whether participants were adults or children).⁸

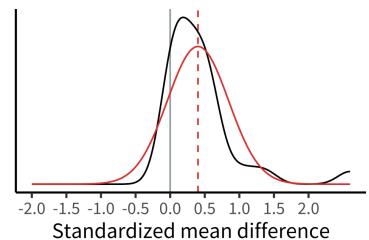


Figure 16.2
 Estimated distribution of population ef-
 fects from random-effects meta-analysis
 of Paluck et. al's dataset (heavy red
 curve) and estimated density of studies'
 point estimates (thin black curve).

⁸ One common approach to investi-
 gating moderators in meta-analysis is
 meta-regression, in which moderators
 are included as covariates in a random-
 effects meta-analysis model (Thompson
 and Higgins 2002). As in standard re-
 gression, coefficients can then be esti-
 mated for each moderator, representing
 the mean difference in population effect
 between studies with versus without the
 moderator.

 DEPTH

Single-paper meta-analysis and pooled analysis

Thus far, we have described meta-analysis as a tool for summarizing results reported across multiple papers. However, some people have argued that meta-analysis should also be used to summarize the results of multiple studies reported in a single paper (Goh, Hall, and Rosenthal 2016).

For instance, in a paper where you describe 3 different experiments on a hypothesis, you could (1) extract summary information (e.g., M 's and SD 's) from each study, (2) compute the effect size, and then (3) combine the effect sizes in a meta-analysis.

Single-paper meta-analyses come with many of the same strengths and weaknesses we have discussed thus far. One unique weakness, though, is that having a small number of studies means that you typically have low power to detect heterogeneity and moderators. This lack of power sometimes leads researchers to claim that there are no significant differences between their studies. But an alternative explanation is that there simply wasn't enough power to detect those differences!

As an alternative, you can also pool the actual data from the three studies, as opposed to just pooling summary statistics. For example, if you have data from 10 participants in each of the 3 experiments, you could pool them into a single dataset with 30 participants and include random effects of your condition manipulation across experiments (as described in chapter 7). This strategy is often referred to as **pooled** or **integrative**

data analysis (and occasionally as “mega-analysis”, which sounds cool).

Study 1			Pooled data analysis			Meta-analysis									
Study	Participant	Group	Prejudice	Age	Study	Participant	Group	Prejudice	Age	Study	Effect size (d)	Age			
1	1	Treatment	2	18	1	1	Treatment	2	18	1	8	18			
1	2	Treatment	2	18	1	2	Treatment	2	18	2	5	24			
1	3	Treatment	2	18	1	3	Treatment	2	18	3	1	45			
1	4	Treatment	2	18	1	4	Treatment	2	18						
1	5	Treatment	2	18	1	5	Treatment	2	18						
1	6	Control	10	18	1	6	Control	10	18						
1	7	Control	10	18	1	7	Control	10	18						
1	8	Control	10	18	1	8	Control	10	18						
1	9	Control	10	18	1	9	Control	10	18						
1	10	Control	10	18	1	10	Control	10	18						
Study 2			Pooled data analysis			Meta-analysis									
Study	Participant	Group	Prejudice	Age	Study	Participant	Group	Prejudice	Age	Study	Effect size (d)	Age	Study	Effect size (d)	Age
2	1	Treatment	5	24	2	2	Treatment	5	24	2	2	24	2	2	24
2	2	Treatment	5	24	2	4	Treatment	5	24	2	3	24	2	4	24
2	3	Treatment	5	24	2	5	Treatment	5	24	2	5	24	2	6	24
2	4	Treatment	5	24	2	6	Control	10	24	2	7	24	2	7	24
2	5	Treatment	5	24	2	8	Control	10	24	2	9	24	2	8	24
2	6	Control	10	24	2	10	Control	10	24	2	10	24	2	10	24
2	7	Control	10	24	3	1	Treatment	9	45	3	2	45	3	2	45
2	8	Control	10	24	3	3	Treatment	9	45	3	3	45	3	3	45
2	9	Control	10	24	3	4	Treatment	9	45	3	5	45	3	4	45
2	10	Control	10	24	3	6	Control	10	45	3	7	45	3	6	45
Study 3			Pooled data analysis			Meta-analysis									
Study	Participant	Group	Prejudice	Age	Study	Participant	Group	Prejudice	Age	Study	Effect size (d)	Age	Study	Effect size (d)	Age
3	1	Treatment	9	45	3	7	Control	10	45	3	8	45	3	9	45
3	2	Treatment	9	45	3	10	Control	10	45	3	10	45	3	10	45
3	3	Treatment	9	45											
3	4	Treatment	9	45											
3	5	Treatment	9	45											
3	6	Control	10	45											
3	7	Control	10	45											
3	8	Control	10	45											
3	9	Control	10	45											
3	10	Control	10	45											

Figure 16.3
Meta-analysis vs. pooled data analysis.

One of the benefits of pooled data analysis is that it can give you more power to detect moderators. For instance, imagine that the effect of an intergroup contact treatment is moderated by age. If we performed a traditional meta-analysis, we would only have three observations in our data set, yielding very low power. However, we have many more observations (and much more variation in the moderator) in the pooled data analysis, which can lead to higher power (figure 16.3).

Pooled data analysis is not without its own limitations (Cooper and Patall 2009). And, of course, sometimes it doesn't make as much sense to pool datasets (e.g., when measures are different from one another). Nonetheless, we believe that pooled data analysis and meta-analysis are both useful tools to keep in mind in a paper reporting multiple experiments!

7869 *16.2 Bias in meta-analysis*

7870 Meta-analysis is a great tool for synthesizing evidence across studies, but
7871 the accuracy of a meta-analysis can be compromised by bias. We'll talk
7872 about two categories of bias here: **within-study** and **across-study** biases.
7873 Either type can lead to meta-analytic estimates that are too large, too
7874 small, or even in the wrong direction altogether.

7875 *16.2.1 Within-study biases*

7876 Within-study biases—such as demand characteristics, confounds, and
7877 order effects, all discussed in chapter 9—not only impact the validity of
7878 individual studies, but also any attempt to synthesize those studies. And
7879 of course, if individual study results are affected by analytic flexibility
7880 (*p*-hacking), meta-analyzing these will result in inflated effect size esti-
7881 mates. In other words: garbage in, garbage out.

7882 For example, Paluck, Green, and Green (2019) noted that early stud-
7883 ies on intergroup contact almost exclusively used non-randomized de-
7884 signs. Imagine a hypothetical study where researchers studied a com-
7885 pletely ineffective intergroup contact intervention, and non-randomly
7886 assigned low-prejudice people to the intergroup contact condition and
7887 high-prejudice people to the control condition. In a scenario like this,
7888 the researcher would of course find that the prejudice was lower in the

7889 intergroup contact condition. But the effect would not be a true contact
7890 intervention effect, but rather a spurious effect of non-random assign-
7891 ment (i.e., confounding). Now imagine meta-analyzing many studies
7892 with similarly poor designs. The meta-analyst might find impressive
7893 evidence of an intergroup contact effect, even if none existed.

