Transparent Practices for Quantitative Empirical Research

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ABSTRACT

Transparent research practices enable the research design, materials, analytic methods, and data to be thoroughly evaluated and potentially reproduced. The HCI community has recognized research transparency as one quality aspect of paper submission and review since CHI 2021. This course addresses HCI researchers and students who are already knowledgeable about experiment research design and statistical analysis. Building upon this knowledge, we will present current best practices and tools for increasing research transparency. We will cover relevant concepts and skills in Open Science, frequentist statistics, and Bayesian statistics, and uncertainty visualization. In addition to lectures, there will be hands-on exercises: The course participants will assess transparency practices in excerpts of quantitative reports, interactively explore implications of analytical choices using RStudio Cloud, and discuss their findings in small groups. In the final session, each participant will choose a case study based on their interest and assess its research transparency together with their classmates and instructors.

CCS CONCEPTS

• **Human-centered computing → HCI design and evaluation methods**; **Visualization techniques**; **Visualization design and evaluation methods**.

KEYWORDS

transparent statistics, open science, uncertainty visualization, Bayesian statistics

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1 MOTIVATION AND SCOPE

"CHI papers should strive for research transparency regardless of the contribution type and methodology."

— CHI 2022 Guide to a successful submission [4]

Transparent research practices enable the research design, materials, analytic methods, and data to be thoroughly evaluated and potentially reproduced. The importance of transparent research practices is widely recognized. As of June 2019, the Transparency and Openness Promotion (TOP) Guidelines [30] are implemented by 4,985 journals [28]—among them are prominent outlets from a variety of scholarly disciplines, e.g., *Science, Nature Human Behavior, Psychological Science, American Economic Association.*

In the last decade, the field of HCI has been continuously engaging in the conversation related to replicability and transparency (e.g., RepliCHI movement [55–58], Transparency movement [6, 19, 20, 50]). These efforts manifested in the community-led effort in 2019 [5] to add a section on research transparency to the *Guide to a successful submission* [2] and *Reviewing* [3], which was officially adopted since CHI 2021. However, other HCI outlets have yet to catch up: only 12% of HCI-related journals adopted the TOP guideline [1]. As for researchers' practices, a survey of CHI authors shows several misunderstandings about transparent practices for research materials and data [49]. The report by OECD points out that even seasoned researchers also need to acquire new Open Science skills [33, p. 92]. Education can improve the research practices of individuals (bottom-up) and expand community support for transparent research policies (top-down). However, the report by the U.S. National Academies of Sciences, Engineering, and Medicine indicates that such education is still rare in academic institutions [31, pp. 153–154]. This report also recommends that professional societies train students and researchers as well as supporting development of educational programs. To date, **neither SIGCHI nor ACM provides training in transparent research practice or Open Science**.

The field of HCI has a wide variety of methods to acquire knowledge: quantitative, qualitative, design, and engineering—to name a few [35]. **The scope of this course focuses on *quantitative empirical research.*** A large body of research from the field of HCI and visualization had also contributed to improving transparent practices in quantitative research (e.g., [7, 10, 11, 13, 21, 22, 44, 47]). **This course will present current best practices and tools for research transparency.**

2 INTENDED AUDIENCE AND PREREQUISITES

The intended audience is HCI researchers and students who already have elementary knowledge in quantitative research design and statistical analysis. For example, they should already know the differences between the within-subjects and between-subjects design. They should have performed statistical analysis on a few datasets. They should also be familiar with how research articles report their method and results.

In the course, we will use R to demonstrate analytic decisions, statistical analysis methods, and visualization techniques. The knowledge and experience of R will be beneficial for future adoption. The participants may have a better learning experience if they previously used an interpreted language (e.g., Python, R). Nevertheless, the participants are not expected to be proficient at R to understand the course materials. In the course, the participants will access RStudio Cloud through their web browser. No other prior software setup is required.

3 BENEFITS AND LEARNING OUTCOMES

After the course, we expect the participants to be able to get started on improving their own research practices, assessing research transparency in articles they read and review, as well as evaluating institutional policies that may impact research transparency. Toward these goals, we design this course with the following specific learning outcomes:

The course participants…

- aware of decisions made in the course of quantitative research and the importance of making them transparent,
- know a range of practices, methods, and tools to improve research transparency,
- can apply principles to evaluate and compare the transparency of statistical and visualization techniques, and
- can preregister and deposit their research artifacts in FAIR repositories.

4 CONTENT AND PRACTICAL WORK

Research transparency spans from planning to sharing results. We have organized it into four sections.

4.1 Planning research and sharing research artifacts

Planning involves deciding on the type of research questions, choosing variables to study, defining which variables and how they will be measured, and deciding on how many participants to recruit. Such decisions affect how to collect and analyze data. Ambiguities in describing the plan impede attempts to verify, replicate, and build upon the findings.

This section will introduce the participants to lists of research decisions (e.g., [52]). We will show examples of how these decisions could influence data analysis. There will be hands-on practice in identifying ambiguities and omissions of research decisions from excerpts of research papers. We will discuss strategies for planning sample sizes [23], and the participants will explore how their decisions impact the statistical power using a simulation tool (e.g., [51]).

