A brief tour of research transparency for quantitative research

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This tutorial is designed based on the open materials of the courses presented at CHI 2022–23, VIS 2023, and MuC 2023 by Chat Wacharamanotham, Fumeng Yang, Abhraneel Sarma, Xiaoying Pu, and Lace Padilla. https://osf.io/27r5z

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Previously: Assistant professor at University of Zurich; Lecturer at Swansea University (UK); PhD in Human–Computer interaction from RWTH Aachen University

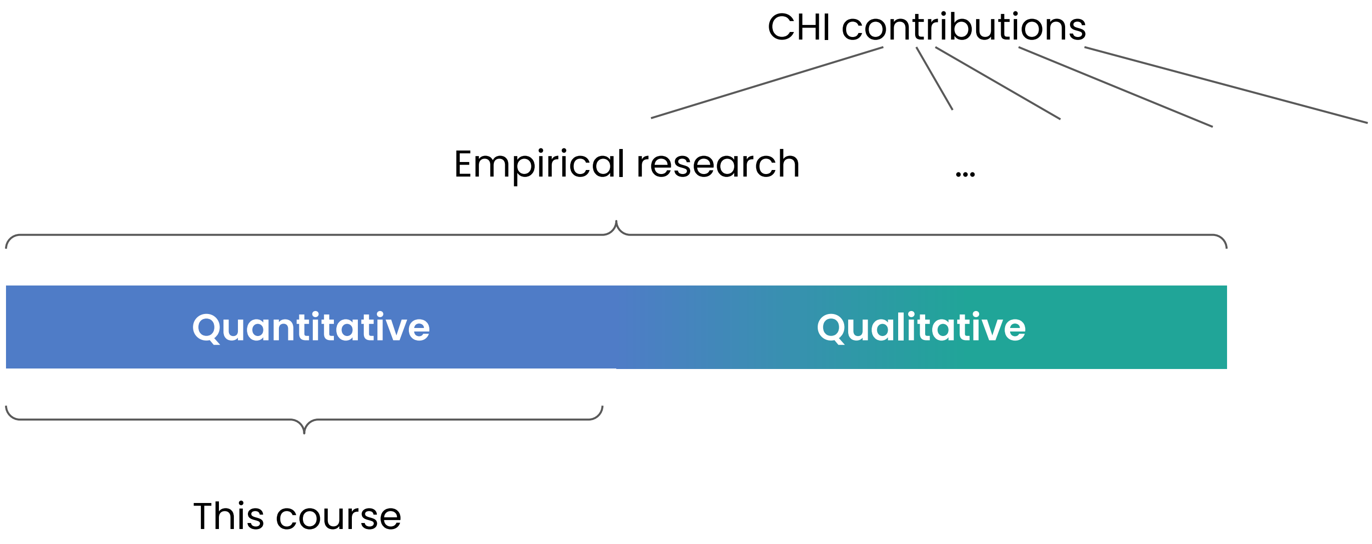
Research: Improving how computer can help people do better and transparent science

Past research: Interaction techniques for touch input on and above screens

Roles in the CHI conferences: Associate Chair (2022–23) • Best Paper Award Committee (2022) • Student Research Competition Co-chair (2023) • Associate editor of IJHCS (International Journal of Human-Computer Studies) • Organizer of JoVI (The Journal of Visualization and Interaction)

https://chatw.ch

Scope


CHI contributions
Empirical research
...
Quantitative
Qualitative
This course

Scope and style

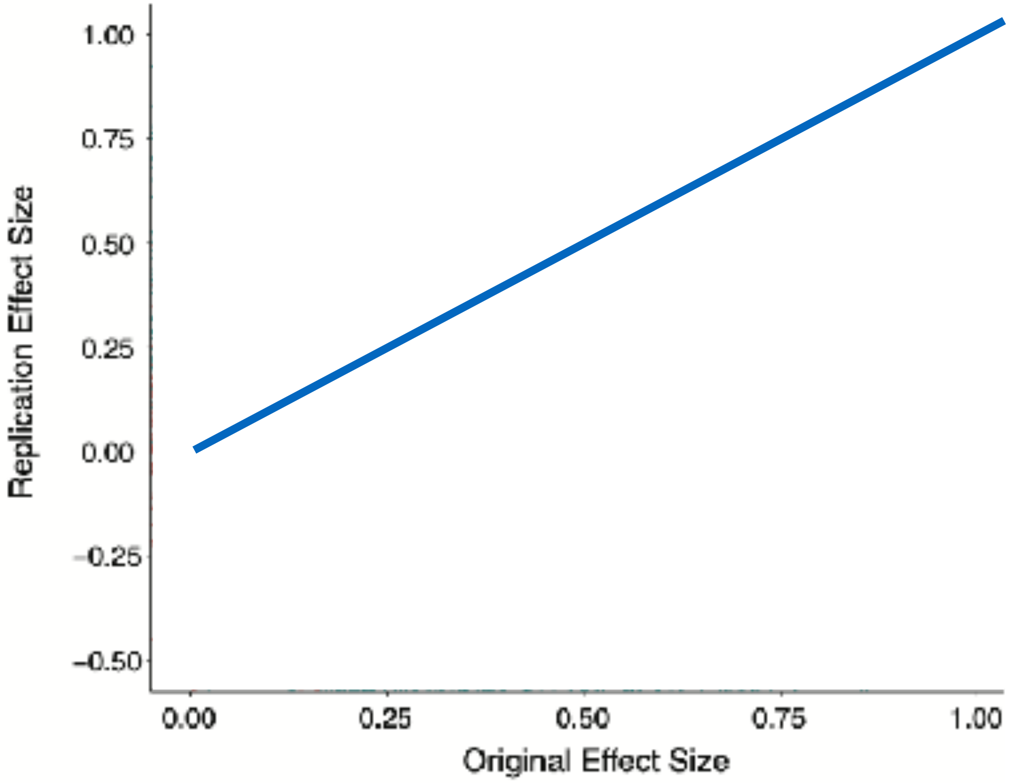
Photo by S5A-0043 via Wikipedia

Hop-on hop-off tour

Download this slide set and dig deeper with you research project

👉 indicates important pointers

Why should we care about research transparency?


1.00
0.75
0.50
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Replication Effect Size
0.00
0.25
0.50
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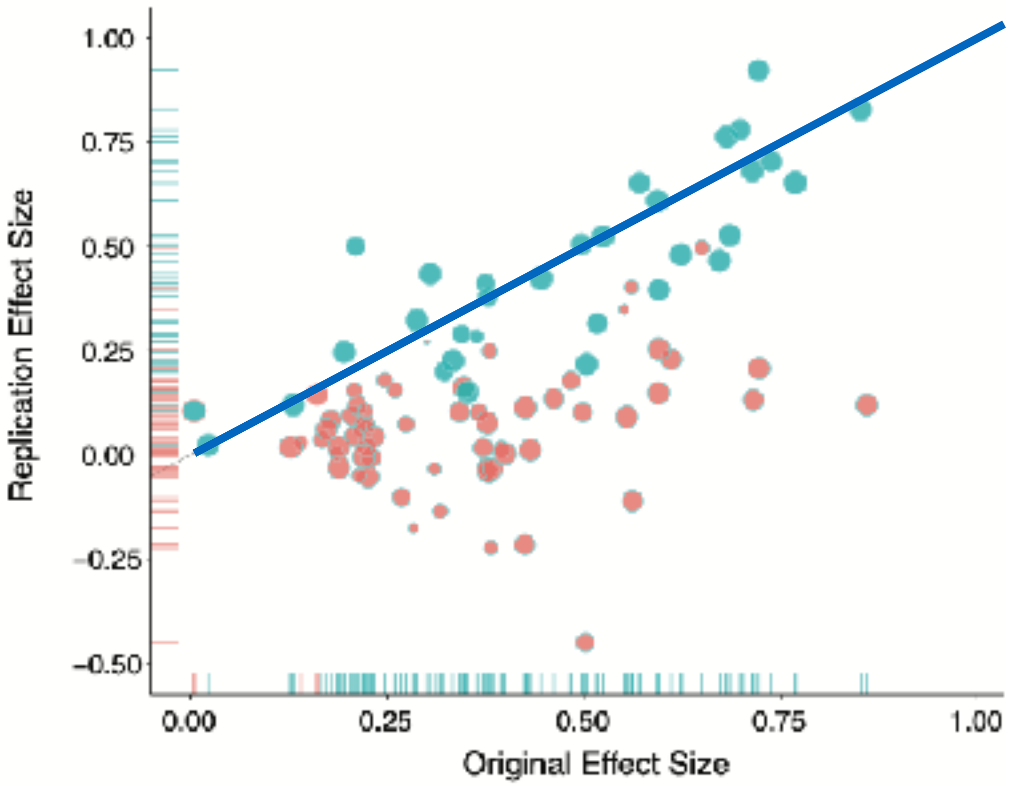
Original Effect Size


1.00
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Replication Effect Size
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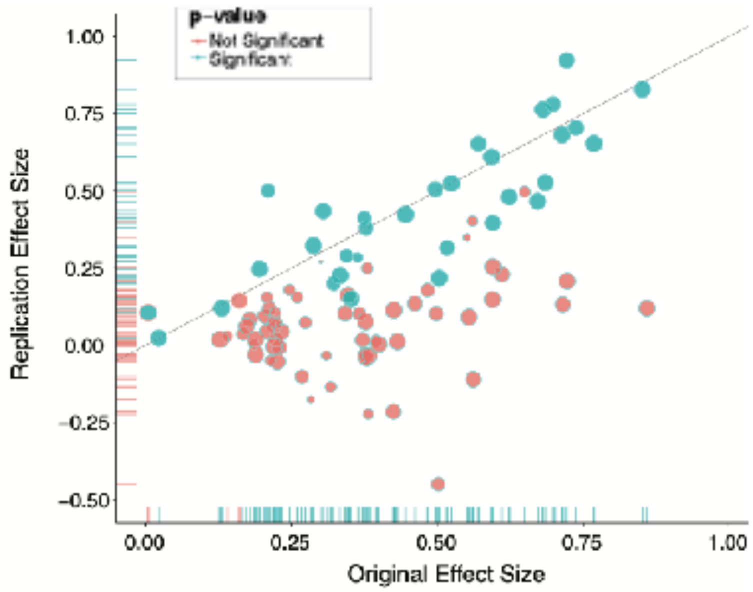
Original Effect Size

Over half of psychology studies fail to replicate



100 psychology studies

Smaller effect sizes in 83% of the replication studies

Statistically significant results:

- 97% of original studies
- 36% in the replications

Source: Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. Science, 349(6251).

Replicability

Closely matched method

+

New data

=

Consistent results

Reproducibility

Same data analysis method

+

Same data

=

Same results

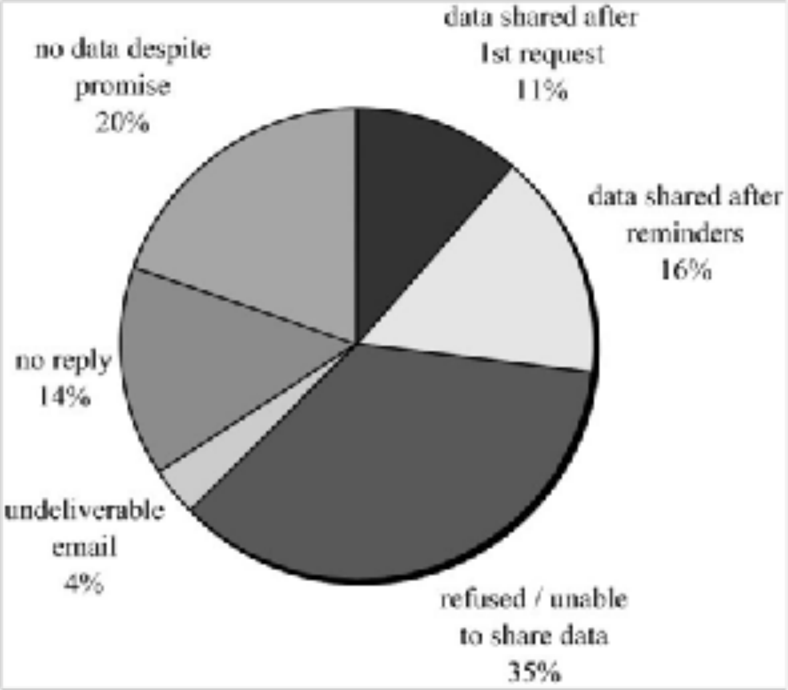
Reproducibility is a lower bar, but still important for evaluating the claims of research results

According to Clearbout terminology, which differs from ACM's terminology. See discussion in Plesser HE (2018) Reproducibility vs. Replicability: A Brief History of a Confused Terminology. Front. Neuroinform. 11:76.

“If researchers want to use data or code from my paper, they can contact me”

A team of psychology researchers requested data from the authors of 141 articles published in prestigious psychology journals in the previous year.

27% success rate



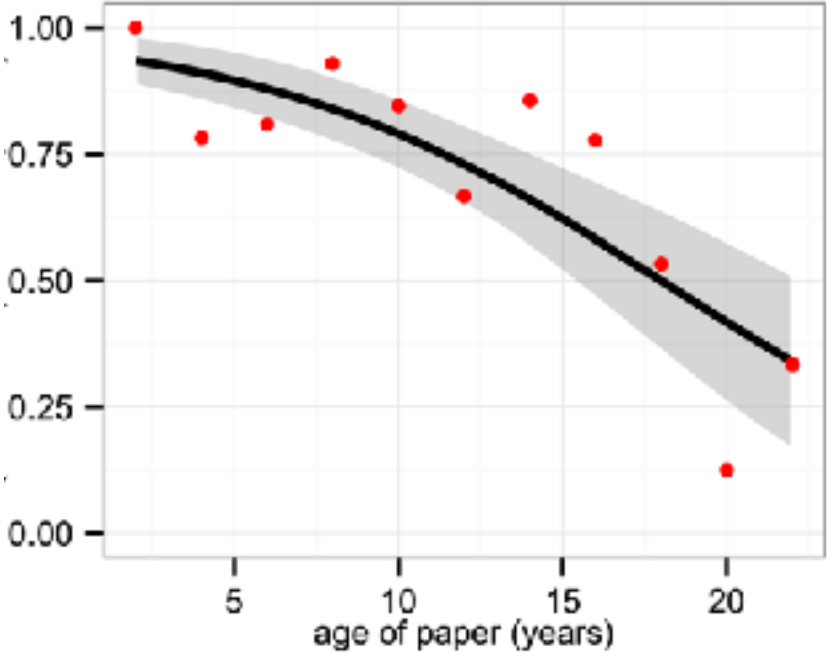
Wicherts et al. The poor availability of psychological research data for reanalysis. American Psychologist 61, 7 (2006), 726 – 728.