7894 To mitigate this problem, meta-analysts often exclude studies that
7895 may be especially affected by within-study bias. (For example, Paluck,
7896 Green, and Green 2019 excluded non-randomized studies). Of course,
7897 these decisions can't be made on the basis of their effects on the
7898 meta-analytic estimate or else this post-hoc exclusion itself will lead to
7899 bias! For this reason, inclusion and exclusion criteria for meta-analyses
7900 should be preregistered whenever possible.

7901 Sometimes certain sources of bias cannot be eliminated by excluding
7902 studies—often because studies in a particular domain share certain fun-
7903 damental limitations (for example, attrition in drug trials). After data
7904 have been collected, meta-analysts should also assess studies' risks of bias
7905 qualitatively using established rating tools (Sterne et al. 2016). Doing so
7906 allows the meta-analyst to communicate how much within-study bias
7907 there may be.⁹

7908 Meta-analysts can also conduct sensitivity analyses to assess how much
7909 results might be affected by different within-study biases or by exclud-

⁹ If you're interested in assessing within-study bias, you can take a look at the Risk of Bias tool (<https://sites.google.com/site/riskofbiastool/welcome/rob-2-0-tool>) developed by Cochrane, an organization devoted to evidence synthesis.

7910 ing certain types of studies (Mathur and VanderWeele 2022). For exam-
7911 ple, if nonrandom assignment is a concern, a meta-analyst may run the
7912 analyses including only randomized studies, versus including all stud-
7913 ies, in order to determine how much including nonrandomized stud-
7914 ies changes the meta-analytic estimate. These two options parallel our
7915 discussion of experimental preregistration in chapter 11: To allay con-
7916 cerns about results-dependent meta-analysis, researchers can either pre-
7917 register their analyses ahead of time or else be transparent about their
7918 choices after the fact. Sensitivity analyses can allay concerns that a spe-
7919 cific choice of exclusion criteria is critically related to the reported re-
7920 sults.

7921 16.2.2 *Across-study biases*

7922 Across-study biases occur if, for example, researchers selectively report
7923 certain types of findings or selectively publish certain types of findings
7924 (publication bias, as discussed in chapter 3 and chapter 11). Often, these
7925 across-study biases favor statistically-significant positive results, which
7926 means the meta-analytic estimate based on those studies will be inflated
7927 relative to the true effect.

 ACCIDENT REPORT

Quantifying publication bias in the social sciences

It's typically very hard to quantify publication bias because you don't know how many studies are out there in researchers' "file drawers"—unpublished studies are by definition not available. But a recent study took advantage of a unique opportunity to try and quantify publication bias within a known pool of studies.

Time-sharing Experiments in the Social Sciences (TESS) is an innovative project that lets researchers apply to run experiments on nationally-representative samples in the U.S. In 2014, Franco, Malhotra, and Simonovits (2014) and colleagues took advantage of this application process by examining the entire population of 221 studies conducted through TESS.

Using this information, Franco and colleagues examined the records of these studies to determine whether the researchers found statistically significant results, a mixture of statistically significant and non-significant results, or only non-significant results. Then, they examined the likelihood that these results were published in the scientific literature.

Over 60% of studies with statistically significant results were published, compared to a mere 25% of studies that produced only statistically non-significant results. This finding was important because it quantified how strong publication bias actually was, at least in one particular population of studies. This estimate may not be general: for example, perhaps TESS

studies were easier to put in the file drawer because they cost nothing for the researchers to run. But even a lower level of publication bias can have a substantial effect on a meta-analysis, meaning that it is crucial to check for—and potentially, correct for—publication bias.

7929

Like within-study biases, meta-analysts often try to mitigate across-study biases by being careful about what studies make it into the meta-analysis. Meta-analysts don't only want to capture high-profile, published studies on their effect of interest, but also studies published in low-profile journals and the so-called “gray literature” [i.e., unpublished dissertations and theses; Lefebvre et al. (2019)].¹⁰

There are also statistical methods to help assess how robust the results may be to across-study biases. Among the most popular tools to assess and correct for publication bias is the funnel plot (Duval and Tweedie 2000; Egger et al. 1997). A funnel plot shows the relationship between studies' effect estimates and their precision (usually their standard error). These plots are called “funnel plots” because if there is no publication bias, then as precision increases, the effects “funnel” towards the meta-analytic estimate. As the precision is smaller, they spread out more because of greater measurement error. Figure 16.4 is an example of one type of funnel plot (Mathur and VanderWeele 2020b) for a simulated meta-analysis of 100 studies with no publication bias.

Tsuji et al. 2020 Mathur and VanderWeele 2021

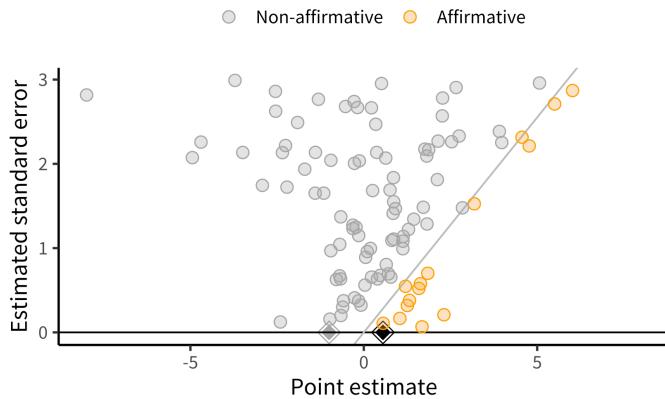


Figure 16.4

Significance funnel plot for a meta-analysis simulated to have no publication bias. Orange points: studies with $p < 0.05$ and positive estimates. Grey points: studies with $p \geq 0.05$ or negative estimates. Black diamond: random-effects estimate of $\hat{\mu}$.

CODE

For this plot, we use the `PublicationBias` package and the `significance_funnel()` function. (An alternative function is the `metafor` function `funnel()`, which results in a more “classic” funnel plot.) We use our fitted model `re_model`:

```
significance_funnel(yi = re_model$yi, vi = re_model$vi)
```

Because meta-analysis is such a well-established method, many of the relevant operations are “plug and play.”