We will demonstrate how to preregister these research and analytical decisions. We will show several examples of preregistration and final research to illustrate the fact that "preregistration is a plan, not a prison" [9]—changes and further exploratory analyses are possible and can be made transparent. We will discuss types of research artifacts and how to share them according to the FAIR principles (**F**indability, **A**ccessibility, **I**nteroperability, and **R**euse). We will also discuss ethical concerns in data collection and sharing.

4.2 Choosing statistical methods and reporting their results

This course recognizes that many statistical approaches are valid, and each approach has its own merits and challenges. Instead of presenting *one best method*, we will present a set of guiding principles [48] (provided in Appendix A) that allow the course participants to evaluate transparency. We will sample several statistical techniques and apply them to example datasets. Participants will have access to pre-written analysis R scripts. They will be able to experiment with different analytic decisions and discuss the implications from the perspective of transparency with their classmates.

For **frequentist statistics** (e.g., t-test, Wilcoxon, or ANOVA), we will discuss common mistakes in interpreting p-values and confidence intervals. We will discuss the differences in the understandability and usability between simple and standardized effect sizes. We will also discuss the implications of the presence and the absence of pre-study power analyses. We will cover important statistical results that are necessary for meta-analysis.

For **Bayesian statistics**, we will start by introducing Bayesian statistical concepts, including prior and posterior distributions as well as the likelihood function. We will then walk through the implementation of several Bayesian models, and compare them with the frequentist analogs, followed up by extensions to these models with respect to increasing transparency. We will later focus on interpreting the posterior distributions of Bayesian models to estimate the probabilities of an effect. If time permits, we will also discuss other opportunities: (1) choosing prior distributions to improve both the models and transparency in the results; (2) using metrics such as information criteria to disclose transparency in model evaluation and selection; and (3) following best practices such as posterior predictive checks to increase the transparency in reviewing processes.

4.3 Visualizing the results

Continuing from our session on statistical methods, we will equip participants with mindsets and tools to create transparency-oriented visualizations during their analysis as well as for their papers. Such visualizations for analysis results can make a paper more transparent in multiple ways, including improving faithfulness, robustness, process transparency, and clarity (which are transparent statistics principles, see Appendix A).

We will first introduce the idea that visualizing uncertainty information is staying faithful to their statistical analysis. Without proper uncertainty representation, we risk exaggerating the certainty of our findings [15]. Drawing from recent literature [40], we will show different uncertainty visualizations designs and the concepts behind the variations. Notably, there are no one-size-fits-all solutions for uncertainty communication. Thus, we will teach the practice of selecting the most ethical and transparent option at each decision point within the data visualization pipeline. These concepts include frequency vs. probability framing, implicit vs. explicit uncertainty, and aleatory vs. epistemic uncertainty. Then, we will include an interactive activity where participants interpret frequency-based plots and discuss the potential pros and cons of example visualizations based on the concepts they just learned. We will show how multiverse analyses can increase the robustness of statistical analysis [11], and techniques for visualizing their results.

More practically, we will identify the visualization opportunities in the two versions of statistical analysis introduced in the last section. To improve process transparency, we will show examples of visualizations used throughout the analysis, advocating for visualizations as a reflex during analysis. These visualizations include plots for the raw data, summary plots, plots for confidence distributions (frequentist) or posterior distributions (Bayesian), and other model diagnostic plots. For demonstration, we will use R packages including `ggplot2` [53], `tidybayes` [18], and `ggdist` [17]. The focus of this part is on how the properties of these visualization techniques lend themselves to transparency. Therefore, all participants will benefit from this part regardless of their preference and skills in R. In addition, we will offer practical guidelines for making visualizations clear and simple as possible, especially for publication in research manuscripts [16]. These guidelines include "establishing viewing order" and "matching effective visual encoding with importance." As an activity, we will provide negative and positive examples from recent publications, or elicit visualizations for reporting results from the participants, and use the guidelines to help everyone improve on these visualizations.

4.4 Participant's case studies on research transparency

We wish to give the participants a personal experience where transparency depends on the perspective and background knowledge of the readers. Since our course will cover only a small set of statistical analysis techniques and dataset types, we wish to allow the participants to choose specific issues they are curious about and discuss the topics from the transparency perspective.

Between the third and the fourth session of the course, we will ask each participant to prepare case studies on research transparency to share with the classmates. They may select the cases from their own published research or research articles they have read. The participants may also draw examples from Open Access VIS [14]—an annotated index of the research articles published at VIS conference based on their transparency practices.

In the fourth session of the course, we will group the participants into breakout rooms according to the synergy of their case studies. An instructor will moderate the discussion and give feedback in each room. We will draw collective lessons learned and discuss them in a plenary at the end of the course.

5 LIMITATIONS

We do not expect that after a four-session course the participants will immediately transform their entire research practices to be transparent. Such transformation will require looking into specifics of research methods and application domains. This course will provide **a broad overview** on what to be cognizant of, **pointers** on where to learn in-depth, and **practical experience** of a range of important skills. This teaching strategy will provide a foundation that is adequately broad as well as samples of experiences that will pique participants' curiosity to further their knowledge.