“If researchers want to use data or code from my paper, they can contact me”

Researchers from the field of biology requested data from 516 articles published between 2–20 years

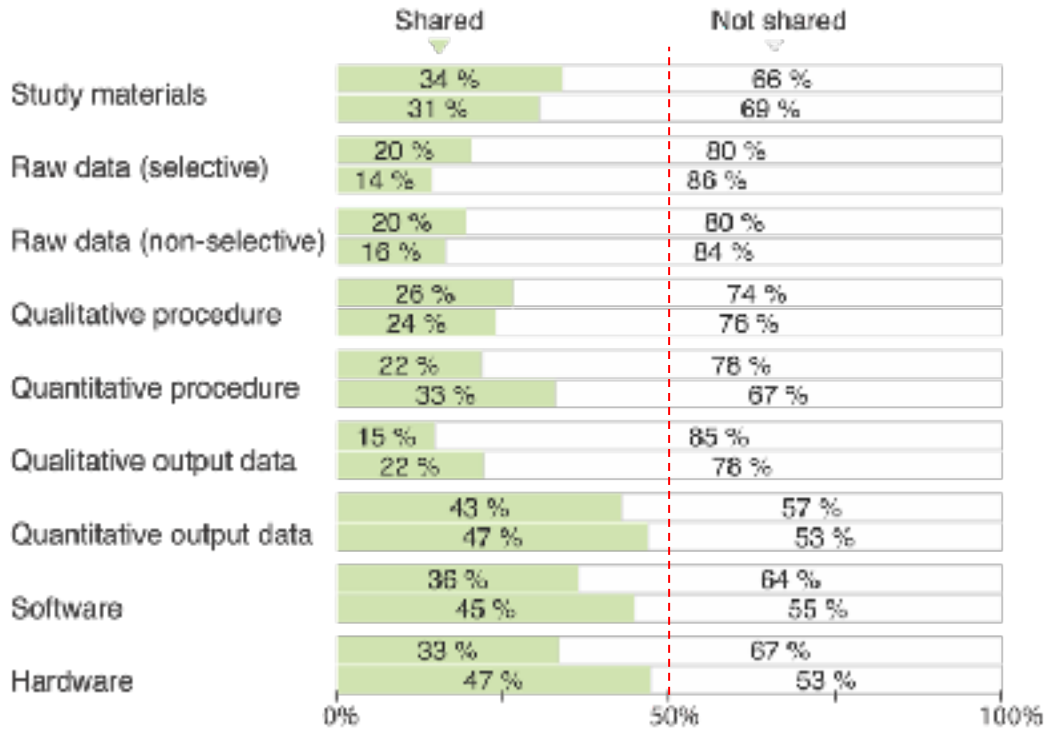
The odds of data still exist fall 17% per year

P(data still exist | author responded to the request)



Vines et al. [The Availability of Research Data Declines Rapidly with Article Age.](#) Current Biology 24, 1 (2019), 94–97.

Survey to authors of
CHI 2018, 2019

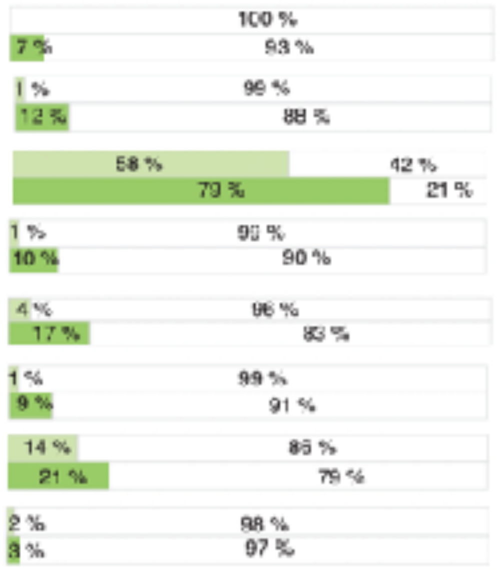


Percents of respondents

Wacharamanotham et al. (2020) [Transparency of CHI Research Artifacts: Results of a Self-Reported Survey]. In Proc. of CHI 2020.

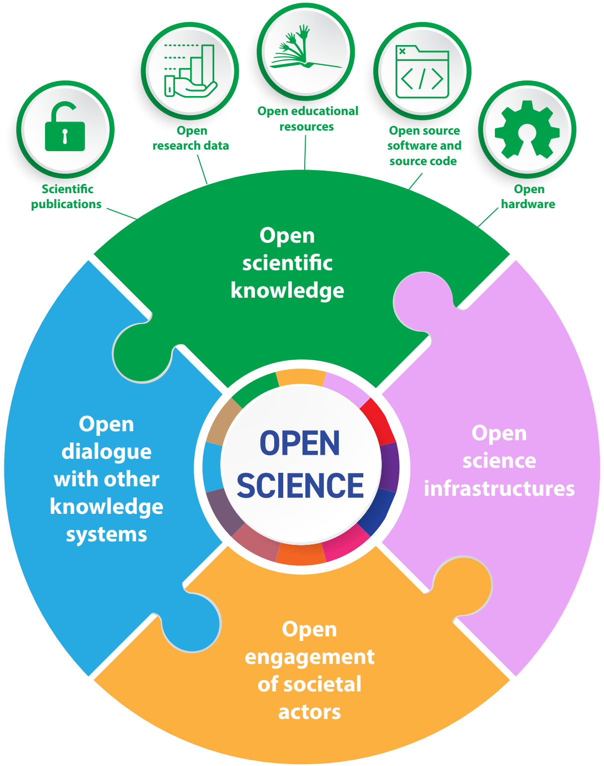
Content analysis of papers from
CHI 2017, 2022

Mapped to equivalent categories on the left



Percents of sampled papers

Niksirat et al. (2023) [Changes in Research Ethics, Openness, and Transparency in Empirical Studies between CHI 2017 and CHI 2022]. In Proc. of CHI 2023.



193 member states of the UNESCO promote Open Science

"[Open scientific knowledge] also refers to the possibility of **opening research methodologies and evaluation processes.**"

Guide to a Successful Submission

Transparency

Research transparency is of utmost importance in a CHI paper. It allows reviewers to understand and assess submitted work thoroughly, and it allows members of the research community to understand, analyze, and build upon the work in published CHI papers. As such transparency is taken into account very seriously in the review process.

CHI papers should strive for research transparency regardless of the contribution type and methodology. Different contribution types, (e.g. technical contributions, quantitative studies, and qualitative studies) use different criteria for assessing transparency.

Contributions that are technology-oriented (e.g., a new technique or algorithm) and **contributions that are quantitative studies** (i.e., experiments with statistically analyzed results) are expected to be verifiable, reproducible (e.g., others should be

Source: [CHI 2025 Guide to a Successful Submission]

Conceptualizing research transparency for HCI

“**Research transparency** refers to honesty and clarity in all communications about the research processes and outcomes to the extent possible.”

- “honesty and clarity” — sometimes have trade-off
- “all communications” — among researchers and beyond
- “process and outcomes” — emphasis may differ across research methods
- “to the extent possible” — weigh transparency with ethics, privacy, intellectual properties, and other values

This preprint gives ideas on how to be transparent in many types of HCI research (also beyond quantitative)

From a working paper by Yvonne Jansen, Jan B. Vornhagen, Olga Iarygina, Kavous Salehzadeh Niksirat, Lonni Besançon, Pierre Dragicevic, Julien Gori, and Chat Wacharamanotham. "The Many Ways of Being Transparent in Human-Computer Interaction Research” https://osf.io/2wze6_v1

Plan

Transparency in **planning** studies

With a focus on experimental studies

Transparency in **data analysis**

General concerns + exercises in preregistration

Transparency in **reporting**

Examples in frequentist statistics + pointers

Transparency in **visualizing research data**

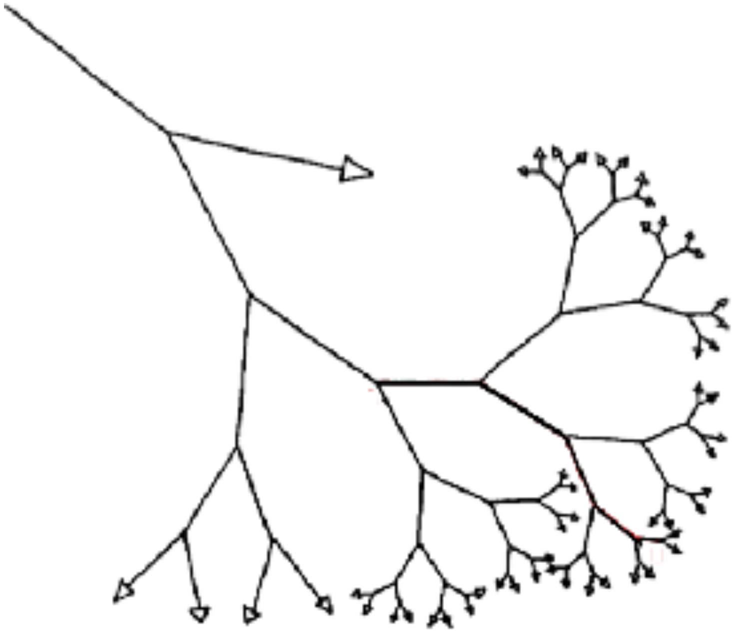
Principles + examples

Transparency in research **materials**

What, how, and where to share

Transparency in planning studies

Choices in research



Some choices in data analysis

- Choosing between different options of dealing with incomplete or missing data on ad hoc grounds
- Specifying pre-processing of data (e.g., cleaning, normalization, smoothing, motion correction) in an ad hoc manner
- Deciding how to deal with violations of statistical assumptions in an ad hoc manner

Diagram from [Marjan Bakker's slide]
Choices from **Degrees of freedom in planning, running, analyzing, and reporting psychological studies:** A checklist to avoid p-hacking (Wicherts et al., 2016)

Choices in research

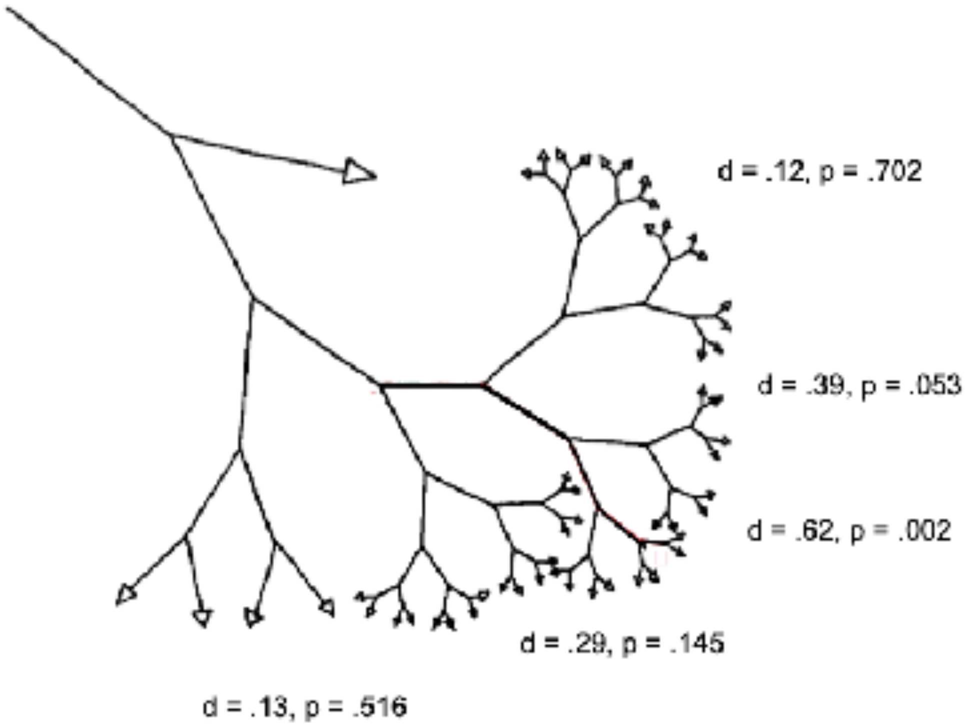


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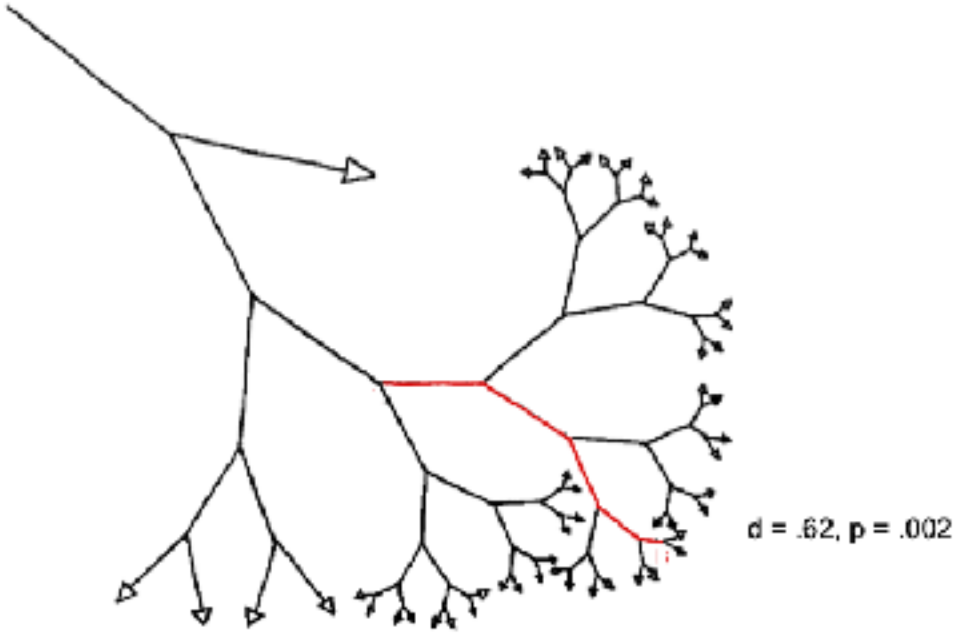
Diagram from [Marjan Bakker's slide]
Choices from **Degrees of freedom in planning, running, analyzing, and reporting psychological studies:** A checklist to avoid p-hacking (Wicherts et al., 2016)