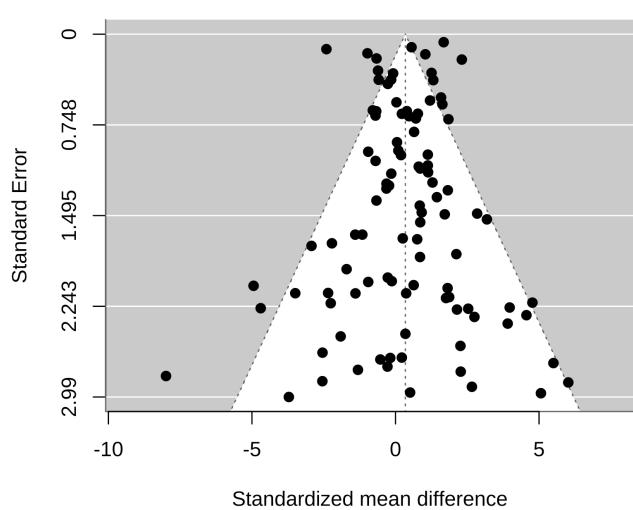


Figure 16.5
Classic funnel plot.

⁷⁹⁴⁸ As implied by the “funnel” moniker, our plot looks a little like a funnel.

⁷⁹⁴⁹ Larger studies (those with smaller standard errors) cluster more closely

⁷⁹⁵⁰ around the mean of 0.34 than do smaller studies, but large and small

⁷⁹⁵¹ studies alike have point estimates centered around the mean. That is,

⁷⁹⁵² the funnel plot is symmetric.¹¹

⁷⁹⁵³ Not all funnel plots are symmetric! figure 16.6 is what happens to our

⁷⁹⁵⁴ hypothetical meta-analysis if all studies with $p < 0.05$ and positive es-

⁷⁹⁵⁵ timates are published, but only 10% of studies with $p \geq 0.05$ or with

⁷⁹⁵⁶ negative estimates are published. The introduction of publication bias

⁷⁹⁵⁷ dramatically inflates the pooled estimate from 0.34 to 1.15. Also, there

⁷⁹⁵⁸ appears to be a correlation between studies’ estimates and their stan-

⁷⁹⁵⁹ dard errors, such that smaller studies tend to have larger estimates than

¹¹ Classic funnel plots look more like figure 16.5). Our version is different in a couple of ways. Most prominently, we don’t have the vertical axis reversed (which we think is confusing). We also don’t have the left boundary highlighted, because we think folks don’t typically select for negative studies.

7960 do larger studies. This correlation is often called **funnel plot asymmetry**
 7961 because the funnel plot starts to look like a right triangle rather than a
 7962 funnel. Funnel plot asymmetry *can* be a diagnostic for publication bias,
 7963 though it isn't always a perfect indicator, as we'll see in the next subsec-
 7964 tion.

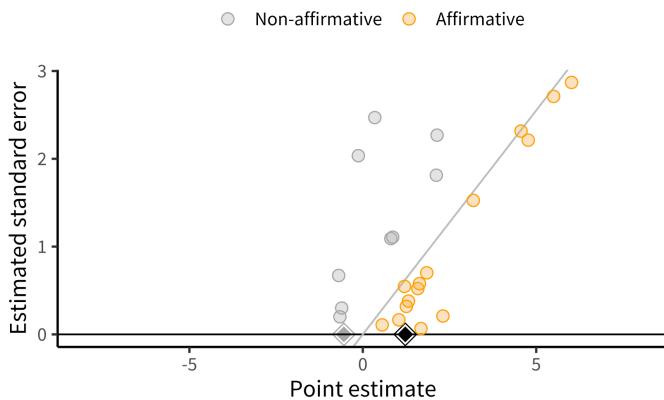


Figure 16.6

Significance funnel plot for the same simulated meta-analysis after publication bias has occurred. Orange points: studies with $p < 0.05$ and positive estimates. Grey points: studies with $p \geq 0.05$ or negative estimates. Black diamond: random-effects estimate of $\hat{\mu}$.

7965 16.2.1 Across-study bias correction

7966 How do we identify and correct bias across studies? Given that some
 7967 forms of publication bias induce a correlation between studies' point
 7968 estimates and their standard errors, several popular statistical methods,
 7969 such as Trim-and-Fill (Duval and Tweedie 2000) and Egger's regression
 7970 (Egger et al. 1997) are designed to quantify funnel plot asymmetry.

7971 Funnel plot asymmetry does not always imply that there is publication
 7972 bias, though. Nor does publication bias always cause funnel plot asym-
 7973 metry. Sometimes funnel plot asymmetry is driven by genuine differ-

7974 ences in the effects being studied in small and large studies (Egger et al.
7975 1997; Lau et al. 2006). For example, in a meta-analysis of intervention
7976 studies, if the most effective interventions are also the most expensive
7977 or difficult to implement, these highly effective interventions might be
7978 used primarily in the smallest studies (“small study effects”).

7979 Funnel plots and related methods are best suited to detecting publication
7980 bias in which (1) small studies with large positive point estimates are
7981 more likely to be published than small studies with small or negative
7982 point estimates; and (2) the largest studies are published regardless of
7983 the magnitude of their point estimates. That model of publication bias
7984 is sometimes what is happening, but not always!

7985 A more flexible approach for detecting publication bias uses **selection**
7986 **models**. These models can detect other forms of publication bias that
7987 funnel plots may not detect, such as publication bias that favors *significant*
7988 results. We won’t cover these methods in detail here, but we think
7989 they are a better approach to the question, along with related sensitivity
7990 analyses.¹²

7991 You may also have heard of “*p*-methods” to detect across-study biases
7992 such as *p*-curve and *p*-uniform (Simonsohn, Nelson, and Simmons
7993 2014; Van Assen, Aert, and Wicherts 2015). These methods essentially
7994 assess whether the significant *p*-values “bunch up” just under 0.05,

¹² High-level overviews of selection models are given in McShane, Böckenholt, and Hansen (2016) and Maier, VanderWeele, and Mathur (2022). For more methodological detail, see Hedges (1984), Iyengar and Greenhouse (1988), and Vevea and Hedges (1995). For a tutorial on fitting and interpreting selection models, see Maier, VanderWeele, and Mathur (2022). For sensitivity analyses, see Mathur and VanderWeele (2020b).

7995 which is taken to indicate publication bias. These methods are increas-
7996 ingly popular in psychology and have their merits. However, they are
7997 actually simplified versions of selection models (e.g., Hedges 1984) that
7998 work only under considerably more restrictive settings than the original
7999 selection models [for example, when there is not heterogeneity across
8000 studies; McShane, Böckenholt, and Hansen (2016)]. For this reason, it
8001 is usually (although not always) better to use selection models in place
8002 of the more restrictive *p*-methods.