6 INSTRUCTORS

Chat Wacharamanotham is an Assistant Professor at the University of Zurich (UZH). The focus of his work is on understanding and developing tools for planning, reporting, reading, and sharing quantitative research [12, 32, 51, 59, 60]. He is also a co-organizer of the Transparent Statistics in Human–Computer Interaction group. He has five years of experience teaching a research method course for graduate students. In 2019, he received the UZH teaching award in recognition of "teaching, which stimulates dialogue between lecturers and students as well as exchange between students in the best possible way" [34].

Fumeng Yang is a PhD candidate at Brown University. Her research interests are designing visualizations and exploring computational approaches to help researchers and end-users think scientifically [26, 36]. She served as a Student Volunteers chair for IEEE VIS 2018, 2019, and 2020, where she interacted with and instructed a cohort of students in a series of conference events.

Xiaoying Pu is a Ph.D. candidate at the University of Michigan. In her research, she takes a human-centered approach to communicating uncertainty and statistics with visualizations [41, 43]. She has organized a CHI 2021 SIG on visualization grammars [42] and contributed to a research transparency tutorial at IEEE VIS 2020. Her website is xiaoyingpu.github.io.

Abhraneel Sarma is a PhD student at Northwestern University. His research interests include studying how people make decisions using visualizations, and how visualizations can be used for improving statistical analysis or reporting statistical results. In addition, he has studied how users implement certain aspects of a Bayesian models [47] and has developed tools for conducting multiverse analysis which is an approach for more transparent statistical research [46].

Lace Padilla is an Assistant Professor at the University of California Merced. Her program focuses on how people make uncertain decisions with forecast visualizations to improve visualization techniques and uncertainty literacy. She works collaboratively with domain experts to empirically test current uncertainty communication approaches and develop new techniques in contexts such as wildfire risk reduction (PI, NSF award #2122174), pandemic forecasting (co-PI, NSF award #2028374), energy grid resiliency (sub-contract, DOE award), and hurricane forecasting [25, 38, 39, 45]. She has co-authored a forthcoming chapter reviewing modern uncertainty visualization techniques, entitled Uncertainty Visualization [37].

7 RESOURCES

- Chapter 1 of the Transparent Statistics Guidelines [48] provides the full description of the principles, their rationale, and application examples.
- For the course participants who wish to expand their knowledge on estimation-approach in frequentist statistics, we

recommend Cumming & Calin-Jageman's book *Introduction to the New Statistics* [8].

- For the course participants who wish to familiarize themselves with Bayesian statistics, we recommend skimming Betancourt's article *Towards A Principled Bayesian Workflow* [29] This article provides instructive visualizations and R codes. And for those who wish to dig deeper, we recommend McElreath's book *Statistical rethinking* [27] or Lambert's book *A student's guide to Bayesian statistics* [24].
- For the course participants who wish to learn R and `ggplot`, we recommend the *R for Data Science* [54]—which is available online free of charge. R proficiency is not a prerequisite for this course.

8 ACCESSIBILITY

The content of our course necessitates many data visualizations. We regret that such content may impose a barrier for people with visual impairments. For people with hearing impairment, we requested an automatic real-time transcription (e.g., those provided in Zoom) in this course proposal. We are not aware of further accessibility barriers.

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A TRANSPARENT STATISTICS GUIDING PRINCIPLES

Quoted and abbreviated from [48]).

(1) **Faithfulness:** A transparent statistical report should strive to capture and convey the "truth" as accurately as possible, especially concerning the uncertainty within the data.
(2) **Robustness:** In order to minimize the likelihood of inaccurate (unfaithful) results, data analysis and reporting strategies that are robust to departures from statistical assumptions—or that make few assumptions—should ideally be preferred.
(3) **Resilience:** Data analysis and reporting strategies should be resilient to statistical noise, i.e., they should yield similar outcomes across hypothetical replications of the same study.
(4) **Process Transparency:** Data analysis and reporting strategies need to be explained rather than implied. The decisions made during the analysis and report writing should be communicated as explicitly as possible.
(5) **Clarity:** Study reports should be easy to process—even when they target experts. Ideally study reports should be accessible to most members of the HCI community, instead of being comprehensible by only a handful of specialists.
(6) **Simplicity:** When choosing between two data analysis procedures, the simplest procedure should ideally be preferred even if it is slightly inferior in other respects.
(7) **Non-contingency:** When possible and outside exploratory analyses, data analysis and reporting strategies should avoid decisions that are contingent on data, e.g., "if the data turns out like this, compute this, or report that".
(8) **Precision and economy:** Even if full transparency is achieved, a study report where nothing conclusive can be said would be a waste of readers' time, and may prompt them to seek inexistent patterns. Data quality, high statistical power, and high statistical precision are important goals to pursue.
(9) **Material availability:** Sharing as much study material as possible is a core part of transparent statistics, as it greatly facilitates peer scrutiny and replication.

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