Choices in the **design phase**



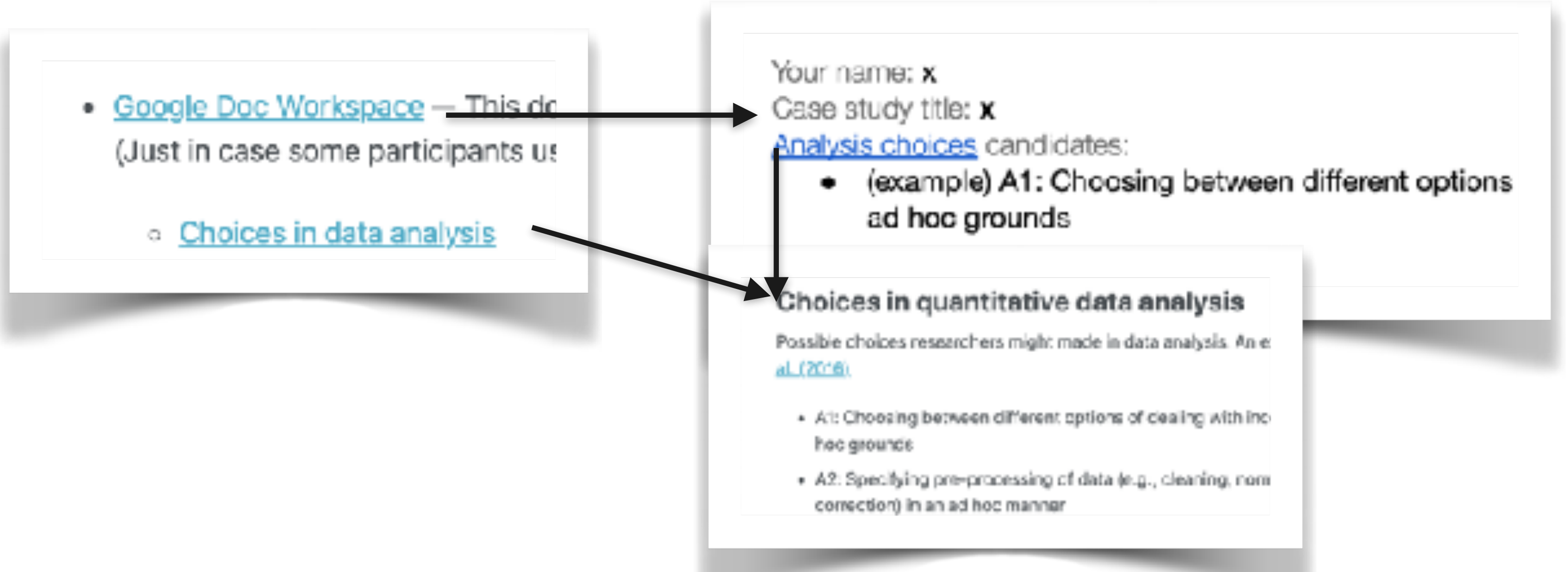
Establishing transparency in decisions made at the research design phase

- Make justifiable choices
- Report the choices made
- Discuss implications of the paths not taken

Diagram from [Marjan Bakker's slide]

Exercise 1: Choices in data analysis (5 minutes)

1. Go to the talk page https://chatw.ch/transparency-4-quant
2. Click on the link to Google Doc workspace, and grab a space on the template
3. Look through the list of analysis choice and choose 2–3 choices from your case study
4. Briefly describe these choices. (We will use them in a breakout room discussion later.)



Exercise 2: Discuss choices and changes (20 minutes)

1. In your breakout room, take turn to describe the case study and the analysis choices (max. 3 minutes per person)
2. Choose <u>one</u> analysis choice from <u>a</u> case to work together.
3. Discuss:
    - When might this decision be made?
    - When might the researchers change this decision?
    - Which factor(s) might have led to this change?

Example: **How many participants?**

Spectrum of justifiable choices [1]

- 👍 *A priori* power analysis [2] or precision planning [3]
- Based on previous work investigating similar effects
- Resource constraints
- Subfields' local standard [4] or other heuristics
- Unjustified
- 👎 *p*-hacking by adding participants until getting statistical significance

[1] From **Sample Size Justification** (Lakens, 2022) + Chat's opinionated selection considering CHI environment
[2] A detailed tutorial for power analysis in G*Power and in R: **A Practical Primer To Power Analysis for Simple Experimental Designs** (Perugini et al., 2018)
[3] Book chapter with interactive tools in Excel: **Introduction to the New Statistics** (Cumming & Calin-Jageman, 2016) Ch. 10, section *Precision for planning*
[4] E.g., Local Standards for Sample Size at CHI (Caine, 2016), Local Standards for Anonymization Practices in Health, Wellness, Accessibility, and Aging Research at CHI (Abbott et al., 2019, p.7)

Table 1. Overview of possible justifications for the sample size in a study.

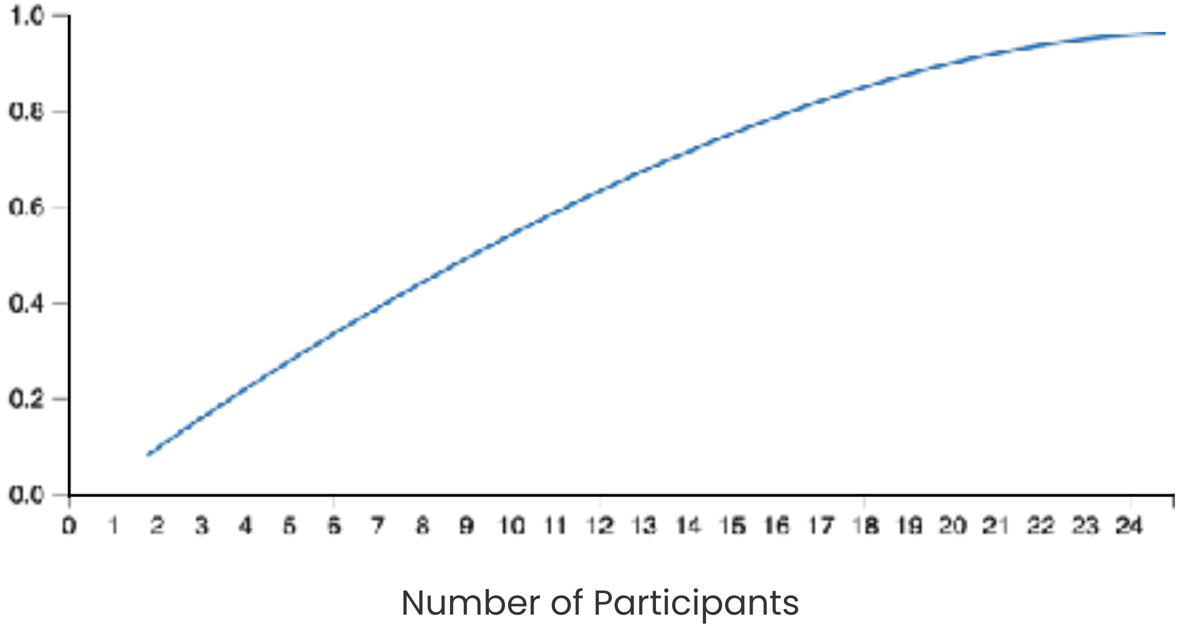
Type of justification	When is this justification applicable?
Measure entire population	A researcher can specify the entire population, it is finite, and it is possible to measure (almost) every entity in the population.
Resource constraints	Limited resources are the primary reason for the choice of the sample size a researcher can collect.
Accuracy	The research question focusses on the size of a parameter, and a researcher collects sufficient data to have an estimate with a desired level of accuracy.
A-priori power analysis	The research question has the aim to test whether certain effect sizes can be statistically rejected with a desired statistical power.
Heuristics	A researcher decides upon the sample size based on a heuristic, general rule or norm that is described in the literature, or communicated orally.
No justification	A researcher has no reason to choose a specific sample size, or does not have a clearly specified inferential goal and wants to communicate this honestly.

Table 2. Overview of possible ways to evaluate which effect sizes are interesting.

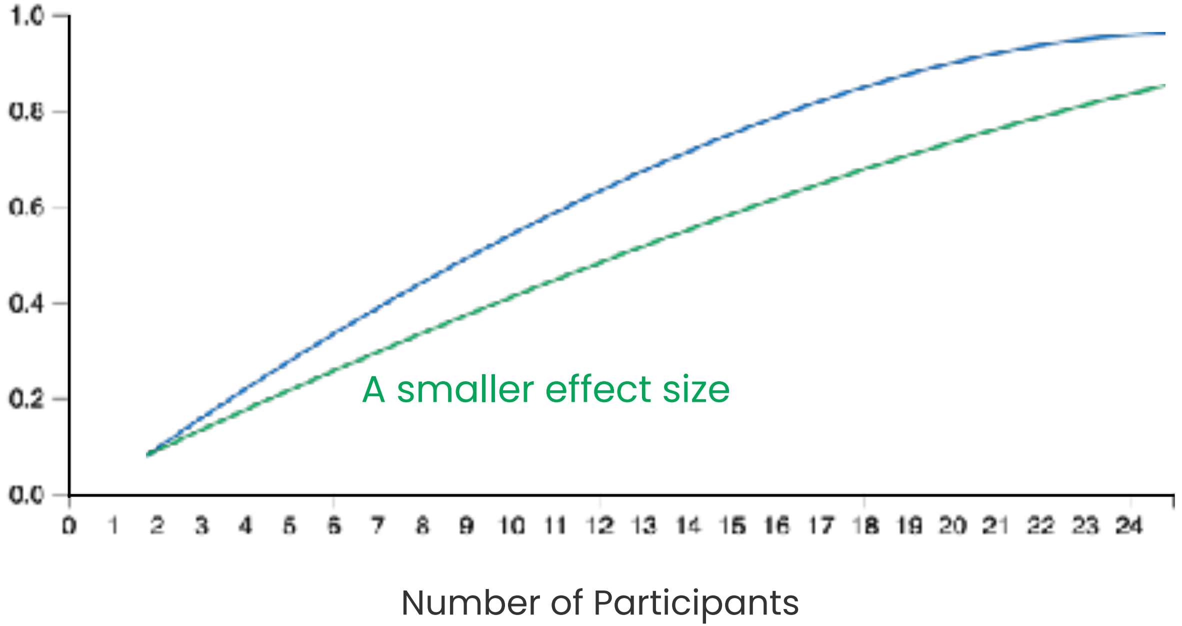
Type of evaluation	Which question should a researcher ask?
Smallest effect size of interest	What is the smallest effect size that is considered theoretically or practically interesting?
The minimal statistically detectable effect	Given the test and sample size, what is the critical effect size that can be statistically significant?
Expected effect size	Which effect size is expected based on theoretical predictions or previous research?
Width of confidence interval	Which effect sizes are excluded based on the expected width of the confidence interval around the effect size?
Sensitivity power analysis	Across a range of possible effect sizes, which effects does a design have sufficient power to detect when performing a hypothesis test?
Distribution of effect sizes in a research area	What is the empirical range of effect sizes in a specific research area, and which effects are a priori unlikely to be observed?

Sample Size Justification (Lakens, 2022, p. 2)

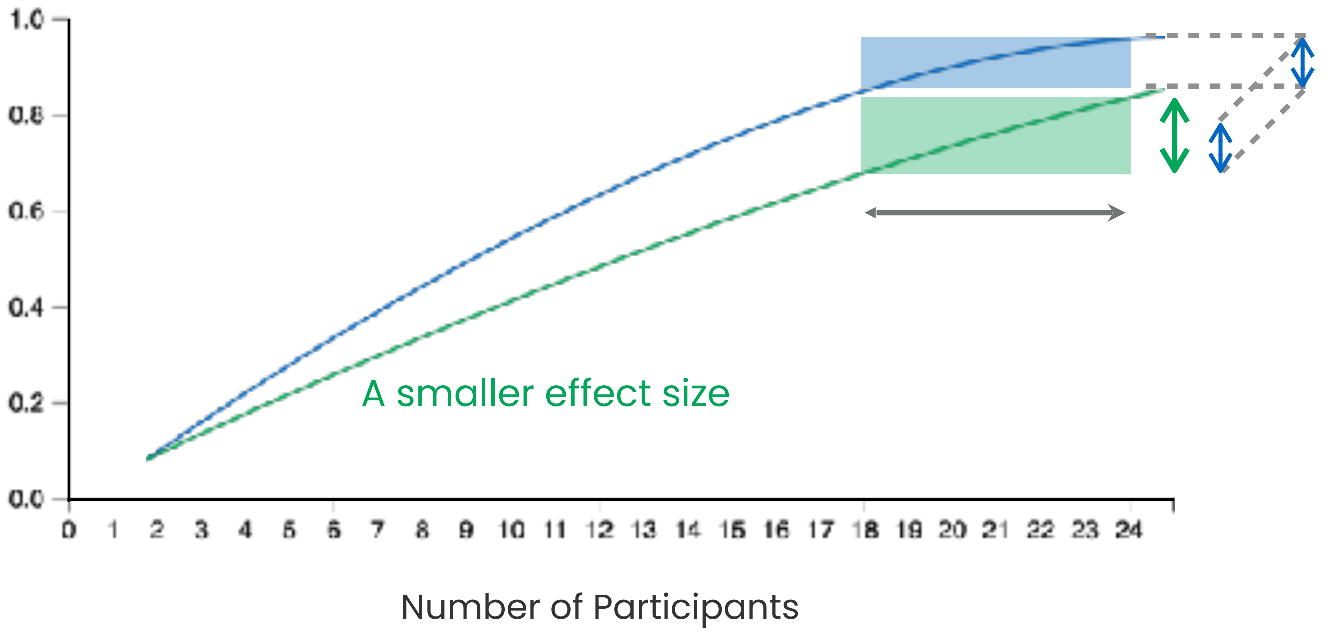
Statistical power: the probability of detecting an effect from an experiment when the effect exists in the population.



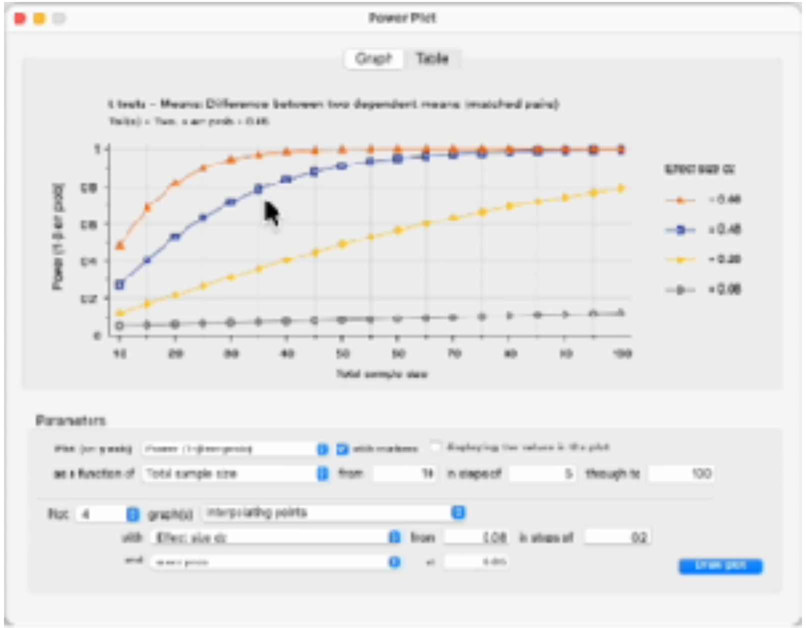
Statistical power: the probability of detecting an effect from an experiment when the effect exists in the population.



Statistical power: the probability of detecting an effect from an experiment when the effect exists in the population.