8003 Going back to our running example, Paluck et al. used a regression-
8004 based approach to assess and correct for publication bias. This approach
8005 provided significant evidence of a relationship between the standard
8006 error and effect size (i.e., an asymmetric funnel plot). Again, this asym-
8007 metry could reflect publication bias or other sources of correlation be-
8008 tween studies' estimates and their standard errors. Paluck et al. also used
8009 this same regression-based approach to try to correct for potential pub-
8010 lication bias. Results from this model indicated that the bias-corrected
8011 effect size estimate was close to zero. In other words, even though
8012 all studies estimated that intergroup contact decreased prejudice, it is
8013 still possible that there are unpublished studies that did not find this (or
8014 found that intergroup contact increased prejudice).

 ACCIDENT REPORT

Garbage in, garbage out? Meta-analyzing potentially problematic research

Botox can help eliminate wrinkles. But some researchers have suggested that, when used to paralyze the muscles associated with frowning, Botox may also help treat clinical depression. As surprising as this claim may sound, a quick examination of the literature would lead many to conclude that this treatment works. Studies that randomly assign depressed patients to receive either Botox or saline injections do indeed find that Botox recipients show decreased depression. And when you combine all available evidence in a meta-analysis, you find that this effect is quite large: $d = 0.83$, 95% CI [0.52, 1.14].

As Coles et al. (2019) argued though, this estimated effect may be impacted by both within- and between-study bias. First, participants are not supposed to know whether they have been randomly assigned to receive Botox or a control saline injections. But only one of these treatments leads the upper half of your face to be paralyzed! After a couple weeks, you're pretty likely to know whether you received the Botox treatment or control saline injection. Thus, the apparent effect of Botox on depression could instead be a placebo effect.

Second, only 50% of the outcomes that researchers measured were reported in the final publications, raising concerns about selective reporting. Perhaps researchers examining the effects of Botox on depression

only reported the measures that showed a positive effect, not the ones that didn't.

Taken together, these two criticisms suggest that, despite the impressive meta-analytic estimate, the effect of Botox on depression is far from certain.

8016

8017 16.3 Chapter summary: Meta-analysis

8018 Taken together, Paluck and colleagues' use of meta-analysis provided
8019 several important insights that would have been easy to miss in a non-
8020 quantitative review. First, despite a preponderance of non-significant
8021 findings, intergroup contact interventions were estimated to decrease
8022 prejudice by on average 0.4 standard deviations. On the other hand,
8023 there was considerable heterogeneity in intergroup contact effects, sug-
8024 gesting important moderators of the effectiveness of these interventions.
8025 And finally, publication bias was a substantial concern, indicating a need
8026 for follow-up research using a registered report format that will be pub-
8027 lished regardless of whether the outcome is positive (chapter 11).

8028 Overall, meta-analysis is a key technique for aggregating evidence across
8029 studies. Meta-analysis allows researchers to move beyond the bias of
8030 naive techniques like vote counting and towards a more quantitative
8031 summary of an experimental effect. Unfortunately, a meta-analysis is

8032 only as good as the literature it's based on, so the aspiring meta-analyst
8033 must be aware of both within- and between-study biases!



DISCUSSION QUESTIONS

1. Imagine that you read the following result in the abstract of a meta-analysis: "In 83 randomized studies of middle school children, replacing one hour of class time with mindfulness meditation significantly improved standardized test scores (standardized mean difference $\hat{\mu} = 0.05$; 95% confidence interval: [0.01, 0.09]; $p < 0.05$).". Why is this a problematic way to report on meta-analysis results? Suggest a better sentence to replace this one.
2. As you read the rest of the meta-analysis, you find that the authors conclude that "These findings demonstrate robust benefits of meditation for children, suggesting that test scores improve even when the meditation is introduced as a replacement for normal class time." You recall that the heterogeneity estimate was $\hat{\tau} = 0.90$. Do you think that this result regarding the heterogeneity tends to support, or rather tends to undermine, the concluding sentence of the meta-analysis? Why?
3. What kinds of within-study biases would concern you in the meta-analysis described in the prior two questions? How might you assess the credibility of the meta-analyzed studies and of the meta-analysis as whole in light of these possible biases?
4. Imagine you conduct a meta-analysis on a literature in which statistically significant results in either direction are much more likely to

be published that non-significant results. Draw the funnel plot you would expect to see. Is the plot symmetric or asymmetric?

5. Why do you think small studies receive more weight in random-effects meta-analysis than in fixed-effects meta-analysis? Can you see why this is true mathematically based on the equations given above, and can you also explain the intuition in simple language?

8035

READINGS

- A nice, free textbook with lots of good code examples: Harrer, M., Cuijpers, P., Furukawa, T., & Ebert, D. (2022). Doing Meta-Analysis with R: A Hands-On Guide. Chapman & Hall/CRC Press. Available free online at https://bookdown.org/MathiasHarrer/Doing_Meta_Analysis_in_R/.

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17 CONCLUSION

8044 You've made it to the end of Experimentology, our (sometimes opin-
8045 ionated) guide to how to run good psychology experiments. In this
8046 book we've tried to present a unified approach to the why and how
8047 of running experiments. This approach begins with the goal of doing
8048 experiments:
8049

8050 Experiments are intended to make maximally unbiased,
8051 generalizable, and precise estimates of specific causal
8052 effects.

8053 This formulation isn't exactly how experiments are talked about in the
8054 broader field, but we hope you've started to see some of the rationale
8055 behind this approach. In this final chapter, we will briefly discuss
8056 some aspects of our approach, as well how this approach connects
8057 with our four themes, TRANSPARENCY, MEASUREMENT PRECISION, BIAS

8058 REDUCTION, and GENERALIZABILITY. We'll end by mentioning some
8059 exciting new trends in the field that give us hope about the future of
8060 experimentology and psychology more broadly.

8061 *17.1 Summarizing our approach*

8062 The Experimentology approach is grounded in both an appreciation of
8063 the power of experiments to reveal important aspects about human psy-
8064 chology and also an understanding of the many ways that experiments
8065 can fail. In particular, the “replication crisis” (chapter 3) has revealed
8066 that small samples, a focus on dichotomous statistical inference, and a
8067 lack of transparency around data analysis can lead to a literature that is
8068 often neither reproducible nor replicable. Our approach is designed to
8069 avoid these pitfalls.

8070 We focus on MEASUREMENT PRECISION in service of measuring causal ef-
8071 fects. The emphasis on causal effects stems from an acknowledgement
8072 of the key role of experiments in establishing causal inferences (chap-
8073 ter 1) and the importance of causal relationships to theories (chapter 2).

8074 In our statistical approach, we focus on estimation (chapter 5) and mod-
8075 eling (chapter 7), helping us to avoid some of the fallacies that come
8076 along with dichotomous inference (chapter 6). We choose measures to
8077 maximize reliability (chapter 8). We prefer simple, within-participant

8078 experimental designs because they typically result in more precise es-
8079 timates (chapter 9). And we think meta-analytically about the over-
8080 all evidence for a particular effect beyond our individual experiment
8081 (chapter 16).

8082 Further, we recognize the presence of many potential sources of bias in
8083 our estimates, leading us to focus on BIAS REDUCTION. In our measure-
8084 ments, we identify arguments for the validity of our measures, decreas-
8085 ing bias in estimation of the key constructs of interest (chapter 8); in our
8086 designs we seek to minimize bias due to confounding or experimenter
8087 effects (chapter 9). We also try to minimize the possibility of bias in
8088 our decisions about data collection (chapter 12) and data analysis (chap-
8089 ter 11). Finally, we recognize the possibility of bias in literatures as a
8090 whole and consider ways to compensate in our estimates (chapter 16).

8091 Finally, we consider GENERALIZABILITY throughout the process. We the-
8092 orize with respect to a particular population (chapter 2) and select our
8093 sample in order to maximize the generalizability of our findings to that
8094 target population (chapter 10). In our statistical analysis, we take into
8095 account multiple dimensions of generalizability, including across par-
8096 ticipants and experimental stimulus items (chapter 7). And in our re-
8097 porting, we contextualize our findings with respect to limits on their
8098 generalizability (chapter 14).

8099 Woven throughout this narrative is the hope that embracing TRANS-
8100 PARENCEY throughout the experimental process will help you maximize
8101 your work. Not only is sharing your work openly an ethical responsi-
8102 bility (chapter 4), it's also a great way to minimize errors while creating
8103 valuable products that both advance scientific progress and accelerate
8104 your own career (chapter 13).

8105 *17.2 Forward the field*

8106 We have focused especially on reproducibility and replicability issues,
8107 but we've learned at various points in this book that there's a replica-
8108 tion crisis (Open Science Collaboration 2015), a theory crisis (Oberauer
8109 and Lewandowsky 2019), and a generalizability crisis (Yarkoni 2020) in
8110 psychology. Based on all these crises, you might think that we are pes-
8111 simistic about the future of psychology. Not so.

8112 There have been tremendous changes in psychological methods since
8113 we started teaching Experimental Methods in 2012. When we began,
8114 it was common for incoming graduate students to describe the ram-
8115 pant *p*-hacking they had been encouraged to do in their undergraduate
8116 labs. Now, students join the class aware of new practices like preregis-
8117 tration and cognizant of problems of generalizability and theory build-
8118 ing. It takes a long time for a field to change, but we have seen tremen-

8119 dous progress at every level—from government policies requiring trans-
8120 parency in the sciences all the way down to individual researchers’ adop-
8121 tion of tools and practices that increase the efficiency of their work and
8122 decrease the chances of error.

8123 One of the most exciting trends has been the rise of meta-science, in
8124 which researchers use the tools of science to understand how to make
8125 science better (Tom E. Hardwicke et al. 2020). Reproducibility and
8126 replicability projects (reviewed in chapter 3) can help us measure the
8127 robustness of the scientific literature. In addition, studies that evalua-
8128 ate the impacts of new policies (e.g., Tom E. Hardwicke et al. 2018)—
8129 can help stakeholders like journal editors and funders make informed
8130 choices about how to push the field towards more robust science.

8131 In addition to changes that correct methodological issues, the last ten
8132 years have seen the rise of “big team science” efforts that advance the
8133 field in new ways (Coles et al. 2022). Collaborations such as the Psy-
8134 chological Science Accelerator (Moshontz et al. 2018) and ManyBabies
8135 (Frank et al. 2017) allow hundreds of researchers from around the world
8136 to come together to run shared projects. These projects are enabled by
8137 open science practices like data and code sharing, and they provide a
8138 way for researchers to learn best practices via participating. In addition,
8139 by including broader and more diverse samples they can help address

8140 challenges around generalizability (Klein et al. 2018).

8141 Finally, the last ten years have seen huge progress in the use of statisti-
8142 cal models both for understanding data (McElreath 2018) and for de-
8143 scribing specific psychological mechanisms (Ma, Körding, and Goldre-
8144 ich 2022). In our own work we have used these models extensively and
8145 we believe that they provide an exciting toolkit for building quantita-
8146 tive theories that allow us to explain and to predict the human mind.

8147 *17.3 Final thoughts*

8148 Doing experiments is a craft, one that requires practice and attention.
8149 The first experiment you run will have limitations and issues. So will
8150 the 100th. But as you refine your skills, the quality of the studies you
8151 design will get better. Further, your own ability to judge others' exper-
8152 iments will improve as well, making you a more discerning consumer
8153 of empirical results. We hope you enjoy this journey!

8154 *References*

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8157 A INSTRUCTOR'S GUIDE

8158 *A.1 Introduction*

8159 This is an instructor's guide to conducting replication projects in courses.
8160 In addition to benefiting the field in ways that have been previously dis-
8161 cussed by some of the authors of this book (e.g., Hawkins et al. (2018),
8162 Frank and Saxe (2012)), replication-based courses can additionally ben-
8163 efit students in these courses. In this guide, we will describe these bene-
8164 fits, explore different ways in which courses may be modified depending
8165 on student level and resources, and provide some guidelines and exam-
8166 ples to help you set up the logistics of your course.

8167 *A.2 Why Teach a Project-Based Course?*

8168 Over the years, we have observed many ways in which our replication-
8169 based courses benefited students above and beyond a more traditional

8170 lecture and problem set-based course. Some of these benefits include:

- 8171 – **Student interest:** Since each student will be free to replicate a
study that is aligned with their research interests, this freedom fa-
cilitates a more direct application of course methods and lessons
8174 to a project that is interesting to each student.
- 8175 – **Usefulness:** If this course is taught in the first year of the program
8176 (as recommended), students may use their replication project as
8177 a way to establish robustness of a phenomenon before building
8178 studies on top of it.
- 8179 – **Realism:** Practice datasets that are typically provided for course
8180 exercises lack the complexity and messiness of real data. By con-
8181 ducting a replication project and dealing with real data, students
8182 learn to apply the tools provided in the course in a way that more
8183 closely demonstrates their usefulness beyond the course.
- 8184 – **Intuition:** Presentations of replication outcomes across the class
8185 along with a discussion of what factors seemed to predict these
8186 outcomes helps students develop a better intuition when reading
8187 the literature for how likely studies are to replicate.
- 8188 – **Perspective:** Frustrating experiences with ambiguity (whether re-
8189 garding experimental methods, materials, or analyses) can moti-
8190 vate students to adopt best practices for their own future studies.