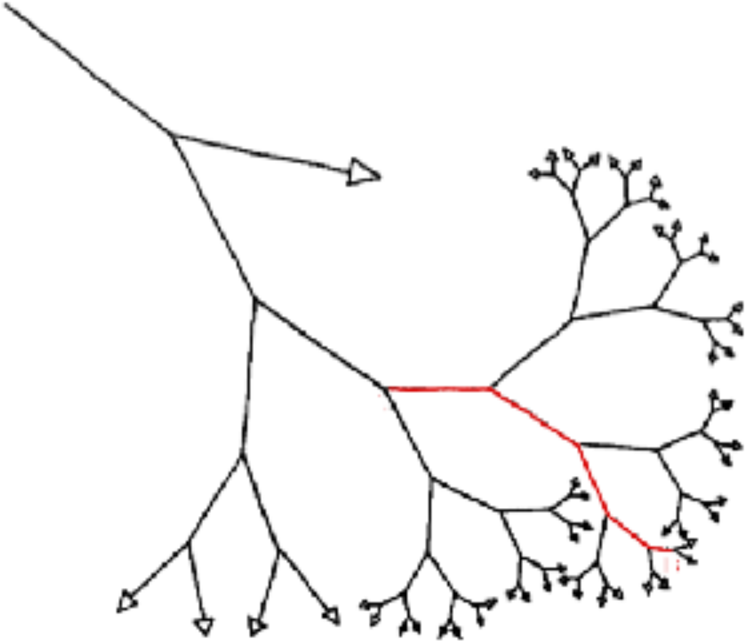
Demo: **Decision in an *a priori* power analysis**



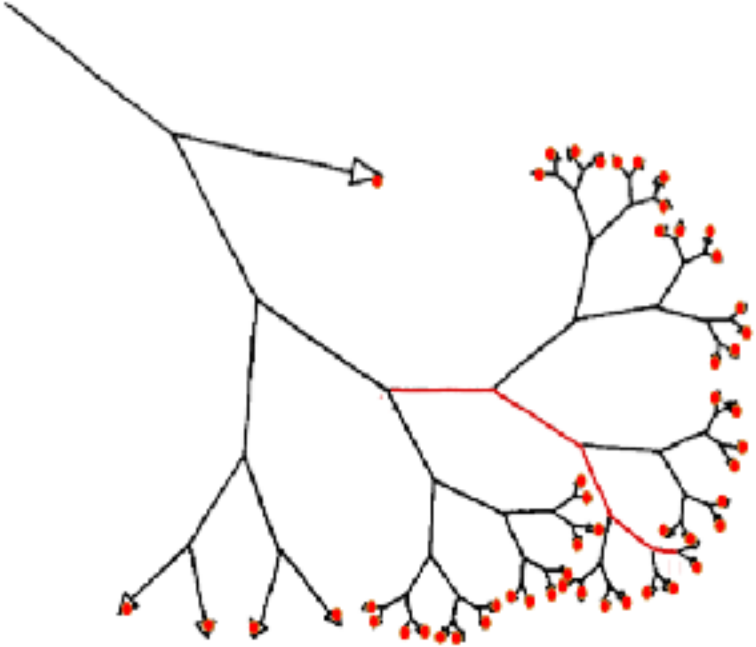
Video recording of the demo [on Youtube]

Transparency in data analysis

Ways to be accountable for data analysis choices



Declare your choices in advance (preregistration)



Explore how different choices affects the results (sensitivity analysis, multiverse analysis)

Diagrams from [Marjan Bakker's slide]

Preregistration

A timestamped record of the plan, including information such as

- A brief narrative description of reason to conduct the research
- Explicitly state the intended purpose (exploratory or confirmatory)
- Hypothesis and prediction of the outcome
- Expected analysis method (ideally a script for data analysis)

Evidence of what and when you planned → increase transparency and credibility

OSF AS PREDICTED

Templates and recipes for preregistering various types of studies are listed on OSF's Registration Forms and Templates page

AsPredicted **preregistration template**

1. **Have any data been collected** for this study already?
2. What's the **main question** being asked or **hypothesis** being tested in this study?
3. Describe the key **dependent variable(s)** specifying how they will be measured.
4. How many and which **conditions** will participants be assigned to?
5. Specify exactly **which analyses** you will conduct to examine the main question/ hypothesis.
6. Describe exactly how **outliers** will be defined and handled, and your precise rule(s) for excluding observations.
7. 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. **Anything else** you would like to pre-register? (e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)

Example: **Preregistration**

Datamations: Animated Explanations of Data Analysis Pipelines (Pu et al., CHI 2021)

Preregistration at https://aspredicted.org/72qc9.pdf

Exercise 3: Drafting a preregistration (20 minutes)

Continue with the case you previously chose.

1. Find the relevant preregistration section from the OSF template
2. Pair-write the preregistration text together
    - One person write
    - Another person help thinking and discussing and take notes of findings from this drafting process. Prepare them as input to the plenary

Preregistration

"Preregistration is a plan, not a prison" [1]

Circumstances that unfold after filing a preregistration may necessitate adjustment

- If you haven't seen the data, file a new preregistration with explicit reference to the previous plan
- Explain the reasons for deviation in the paper

You may add further exploratory analyses as long as they are clearly separated from the preregistered analyses in the paper

Use pilot studies to inform your decisions

Preregistration: A Plan, Not a Prison (DeHaven, 2017 on COS blog)

Preregistration

Critique: *"But most studies in HCI are iterative and exploratory"*

- Preregister the exploratory intention and initial hypotheses
- **Benefit:** Reviewers cannot challenge that the exploratory analyses comes from failing to achieve statistical significance from other tests [1]

[1] **HARK No More: On the Preregistration of CHI Experiments** (Cockburn et al., CHI 2018). The arguments from HCI researchers' perspective makes this paper worth reading as a whole.

For CHI double-blind reviewing process, see instruction for sharing anonymized preregistration in section 3 of Open Practices in Visualization Research (Haroz, 2018, BELIV position paper)

Transparency in reporting

Transparent statistics guiding principles

1. **Faithfulness:** Strive to capture and convey the “truth” as accurately as possible, especially concerning the uncertainty within the data.
2. **Robustness:** Prefer data analysis and reporting strategies that are robust to departures from statistical assumptions—or that make few assumptions
3. **Resilience:** Data analysis and reporting strategies should yield similar outcomes across hypothetical replications of the same study.
4. **Process transparency:** Communicate the decisions made during the analysis and report writing as explicitly as possible.
5. **Clarity:** Study reports should be easy to process—even when they target experts.
6. **Simplicity:** Prefer the simplest procedure even if it is slightly inferior in other respects.
7. **Non-contingency:** Outside exploratory analyses, data analysis and reporting strategies should avoid decisions that are contingent on data
8. **Precision and economy:** Plan for data quality, high statistical power, and high statistical precision
9. **Material availability:** Sharing as much study material as possible

Transparent Statistics Guiding Principles. (Transparent Statistics in Human–Computer Interaction Working Group, 2019)

2. Robustness: Prefer data analysis and reporting strategies that are robust to departures from statistical assumptions—or that make few assumptions

Some people tend to avoid extreme answers, the difference between the rating 5 and 6 may be smaller than those of 8 and 9.

A. **Parametric test** (e.g., *t*-test or ANOVA)

B. **Nonparametric tests** (e.g., Wilcoxon tests, or Mann-Whitney U test)

4. Process transparency: Communicate the decisions made during the analysis and report writing as explicitly as possible.

A. The difference is not statistically significant ($p = 0.5$)
B. The **Wilcoxon test** is not statistically significant (**$W = 1762$**, $p = 0.5$)
C. The **Wilcoxon rank sum test** is not statistically significant ($W = 1762$, $p = 0.5$)

5.Clarity: Study reports should be easy to process—even when they target experts.

A comparison of a novel physical user interface prototyping system (technique B) to the previous state of the art (A)

A. The feedback time differs by 104 ms (95% CI: [81, 126])
B. Technique B has lower feedback time than A by 104 ms (95% CI: [81, 126])
C. [...] Technique B's feedback time tend to be **less than the threshold of human perception (less than about 100ms).**
D. Technique B has lower feedback time with **Cohen's *d* =0.2**

Checklist for reporting statistics: The SAMPL Guidelines

(Lang & Altman, 2016)

General Principles for Reporting Statistical Results

Reporting numbers and descriptive statistics

- Report numbers—especially measurements—with an appropriate degree of precision. For ease of comprehension and simplicity, round as much as is reasonable. For example, mean age can often be rounded to the nearest year without compromising either the clinical or the statistical analysis. If the smallest meaningful difference on a scale is 5 points, scores can be reported as whole numbers; decimals are not necessary.

- Report total sample and group sizes for each analysis.

- Report numerators and denominators for all percentages.

- Summarize data that are approximately normally distributed with means and standard deviations (SD). Use the form: mean (SD), not mean ± SD.

- Summarize data that are not normally distributed with medians and interpercentile ranges, ranges, or both. Report the upper and lower boundaries of interpercentile ranges and the minimum and maximum values of ranges, not just the size of the range

- Do NOT use the standard error of the mean (SE) to indicate the variability of a data set. Use standard deviations, inter-percentile ranges, or ranges instead.

- Display the data in tables or figures. Tables present exact values, and figures provide an overall assessment of the data.[42,43]

Checklist for reporting statistics: The SAMPL Guidelines

(Lang & Altman, 2016)

Reporting hypothesis tests

- State the hypothesis being tested.
- Identify the variables in the analysis and summarize the data for each variable with the appropriate descriptive statistics.
- If possible, identify the minimum difference considered to be clinically important.
- For equivalence and non-inferiority studies, report the largest difference between groups that will still be accepted as indicating biological equivalence (the equivalence margin).
- Identify the name of the test used in the analysis. Report whether the test was one- or two-tailed and for paired or independent samples.
- Confirm that the assumptions of the test were met by the data.
- Report the alpha level (e.g., 0.05) that defines statistical significance.
- At least for primary outcomes, such as differences or agreement between groups, diagnostic sensitivity, and slopes of regression lines, report a measure of precision, such as the 95% confidence interval.
- Do NOT use the standard error of the mean (SE) to indicate the precision of an estimate. The SE is essentially a 68% confidence coefficient: use the 95% confidence coefficient instead.
- Although not preferred to confidence intervals, if desired, P values should be reported as equalities when possible and to one or two decimal places (e.g., $P = 0.03$ or 0.22 not as inequalities: e.g., $P < 0.05$). Do NOT report "NS"; give the actual P value. The smallest P value that need be reported is $P < 0.001$, save in studies of genetic associations.
- Report whether and how any adjustments were made for multiple statistical comparisons.
- Name the statistical software package used in the analysis

Reporting null-hypothesis significance tests

Choice of the test must match statistical assumptions

Degrees of freedom can rescue your paper

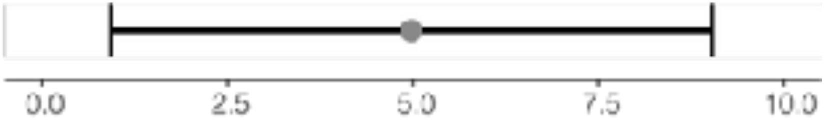
statcheck.io: Check consistency between the *p*-value and parameters (e.g., *t*, *F*, and their degrees of freedom)

The prevalence of statistical reporting errors in psychology (1985–2013) (Nuijten et al., 2016)

Statcheck tutorial (Nuijten & Polanin, 2020)

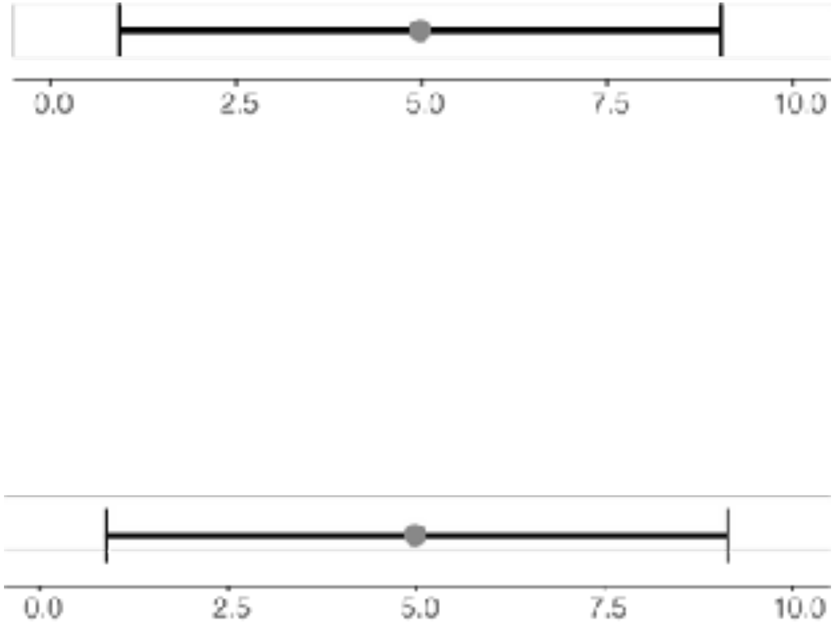
Transparency through visualizing research data

What can you say about these two 95% confidence intervals?

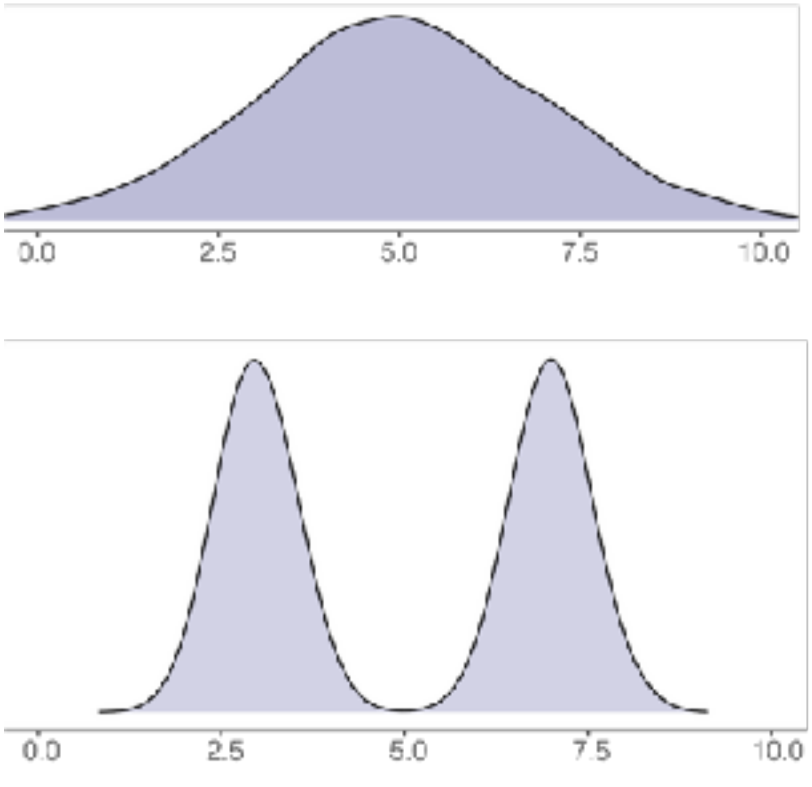


Intervals (95% CI)