8191 A project-based course may look very different depending on student
8192 level (undergraduate vs. graduate/post-doc level) and availability of re-
8193 sources at your institution for a course like this, namely in terms of TA
8194 support and course funding (for data collection). For most of this guide,
8195 we will assume that you have a similar setup to ours (i.e., teaching at the
8196 graduate/post-doc level and have course funding and TAs to support
8197 the course), but we have also spent some time considering ways to ad-
8198 just the course to fit different student levels and availability of resources
8199 (see “Scenarios for different course layouts”).

8200 *A.3 Logistics*

8201 *A.3.1 Syllabus considerations*

8202 If it is your first time teaching this course, you may want to decide ahead
8203 of time whether your course will mainly focus on content, or whether
8204 you will cover *both* content and relevant practical skills. For instance,
8205 if the course is for undergraduate students, you may decide to focus
8206 mainly on content, whereas if the course is for graduate students, they
8207 may find it more useful if the course covers both content and practical
8208 skills they can use in their research.

8209 Another important consideration is how long your course will be. De-
8210 pending on whether your university operates on quarters or semesters,
8211 the pace of the course will differ. For Psych 251, since we are on the
8212 quarter system, we use the 10-week schedule shown below. However,
8213 we have also adapted this schedule to a 16-week course given that it
8214 better represents a majority of other institutions' academic calendars. At
8215 the end of this chapter, we give a set of sample class schedules.

8216 *A.3.2 Grading*

8217 Depending on your course format and teaching philosophy, you may
8218 have preferred grading criteria. As a point of reference, in Psych 251,
8219 we wanted to encompass both the assignments (problemsets and project
8220 components) as well as actual course attendance and participation. In
8221 addition, because the replication project is a central part of the course,
8222 we weighted the project components slightly more than the problem
8223 sets:

- 8224 – 40%: Problem sets (four, at 10% each)
- 8225 – 50%: Final project components, including presentations, data col-
8226 lection, analysis, and writeup
- 8227 – 10%: Attendance and participation in class

8228 *A.3.3 Course budget*

8229 For our course, we usually receive around US\$1,000 for course
8230 funding from the Psychology Department. In addition, when students
8231 from other departments are enrolled, we have been lucky to receive
8232 additional funding from those departments as well, to further support
8233 the course. Still, making sure that the course funds cover all students'
8234 projects is one of the most challenging parts of the course. Assuming
8235 you have a budget to work with, here are some lessons we've learned
8236 along the way regarding budgeting (and if you don't have any funding,
8237 please refer to the section titled "Course Funding" under "Scenarios
8238 for different course layouts"):

- 8239 – Before students pick their study to replicate, provide them with
8240 an estimate of how many participant hours they will be able to
8241 receive for their project
- 8242 – As soon as students pick a study for their replication project, help
8243 each student run a power analysis to confirm that replicating the
8244 study would be within the budget (TAs can help with this)
- 8245 – If a student feels strongly about a study that does not fit within the
8246 budget, consider the following ways to adjust the study: 1) can the
8247 study be made shorter by cutting out unnecessary measures? 2) if
8248 it is a multi-trial study, can the number of trials be reduced? 3)

8249 would their advisors be willing to provide additional funding? 4)

8250 can the study be run on university participant pools?

8251 – As mentioned above, if there are students from other departments

8252 who are enrolled in your course, one possibility to obtain more

8253 funding is to reach out to the heads of those departments to see

8254 whether they would be willing to help support your course.

8255 Once all projects have been approved as within-budget, we encourage

8256 you to create a shared spreadsheet containing each student's name, so

8257 that they can fill in the details of their replication project. Ultimately,

8258 this will help ensure that students are paying fair wages to their parti-

8259 pants and keep track of how the course funds are being divided up.

8260 *A.3.4 Course-related Institutional Review Board application*

8261 While it may be possible to apply for individual IRB approval for each

8262 student's project, we recommend applying for course-wide standard

8263 IRB approval for all replication projects that are conducted in your class.

8264 Contacting your review board early in the planning stages of the course

8265 should clarify what options you have available.

8266 One important thing to remember when students run their individual

8267 projects is that they should have the course-wide consent form at the

8268 beginning of their studies (and TAs should check this when they review
8269 the paradigms). For reference, this is the consent form that each student
8270 is required to post at the beginning of their study:

8271 “By answering the following questions, you are participating in a study
8272 being performed by cognitive scientists in the Stanford Department of
8273 Psychology. If you have questions about this research, please contact us
8274 at stanfordpsych251@gmail.com. You must be at least 18 years old to
8275 participate. Your participation in this research is voluntary. You may
8276 decline to answer any or all of the following questions. You may de-
8277 cline further participation, at any time, without adverse consequences.
8278 Your anonymity is assured; the researchers who have requested your
8279 participation will not receive any personal information about you.”

8280 *A.4 Scenarios for different course layouts*

8281 Now that we have covered the standard format of the course, we want
8282 to now turn our attention to ways in which this format can be tweaked
8283 in order to fit different needs and resources. We have organized this
8284 section into two main categories: student level, and course resources
8285 (such as TAs and course funding).

A.4.1 Student level

8286 While Psych 251 at Stanford is geared towards graduate students (and
8287 is currently a required class for entering first-year graduate students in
8288 the Psychology Department), we also accept advanced undergraduate
8289 students as well as graduate students from other departments (e.g., Edu-
8290 cation, Human-Computer Interaction, Philosophy, Computer Science).
8291 On the first day of our course, we tell students that they should be com-
8292 fortable with two of the three following topics:
8293

8294 1) Some knowledge of psychological experimentation & subject
8295 matter

8296 2) Statistical programming: things like functions and variables

8297 3) Basic statistics like ANOVA and t-test

8298 If students are only comfortable with one of the three topics above, we
8299 warn them ahead of time that the course may demand more time from
8300 them than the average student.

8301 Now, if you are planning on catering this course for undergraduate stu-
8302 dents, chances are that they have had less exposure to these topics over-
8303 all, so there are multiple ways to calibrate the course accordingly:

8304 1) **Prerequisites:** Require students to have completed courses that
8305 cover at least two of the three topics mentioned above (i.e., a psy-
8306 chology class, a class that covers statistical programming, a class
8307 that covers basic statistics, any two of the three).

8308 2) **Pace:** unlike Psych 251, where the entire course only lasts 10
8309 weeks, a class for undergraduates may benefit from a slower pace,
8310 allowing more time to cover the foundational principles before
8311 diving into the project. For instance, the course could be held
8312 over multiple academic semesters/quarters, with the project goal
8313 of Course #1 being choosing and planning the replication study,
8314 and the project goal of Course #2 being the execution and inter-
8315 pretation of the replication.