Summaries can **obscure** important relationships in distributional data



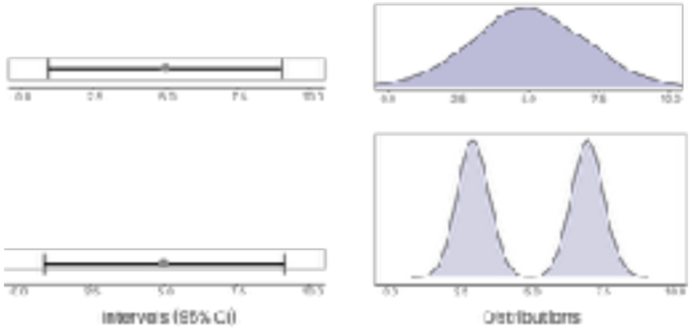
Intervals (95% CI)



Distributions

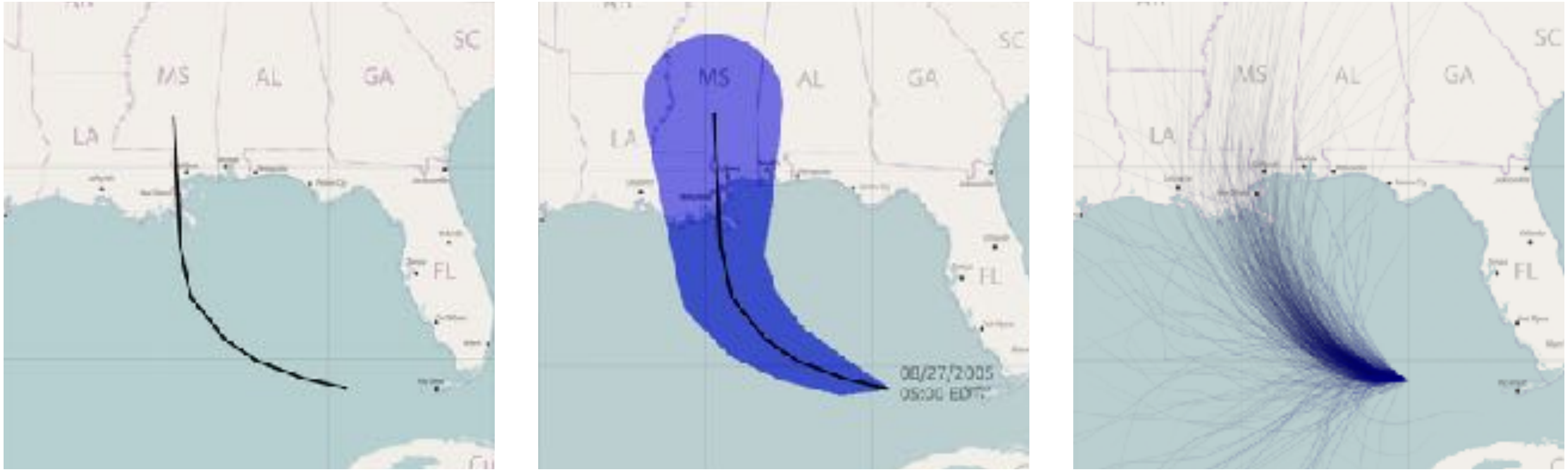
Visualizing uncertainty in the results

Expressiveness principle: the visual representation should represent ***all*** and ***only*** the relationships that exist in the data[1,2]



Expressiveness is a proxy to transparency

[1] Mackinlay, J. (1986). Automating the design of graphical presentations of relational information.
[2] Munzner, T. (2014). Visualization analysis and design. CRC press.



expressiveness →

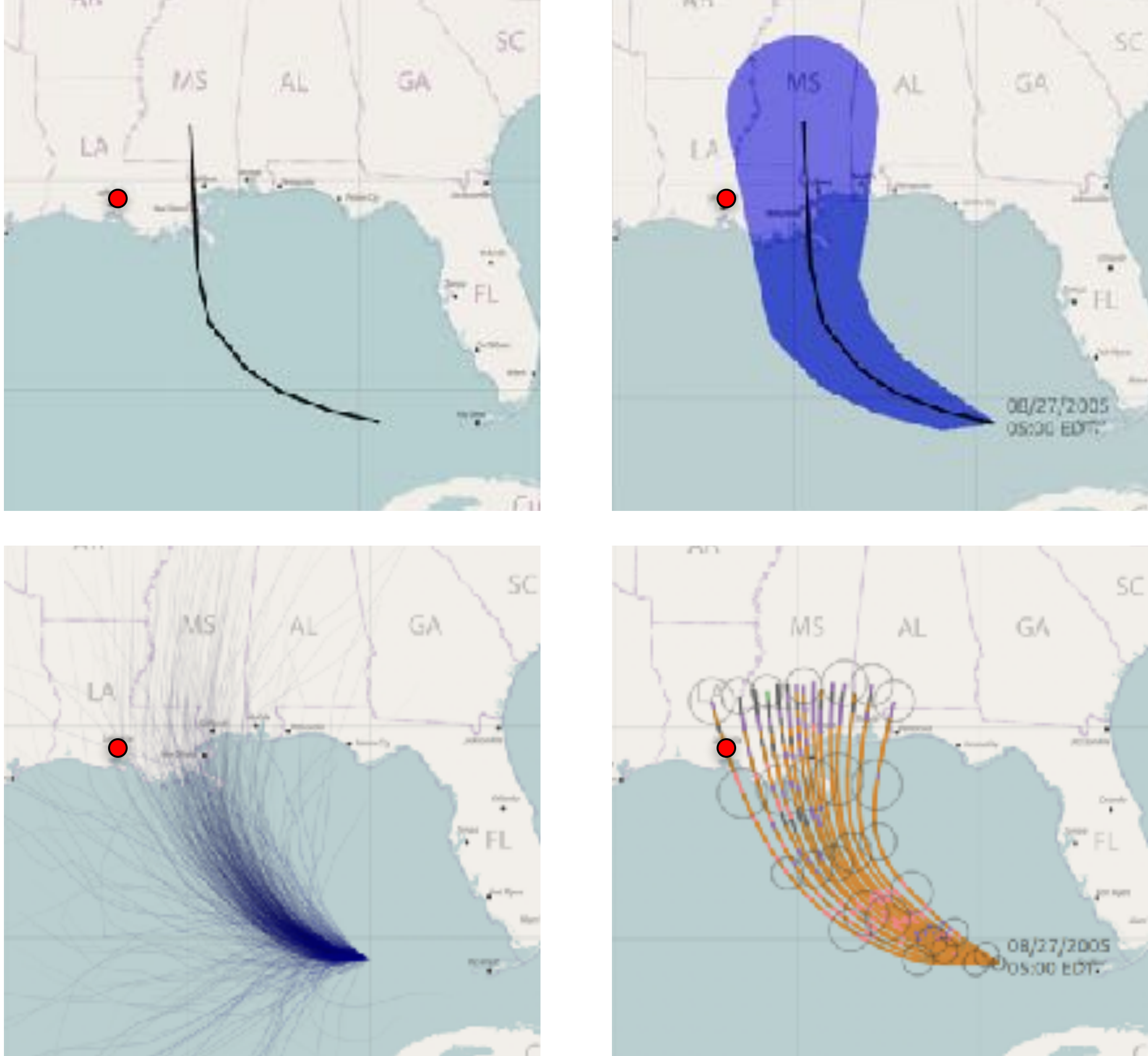
Visualizations of data can vary on a spectrum of expressiveness

Choices of visualization is an aspect of research transparency

[Liu et al., 2018 (IEEE VIS)]

Would you stay or evacuate?

Usable visualizations support users in making accurate inferences



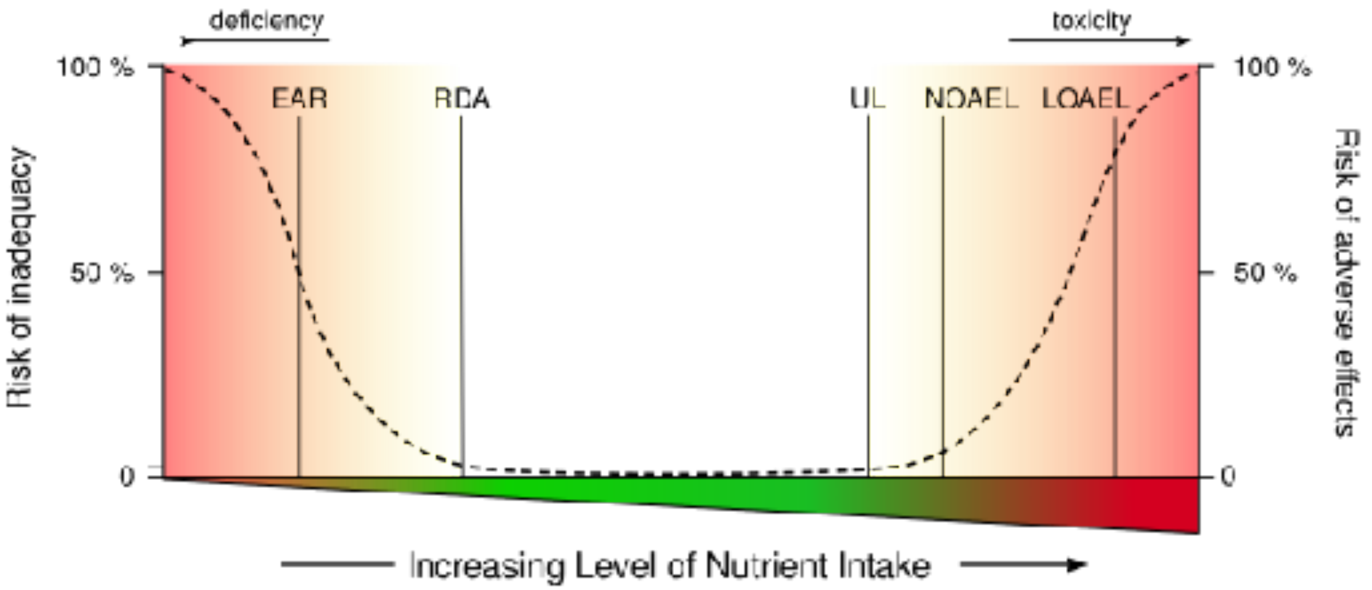
[Liu et al., 2018 (IEEE VIS)](#)
[Padilla et al., 2018 (CRPI)](#)

Dietary Reference Intakes (DRIs): Recommended Dietary Allowances and A

Food and Nutrition Board, Institute of Medicine, National Academies

Life Stage Group	Vitamin A (µg/d)[a]	Vitamin C (mg/d)	Vitamin D (µg/d)[b,c]	Vitamin E (mg/d)[d]	Vitamin K (µg/d)	Thiamin (mg/d)	Rib (mg/
Infants							
0–6 mo	400*	40*	10*	4*	2.0*	0.2*	
6–12 mo	500*	50*	10*	5*	2.5*	0.3*	
Children							
1–3 y	**300**	**15**	**15**	**6**	30*	**0.5**	
4–8 y	**400**	**25**	**15**	**7**	55*	**0.6**	
Males							
9–13 y	**600**	**45**	**15**	**11**	60*	**0.9**	
14–18 y	**900**	**75**	**15**	**15**	75*	**1.2**	

Dietary reference intake (Food and Nutrition Board, Institute of Medicine, National Academies)



Dietary reference intake (Julius Senegal)

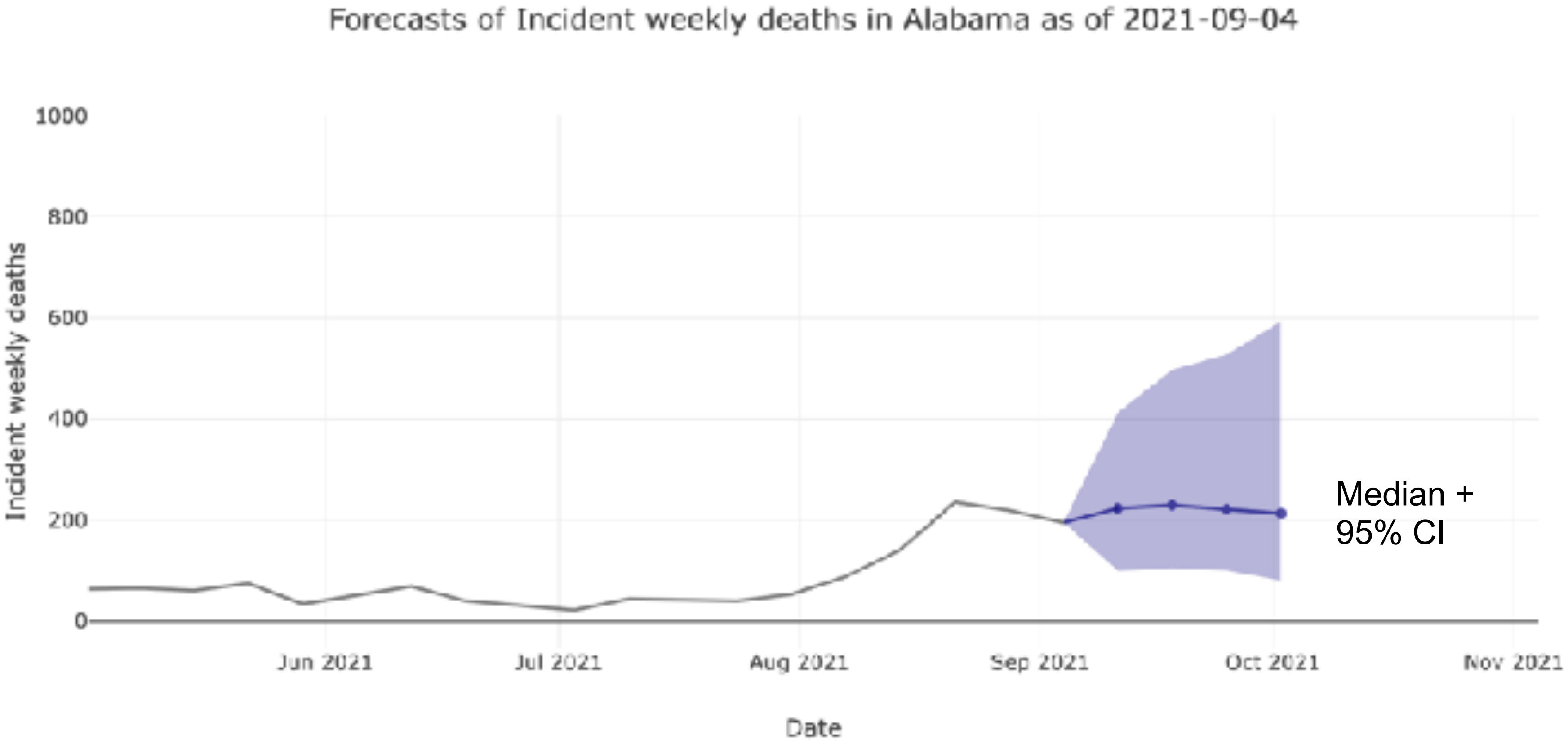
Uncertainty matters

Without uncertainty, viewers may come to ***incorrect*** *conclusions about the data.*

Showing uncertainty:

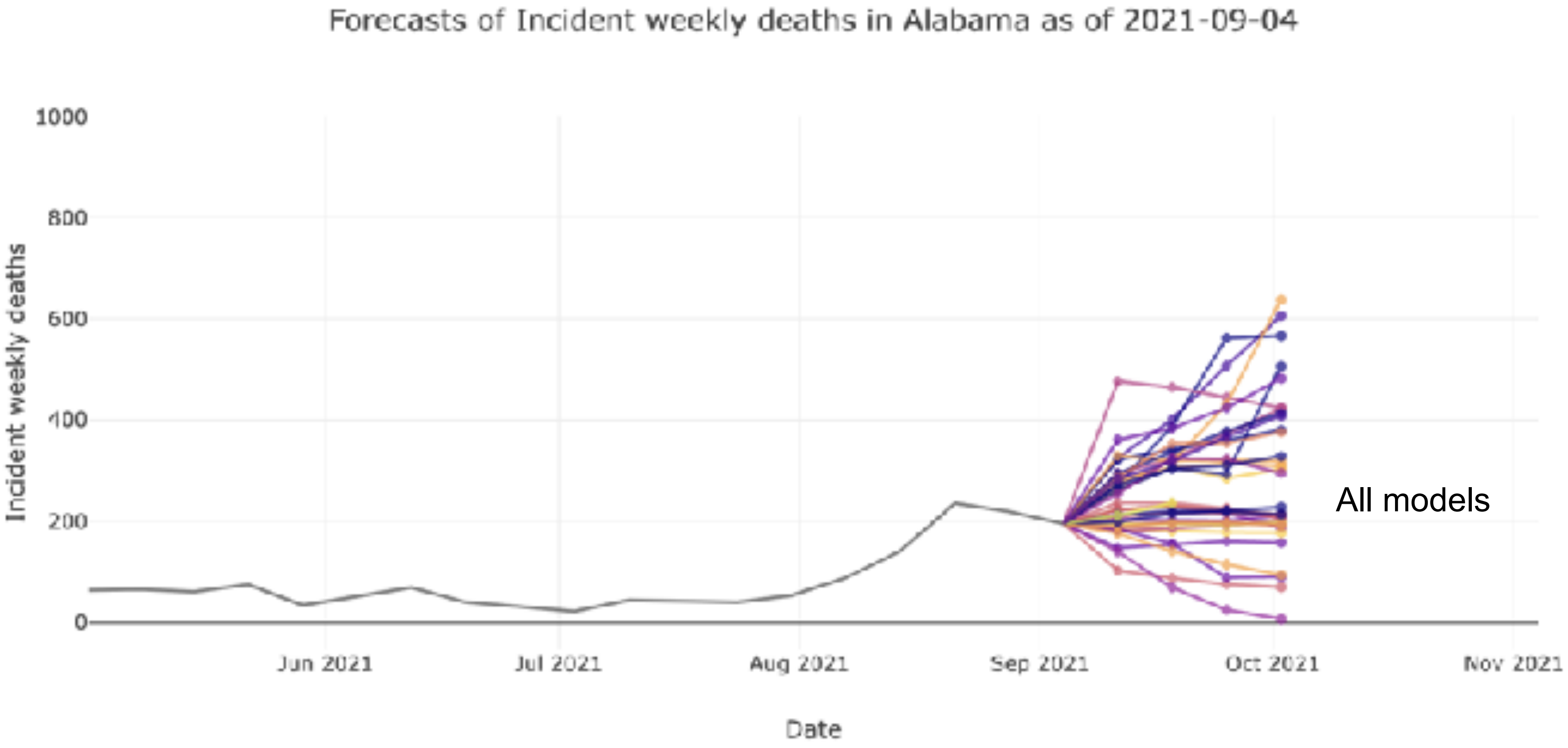
- Increases scientific credibility
- Increases trust
- Let them tune their expectations and assumptions correctly

Usable visualizations support users in making accurate inferences
Showing uncertainty contributes to usability



viz.covid19forecasthub.org | Reich Lab of the University of Massachusetts Amherst

Padilla et al., 2022 (Nature, Scientific Reports)

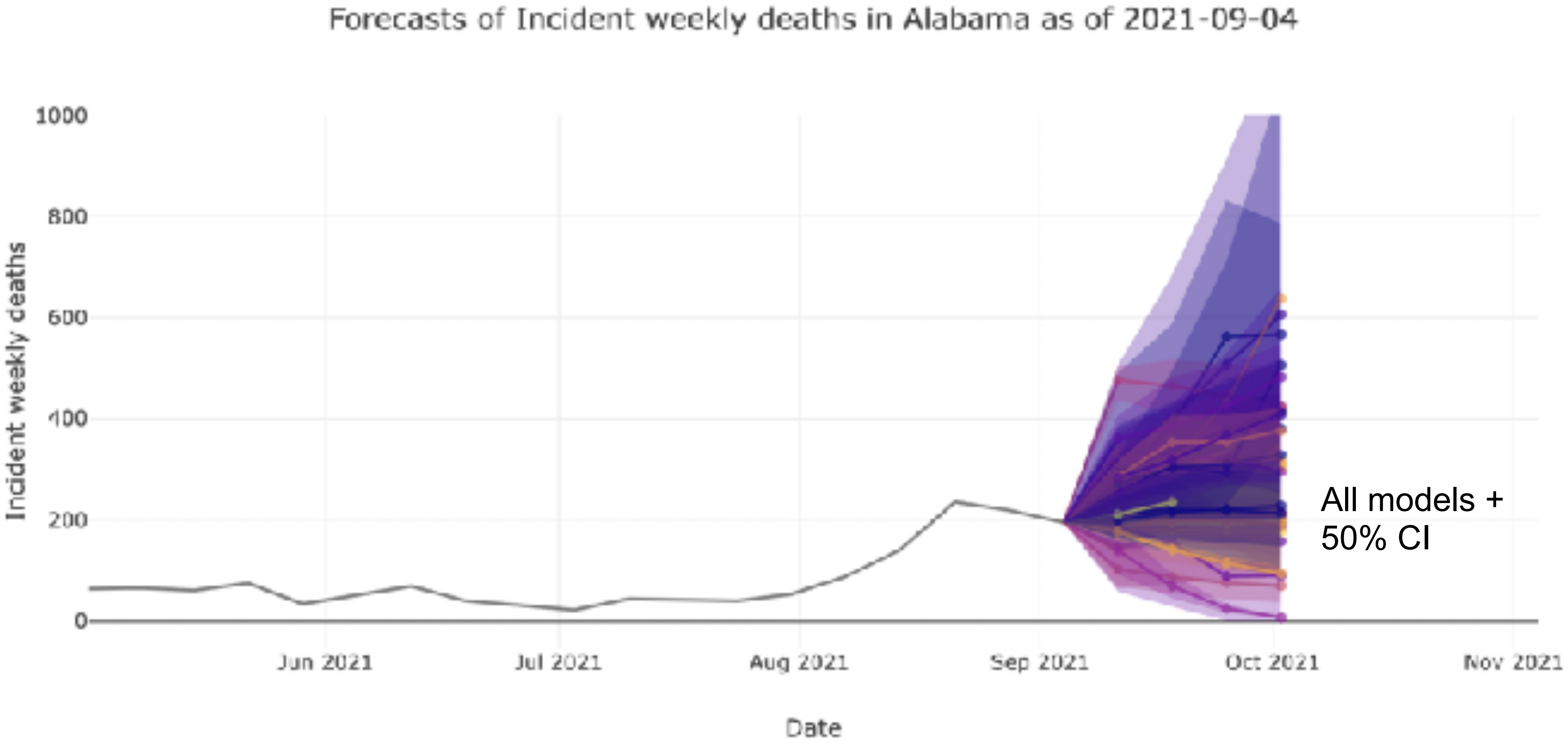


expressiveness

usability

viz.covid19forecasthub.org | Reich Lab of the University of Massachusetts Amherst

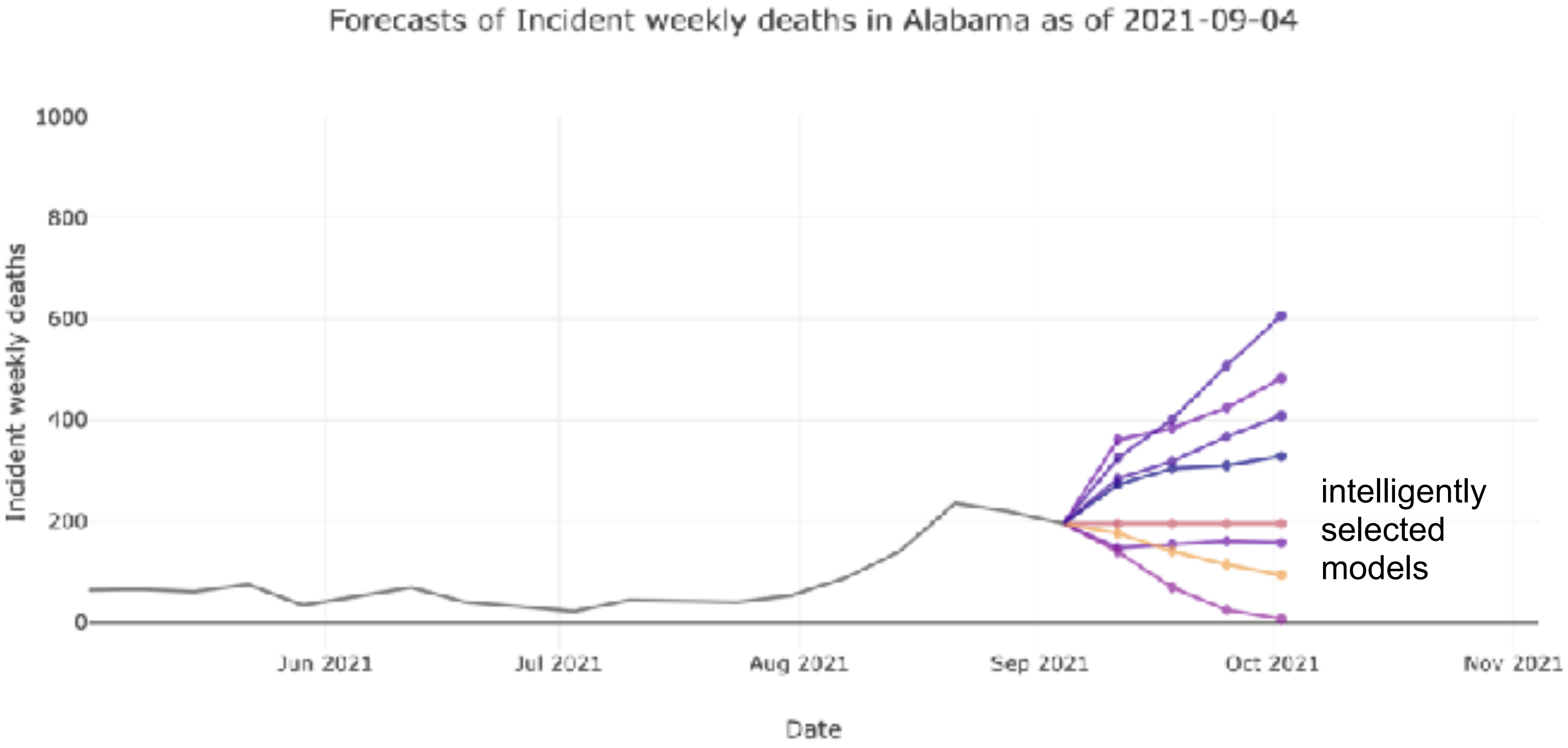
Padilla et al., 2022 (Nature, Scientific Reports)



All models +
50% CI

expressiveness

usability



intelligently selected models

expressiveness

usability

viz.covid19forecasthub.org | Reich Lab of the University of Massachusetts Amherst

Padilla et al., 2022 (Nature, Scientific Reports)

Research transparency through visualization

Balancing tradeoffs between:

- **Expressiveness:** Faithfully represent the data, and
- **Usability:** Support users in making accurate inferences from the data

No single best answer

Consider **context, data set, and audience** when making these decisions

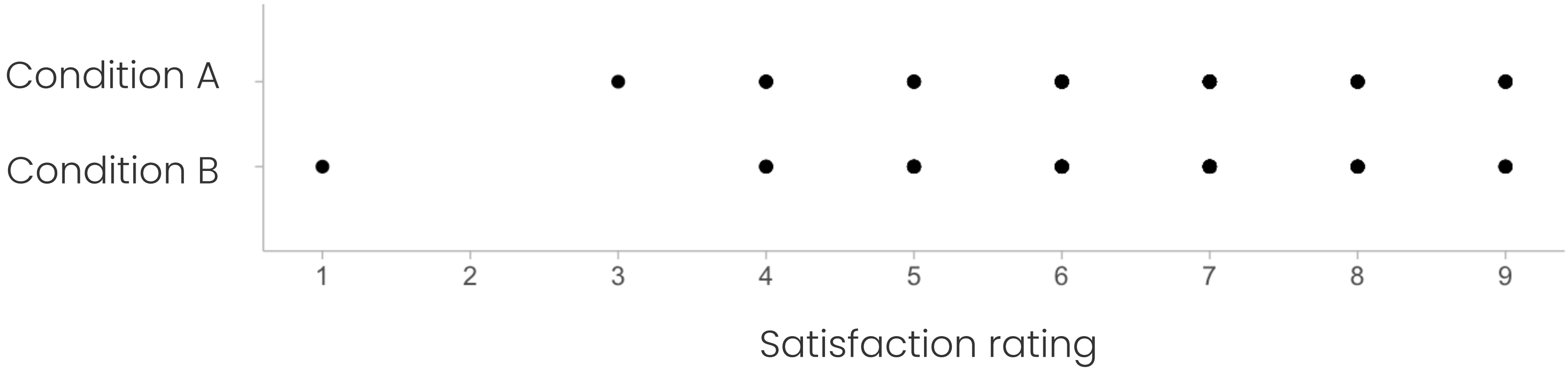
Exercise

Expressiveness: Faithfully represent the data
Usability: Support users in making accurate inferences from the data

1. Critique effectiveness and usability of the following chart
2. Sketch and alternative
3. Justify why your sketch is better

Context:

- A study comparing two conditions
- Collected satisfaction rating 1, 2,...9
- 100 study participants



Transparency in research materials

What to share?

A. Study materials are produced by researchers and presented to participants to elicit their responses (e.g., visual stimuli used during experiment or questionnaires).

Raw data
- **B. Selective:** Data collected at researchers' discretion (e.g., field notes during ethnographic study)
- **C. Nonselective:** Data collected without researcher discretion at the time of collection, (e.g., task completion times logged by software)

Data processing procedure
- **D. Qualitative** (e.g. coding manual)
- **E. Quantitative** (e.g., statistics analysis script)

Processed data
- **F. Output from qualitative processing:** human involved in interpretation (e.g., transcription, annotations, and categorization)
- **G. Output from quantitative processing:** human may involve in defining the rules but not making judgements at the time of processing (e.g., error rate and outliers)

Prototypes
- **H. Software:** Executables and/or source code, excluding those in E.
- **I. Hardware:** (e.g., 3D designs, circuit diagrams)

Ethical considerations:
- to study participants
- to taxpayers who fund your research

Consult your IRB.

Simple anonymization (rename participant ID and shuffle the order) sometimes suffice

If cannot share (e.g., research on company confidential data),
- Share aggregated statistics at the as close to raw as possible
- Describe what materials are generated and provide justification in the paper

For extensive discussion on materials, misunderstandings, and how to share, see:
Wacharamanotham et al., (2020). [Transparency of CHI Research Artifacts: Results of a Self-Reported Survey](). In Proc. of CHI 2020.

How to prepare materials for sharing?

Interoperable file formats, e.g., text csv, Excel Open XML (.xlsx)

👉 Guide on how to organize data in spreadsheet

A clear entry point: README.txt, README.md, or index.html

👉 Github repository template for organizing data

Data dictionary:

Which file containing what data

Column: name, readable description, unit of measurement, and range

👉 OSF guide on data dictionary

For detailed discussion on the whole research materials management process, see **Good enough practices in scientific computing** (Wilson et al., 2017)

A guide on data organization: A reproducible data analysis workflow with R Markdown, Git, Make, and Docker (Peikert & Brandmaier, 2019)

For ultimate reproducible research compendium based on R, check the rrtools package.

Examples supplemental material organization

Structure of this repository

- analyses
  - exp1.R
  - helper scripts
    - CI.helper.R
    - plotting functions.R
- data
  - exp1.csv
  - exp1_column-description.csv
  - exp2.csv
  - exp2_column-description.csv
    - raw data
      - exp2-complete-column-descriptor.csv
      - exp2-complete.csv
      - exp2-raw-BART-data-column-descriptor.csv
      - exp2-raw-BART-data.csv
- markdown
  - exp1.md - The complete analysis script for experiment 1

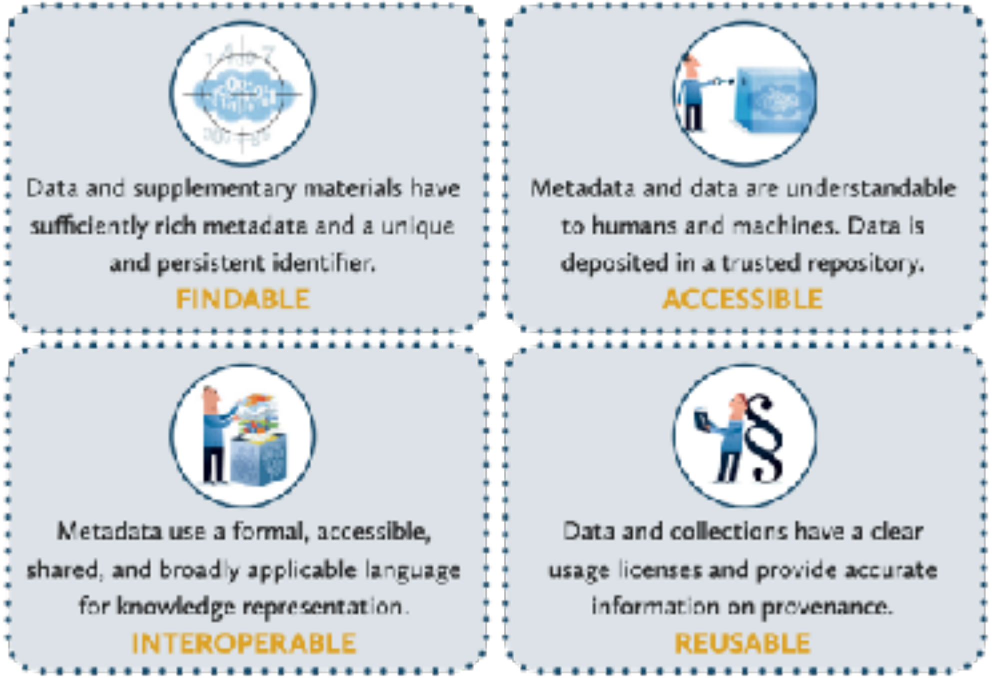
Jansen & Hornbæk (2018) https://github.com/yvonnejansen/posture

Examples supplemental material organization

column_id	data_type	range	description	exact_question
Timestamp	time		timestamp when the participant complete the experiment	
In_charge	integer	[1,7]	self-reported feeling in charge measure	To what extend do you feel in charge?
power	integer	[1,7]	self-reported sense of power	How powerful do you feel?
fatigue	integer	[1,7]	self-reported fatigue	Did you find this task fatiguing?
difficult	integer	[1,7]	self-reported task difficulty	Did you find it difficult to hold your body in the required po
p_id	integer	[1-44]	participant id	
painful	integer	[1,7]	self-reported pain	Did you find it painful to hold your body in the required pos
height	integer	[155,195]	participant's height in cm	
gender	string		participant's gender	
condition_nr	integer	[0,1]	numerical condition assignment	
condition_name	string		condition assignment as string	

Jansen & Hornbæk (2018) https://github.com/yvonnejansen/posture

Where to share?



OSF

One-stop service for whole project life cycle

zenodo

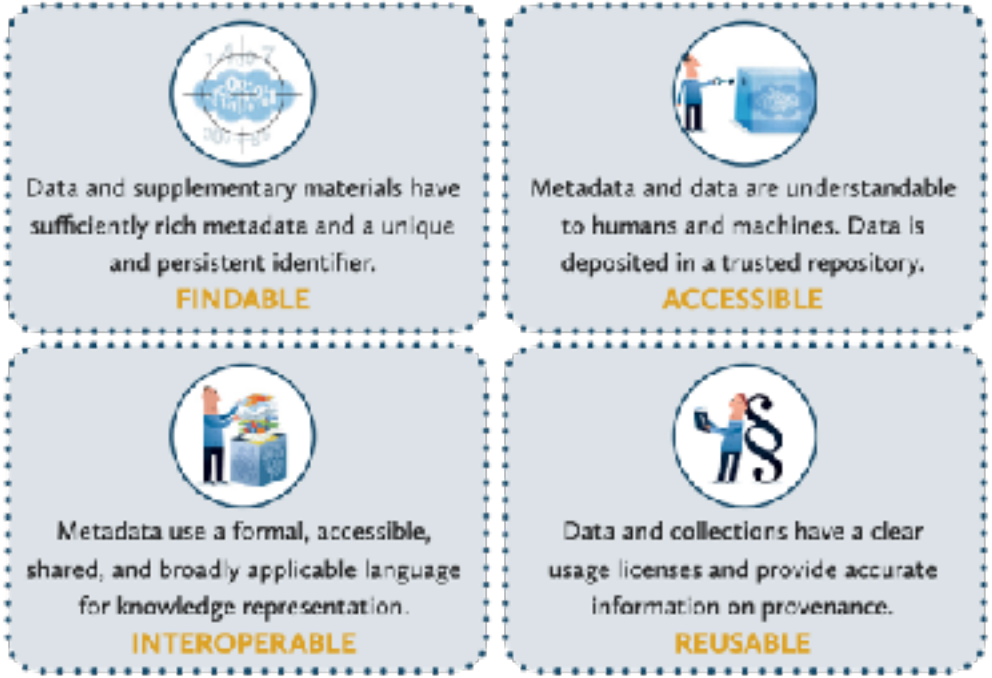
Good for big (>1 GB) files, Has versioned DOIs

re3data.org REGISTRY OF RESEARCH DATA REPOSITORIES

Search engine for specialized data repositories

Diagram: [LIBER Europe]

Where to share?



ACM DL DIGITAL LIBRARY

😕 Findable: Same DOI as the paper, but materials are in single zip file

✅ Accessible: Supplementary materials has no paywall (but not widely known)

Some SIGCHI conferences only allow a video preview as supplementary material

Diagram: [LIBER Europe]

Where to share?

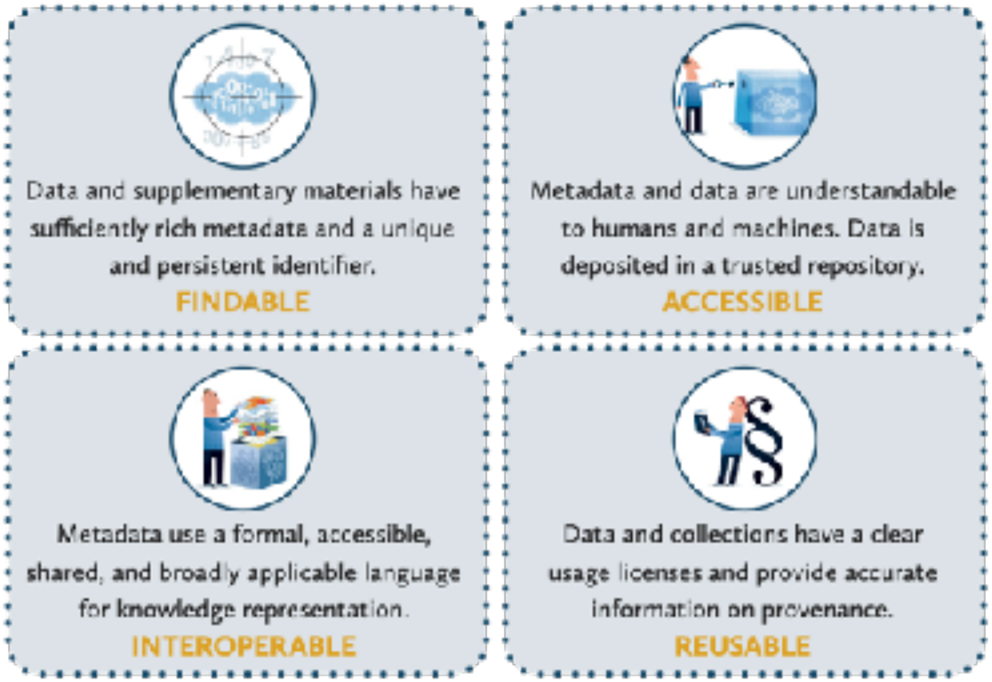


Diagram: [LIBER Europe]

GitHub

✅ Findable

✅ Interoperable: GitHub forking, Git submodule

❌ ~~Accessible~~: Repositories are deletable → broken link, Whodunit?

Recommendation: Add a snapshot of GitHub to OSF or Zenodo

Be
FAIR
Findable
Accessible
Interoperable
Reusable
and
CARE
Collective Benefit
Authority to Control
Responsibility
Ethics

CARE principles

Collective Benefit · Authority to Control · Responsibility · Ethics

Originally developed in the context of indigenous data, we think the principles could be applied broadly. Below are our generalized wording; for the original, see: https://www.gida-global.org/care

Collective benefit: Data ecosystems shall be designed and function in ways that enable inclusive development, improved governance, and equitable outcomes

Authority to Control: Recognizing the rights and interests of people involved in generating the data, especially their rights to free, prior, and informed consent in the collection and use of the data

Responsibility: Researchers are responsible for sharing how the data are used to support collective benefits as well as benefits to individuals who involved in generating the data

Ethics: Minimize potential harm and maximize the benefit of people involved

Sharing sensitive data

Ethical concerns? Consider using one of the Protected Access Repositories

Databrary

AUTHORIZED ACCESS

One of Databrary's distinguishing features is that it provides a proven framework for sharing sensitive and identifiable data within a trusted network of authorized researchers.

To achieve this, access to restricted materials on Databrary requires institutional authorization via the formal Databrary Access Agreement and its three annexes. Annex I is a Statement of Rights and Responsibilities. Annex II can be used to add additional investigators to Databrary from an institution AFTER the initial full agreement has been completed by an investigator and the institution's Authorized Organizational Representative. Annex III is the Databrary Access Guide. It describes some of the core Databrary policies and practices that are important for institutions and researchers to understand and abide by.

PsychData

Terms of Use

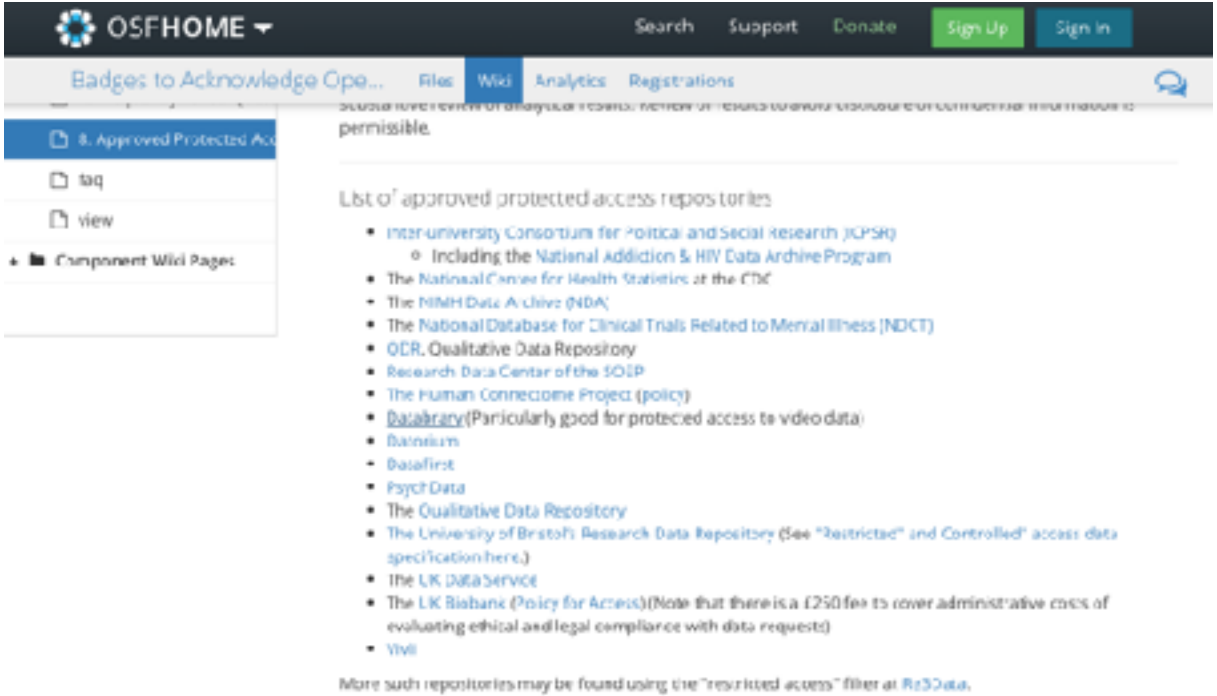
Important information about the use of research data

To receive requested research data, the terms of use must be accepted by means of a data use agreement, which is employed to prevent the commercial use of data as well as to protect the interests of the data providers and ensure the anonymity of research subjects.

- The relinquished data and associated materials may only be used for the purpose of academic research and instruction.
- The relinquished materials may not be forwarded to third parties. Should the data be used in a project team or academic course, it is the data user's responsibility to ensure the terms of use are upheld.
- Any publication that is based completely or partially on the relinquished data and/or associated materials must identify the data providers as well as the ZPID (obligatory citation)
- The ZPID must be informed about publications that are based on the relinquished data and/or associated materials.
- No attempts to reidentify or contact research subjects may be made.