8316 3) **Pair-Group-Based Projects:** In our course, each student is
8317 required to conduct their own replication project. However, this
8318 structure may be overwhelming for undergraduate students who
8319 may have less confidence taking on an entire replication project
8320 by themselves. One option that may alleviate this pressure is to
8321 have students conduct these projects as pairs or as small teams, so
8322 that they can collectively draw on each others' strengths. When
8323 assigning these pairs or teams, it may be especially helpful to try
8324 to ensure a relatively even balance of students who are confident

8325 in each of the three areas outlined above (psychology, statistical
8326 programming, basic statistics).

8327 Now that we've offered a few suggestions to address different student
8328 levels, let's dive into the issue of course resources.

8329 *A.4.2 Course resources*

8330 We think there are two main ways in which your course may have differ-
8331 ent resources from our model: In terms of course assistance (i.e., teach-
8332 ing assistants), and in terms of course funding for student projects. We'll
8333 explore ways to work around each of these in this section:

8334 **Teaching assistants**

8335 As a point of comparison, in general, 2–3 teaching assistants are allo-
8336 cated to Psych 251, which enrolls about 36 students, which comes out to
8337 about 12–18 students per TA. Since a project-based course requires indi-
8338 vidual attention and feedback, we would recommend against a student-
8339 TA ratio that is much higher than that. That means that if you know
8340 you will have just one TA for the class, you should think about reduc-
8341 ing the enrollment cap accordingly. But what if you have *no* TAs? With
8342 some adjustments, there are still ways you can make the course work
8343 sans-TA; we outline a few ideas below:

8344 1) **Peer grading:** As an instructor with no TAs, the area that will
8345 require the biggest lift in terms of time and attention is grading.
8346 One way to overcome this is to introduce a peer-grading system,
8347 in which students grade each others' work. If you choose this
8348 route, two things that may encourage fair grading among your stu-
8349 dents is to 1) distribute a clear and specific rubric that reduces the
8350 amount of subjectivity in the grading process as much as possible,
8351 and 2) anonymize the assignments so that students do not know
8352 whose assignment they are grading. If possible, it may again be
8353 beneficial to assign grading pairs that consist of students that are
8354 relatively knowledgeable in different areas, so that they can pro-
8355 vide feedback that address weak points in each others' work.

8356 2) **Collective troubleshooting:** The second most time intensive area
8357 you will have to make up for is the amount of troubleshooting
8358 you may have to do for students who run into issues implement
8359 their projects, anywhere from getting GitHub and RMarkdown
8360 up and running on their devices, to trouble with data collection
8361 on Mechanical Turk. One way to encourage communal support
8362 among your students is to set up a central discussion board for the
8363 course (e.g., Piazza or a course channel on Slack) where students
8364 can publicly (but anonymously, if desired) post issues they are run-
8365 ning into. Then, you can offer extra credit to students who help

8366 troubleshoot these issues, in order to further incentivize collec-
8367 tive troubleshooting. There will likely still be issues that cannot
8368 be addressed by the students, but this system at least frees up your
8369 time to focus your attention on those that only *you* can address.

8370 3) **Single class-wide project:** Finally, if the collective grading and
8371 troubleshooting methods outlined above do not cut down on
8372 enough time, you could consider walking through a single
8373 replication project as a class.¹ To make a single-project course
8374 work, you could have students nominate studies they would
8375 like to replicate as a class, and then have them vote on the final
8376 choice. Once the target study has been selected, every student
8377 can individually carry out all the steps of the project, including
8378 preregistering and writing up the analysis script. Then, setting
8379 up and running the data collection phase can happen during
8380 class, and once data has been collected, you can distribute it to
8381 the students for them to run it through their analysis script and
8382 interpret the result. Whether you choose to have students grade
8383 each others' work or whether you grade their work yourself, the
8384 fact that the project is standardized should cut down on a lot of
8385 the time you would otherwise spend learning about the details
8386 of every individual project.

¹ This approach does cancel out some of the benefits of a project-based course we mentioned at the start—namely, the project will likely no longer fit each student's specific research interest, so there may be less benefit in terms of specific student interest and usefulness for their program of research, but the other two benefits of realism and intuition (especially if the project is discussed in the context of other replication findings) still stand.

8387 Course funding

8388 In addition to availability of TAs, another way in which your course
8389 may be different from ours is in terms of course funding. If you have
8390 little or not funding for your course (even after reaching out to relevant
8391 members of your department or institution), we suggest the following
8392 adjustments:

8393 1) **Pair-Group-Based Projects:** Similarly to suggestion #3 for ad-
8394 dressing different student levels, one option for limited course
8395 budgets is to have students conduct the replication projects as pairs
8396 or teams to reduce the cost of data collection. This structure may
8397 have the added benefit of encouraging students to problem-solve
8398 together. Alternatively, each student in the pairs or teams could
8399 complete each step of the replication individually (e.g., writing
8400 up the report, analyzing the data, interpreting the result), which
8401 would ensure that each student takes full responsibility for every
8402 step of the project. This structure may also provide opportunities
8403 for interesting discussions at the end of the course around ana-
8404 lytic reproducibility, especially if students in the same teams (with
8405 the same dataset) differed in the conclusions they drew about the
8406 replication outcome.

8407 2) **Funding from Advisors:** In some cases, students come to us with

target studies that require more funding than we are able to allocate, but that they feel particularly invested in (e.g., because of how relevant the study is to their line of research). Once we rule out other ways of making the study fit our budget (e.g., dropping extra control conditions, running a subset of the study), we often ask students whether their advisor would be willing to fund the study. We have found that advisors are often willing to do this, especially if the replication could serve an important role in the development of the student's research program. Similarly, one way to reduce the burden on a limited course budget would be to encourage all students to first ask their advisors about whether they would be willing to fund part or all of the data collection for the replication. While chances are that some advisors will be unwilling or unable to do this, there should still be a meaningful reduction in the number of projects the course will need to fund.

3) Reproduce a Replication: The suggestions above apply if you at least have *some* amount of course funding, but what if you have *no* funding at all? While there are obvious limitations to this solution, one suggestion is to have students reproduce past public replications. For instance, our course Github page², contains public repositories of all past replication projects that have been conducted in our course. Since the data for each replication project

² <https://github.com/psych251>

8430 is available in these repositories, you could provide each of your
8431 students with a dataset and the original paper associated with it,
8432 and assign them to reproduce the results of the replication. Stu-
8433 dents should then be able to follow each step of the replication
8434 project described below (e.g., writing the report, identifying the
8435 key analysis, running the analysis). This format will only work if
8436 students do not view the original final replication reports that are
8437 posted publicly for their project, so it may be necessary to be clear
8438 about this at the beginning of the course.

8439 For those of you who are working with a different course format
8440 (whether in terms of student level or course resources), we hope these
8441 suggestions were useful. If you try out a new idea in your course that
8442 you found helpful, we would be thrilled if you shared them with us!

8443 *A.5 Sample course schedules*

8444 The sample syllabi laid out below are categorized along the following de-
8445 cisions: 1) Material: whether the course focuses on just content or both
8446 content and skills, and 2) Duration: whether the course is 10-weeks
8447 long or 16-weeks long.

8448 For undergraduate instructors, we have labelled advanced topics in pur-
8449 ple. We expect that these topics are best suited for advanced under-
8450 graduate students. As for content around statistics (e.g., Estimation, In-
8451 ference), instructors should decide how much of this content to teach,
8452 depending on how prepared students have been in previous classes.

8453 A.5.1 10 weeks

Table A.1
A sample 10-week syllabus with both skills and content materials.

Week	Day	Topic	Chapter	Appendix
1	M	Class Introduction	1	
1	W	Theories	2	
1	F	Version Control		B
2	M	Reproducible reports	14	C
2	W	Tidyverse Tutorial		D
2	F	Tidyverse Tutorial continued (with TAs)		
3	M	Measurement, Reliability, and Validity	8	
3	W	Design of Experiments	9	
3	F	Sampling	10	
4	M	Project Management	13	
4	W	Experiments 1: Simple survey experiments using Qualtrics		
4	F	Experiments 2: Project-specific Implementation (TAs)		
5	M	Estimation	5	
5	W	Inference	6	
5	F	Sample Size Planning		
6	M	Survey Design		
6	W	Midterm Presentations 1		
6	F	Midterm Presentations 2		

7	M	Preregistration	11
7	W	Meta-analysis	16
7	F	Open Science	3
8	M	Visualization 1	15
8	W	Visualization 2	E
8	F	Exploratory Data Analysis Workshop	
9	M	Sampling, Representativeness, and Generalizability	4
9	W	Data and Participants Ethics	12
9	F	Authorship and Research Ethics	
10	M	Open Discussion	17
10	W	Final Project Presentations 1	
10	F	Final Project Presentations 2	

8454 A.5.2 10 weeks, content only

Table A.2
A sample 10-week syllabus with only content materials.

Week	Day	Topic	Chapter
1	M	Class Introduction	1
1	W	Theories	2
1	F	Replication and reproducibility	3
2	M	Open Science	
2	W	Measurement	8
2	F	Design of experiments 1	9
3	M	Design of experiments 2	
3	W	Sampling	10
3	F	Experimental strategy	
4	M	Preregistration	11
4	W	Data collection	12
4	F	Visualization 1	15
5	M	Visualization 2	
5	W	MIDTERM EXAM	
5	F	Introduction to statistics	
6	M	Estimation 1	5
6	W	Estimation 2	
6	F	Inference 1	6

7	M	Inference 2	
7	W	Models 1	7
7	F	Models 2	
8	M	Meta-analysis	16
8	W	Project management	13
8	F	[Instructor-specific topics]	
9	M	Sampling, Representativeness, and Generalizability	4
9	W	Data and Participants Ethics	12
9	F	Authorship and Research Ethics	
10	M	Conclusion	17
10	W	Conclusion	
10	F	FINAL EXAM	

8455 A.5.3 16 weeks

Table A.3
A sample 16-week syllabus with both skills and content materials.

Week	Day	Topic	Chapter	Appendix
1	1	Class Introduction	1	
1	2	Theories	2	
2	1	Version Control		B
2	2	Reproducible reports	14	C
3	1	Tidyverse Tutorial		D
3	2	Tidyverse Tutorial continued (with TAs)		
4	1	Measurement, Reliability, and Validity	8	
4	2	Design of Experiments	9	
5	1	Sampling	10	
5	2	Project Management	13	
6	1	Experiments 1: Simple survey experiments using Qualtrics		
6	2	Experiments 2: Project-specific Implementation (TAs)		
7	1	Estimation	5	
7	2	Inference	6	
8	1	Sample Size Planning		
8	2	Survey Design		
9	1	Midterm Presentations 1		
9	2	Midterm Presentations 2		

10	1	Preregistration	11
10	2	Meta-analysis	16
11	1	Open Science	3
11	2	Visualization 1	15 E
12	1	Visualization 2	
12	2	Exploratory Data Analysis Workshop	
13	1	Sampling, Representativeness, and Generalizability	4
13	2	Data and Participants Ethics	12
14	1	Authorship and Research Ethics	
14	2	[Instructor-specific topics]	
15	1	Open Discussion	17
15	2	Open Discussion	
16	1	Final Project Presentations 1	
16	2	Final Project Presentations 2	

8456 A.5.4 16 weeks, content only

Table A.4
A sample 16-week syllabus with only content materials.

Week	Day	Topic	Chapter
1	1	Class Introduction	1
1	2	Theories	2
2	1	Replication and reproducibility	3
2	2	Open Science	
3	1	Measurement	8
3	2	Design of experiments 1	9
4	1	Design of experiments 2	
4	2	Sampling	10
5	1	Experimental strategy	
5	2	Preregistration	11
6	1	Data collection	12
6	2	Visualization 1	15
7	1	Visualization 2	
7	2	MIDTERM EXAM	
8	1	Introduction to statistics	
8	2	Estimation 1	5
9	1	Estimation 2	
9	2	Inference 1	6

10	1	Inference 2	
10	2	Models 1	7
11	1	Models 2	
11	2	Meta-analysis	16
12	1	Project management	13
12	2	[Instructor-specific topics]	
13	1	[Instructor-specific topics]	
13	2	Sampling, Representativeness, and Generalizability	4
14	1	Data and Participants Ethics	
14	2	Authorship and Research Ethics	
15	1	Ethics: Open Discussion	
15	2	Conclusion	17
16	1	Conclusion	
16	2	FINAL EXAM	

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8460 **B GIT AND GITHUB (ONLINE ONLY)**

8461 This appendix appears only in the online version of this book at <https://experimentology.io/B-git>.

8462 [//experimentology.io/B-git](https://experimentology.io/B-git).

8463 C R MARKDOWN AND QUARTO (ONLINE

8464 ONLY)

8465 This appendix appears only in the online version of this book <https://>

8466 experimentology.io/C-rmarkdown.

D TIDYVERSE (ONLINE ONLY)

8467

8468 This appendix appears only in the online version of this book <https://experimentology.io/D-tidyverse>.

8469 experimentology.io/D-tidyverse.

E GGPLOT (ONLINE ONLY)

- 8470 This appendix appears only in the online version of this book <https://experimentology.io/E-ggplot>.
- 8471 8472