Sharing sensitive data

Ethical concerns? Consider using one of the [Protected Access Repositories](https://osf.io/tvyxz/wiki/8.%20Approved%20Protected%20Access%20Repositories)



https://osf.io/tvyxz/wiki/8.%20Approved%20Protected%20Access%20Repositories

Pointing the readers to the shared materials

Crossing the paywall: Link to the FAIR repository at the end of the abstract

ABSTRACT

Several fields of science are experiencing a "replication crisis" that has negatively impacted their credibility. Assessing the validity of a contribution via replicability of its experimental evidence and reproducibility of its analyses requires access to relevant study materials, data, and code. Failing to share them limits the ability to scrutinize or build-upon the research, ultimately hindering scientific progress.

Understanding how the diverse research artifacts in HCI impact sharing can help produce informed recommendations for individual researchers and policy-makers in HCI. Therefore, we surveyed authors of CHI 2018–2019 papers, asking if they share their papers' research materials and data, how they share them, and why they do not. The results (34% response rate) show that sharing is uncommon, partly due to misunderstandings about the purpose of sharing and reliable hosting. We conclude with recommendations for fostering open research practices.

This paper and all data and materials are freely available at https://osf.io/3bu6t.

ABSTRACT

Statistical charts complement textual reports by visualizing overall patterns or relations in the data. However, layout algorithms may place charts far from their associated text. Such distant placement can cause reading difficulties, or worse, a misinterpretation. We conducted an eye-tracking experiment comparing reading behaviors in two proximity levels: Placing text and chart on the same page, versus placing them on two different pages. The results indicate that the proximity influences text-reading stronger than chart-reading behavior. We discuss design implications for text-chart layout algorithms and practices. This paper and all data and materials are freely available at https://osf.io/xunt9.

Transparency of CHI Research Artifacts: Results of a Self-Reported Survey
(Wacharamanotham et al., 2020)

Asymmetric effect of text-chart proximity on reading behavior
(Yang & Wacharamanotham, 2020)

Sharing vs. the anonymized reviewing process

When you submit the materials to an anonymized reviewing, consider:

- Preregistration: OSF: view-only link   AsPredicted: anonymous PDF
- Source code:
  - The absolute paths may contain your name
  - Github URL may contain your name or user ID

Although it is the due-diligence of the authors to anonymize materials, minor oversights is not a reason for rejection

Exercise 4: Brainstorm research materials and sharing concerns

(10 minutes)

Continue with the case you previously chose.

1. Brainstorm possible 2–3 research materials that may be generated
2. Choose one research materials and brainstorm 3 concerns that people may have against sharing
3. Discuss ways to mitigate that concern

Reflection

Reflection on research transparency

More transparent = more work?

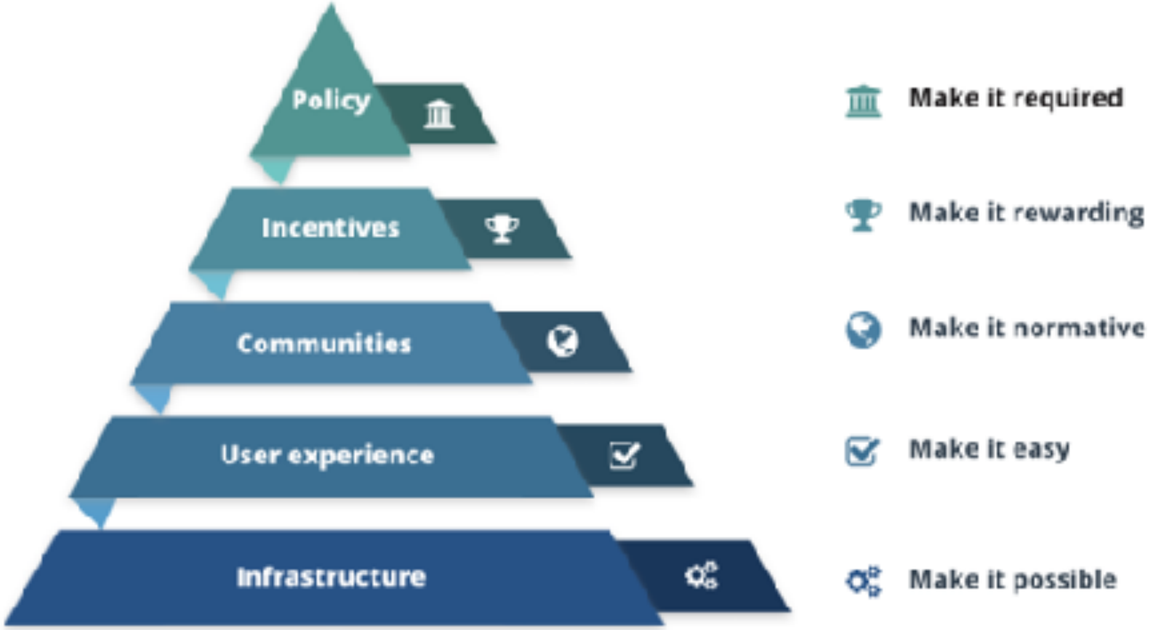
- Some learning needed for the first time, effortless later on
- Pays off: Better methodological rigor to self and to reviewers
- Small step: How can my next paper be more transparent than the last one?

Cultivating research transparency culture

When giving feedback or writing reviews, instead of penalizing the lack of transparency:

- Describe what could be improved
- Describe good consequences of the improvements
- Point to guides and examples

Motivating research transparency in HCI



Source: Center for Open Science [strategy for scale sustainable adoption of open behaviors by researchers]

Challenges in motivating transparency across HCI

Spectrum of empirical research

Replicability is not relevant

Quantitative **Qualitative**

Beyond empirical research

- Engineering
- Design
- Arts

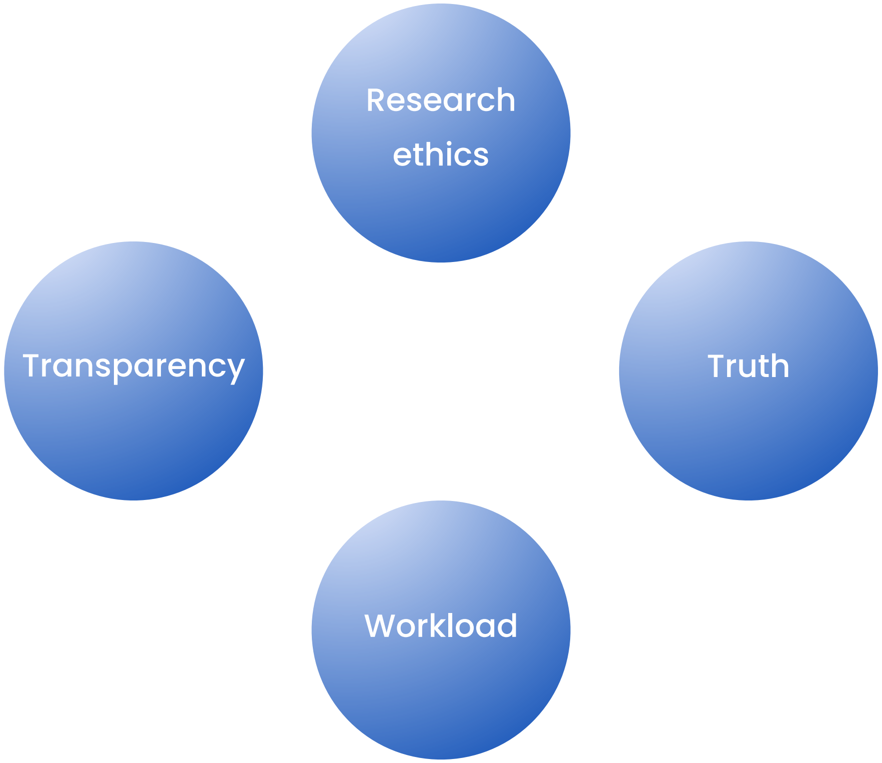
What needs to be transparent?

Tricky research settings

- Sensitive population
- Research conducted in company environments

People may not tell the truth if their data will be public

A balancing act?



Challenges in motivating transparency across HCI

Established researchers

Junior researchers

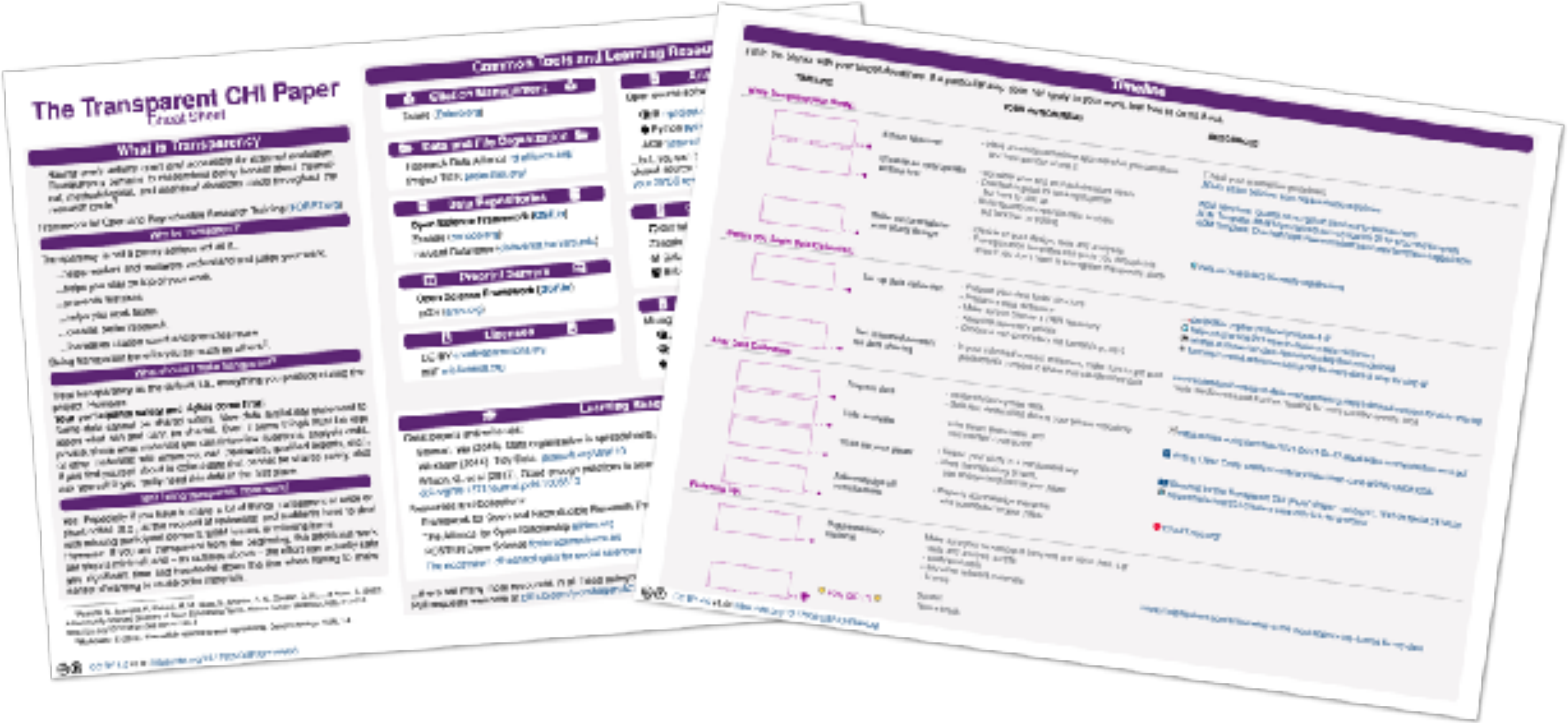
Resourceful institutes

Institutes in low-income countries

Transparency-aware reviewers

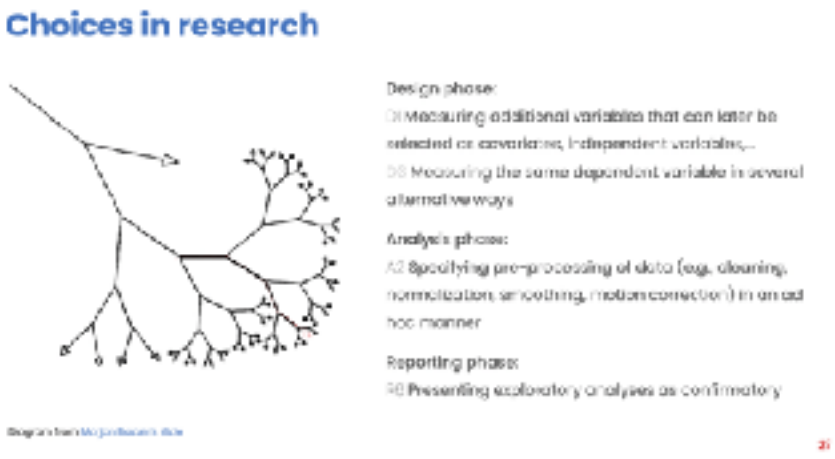
Transparency-unaware reviewers

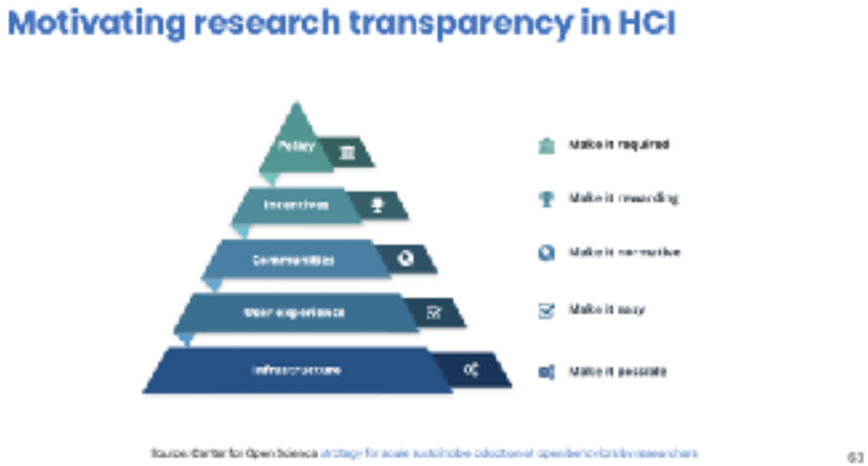
A Cheat Sheet for a Transparent CHI paper



👉 https://osf.io/udq48

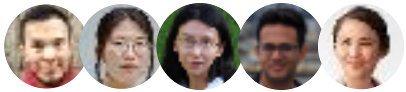
Output of the Dagstuhl Seminar Transparent Quantitative Research as a User Interface Problem





Chat Wacharamanotham

chat@ifi.uzh.ch



This tutorial is designed based on the open materials of the courses presented at CHI 2022–23 by Chat Wacharamanotham, Fumeng Yang, Abhraneel Sarma, Xiaoying Pu, and Lace Padilla. https://osf.io/27r5z