This is a preprint. Please share any constructive feedback with the first author. In the spirit of transparency, we will document all feedback received together with how we addressed it in a (for now future) revision. Please let us know if you want to be credited by name in this documentation or if you prefer to remain anonymous. Thanks!

The Many Ways of Being Transparent in Human-Computer Interaction Research

Yvonne Jansen
yvonne.jansen@cnrs.fr
Univ. Bordeaux, CNRS, Inria, LaBRI
France

Jan B. Vornhagen
javo@itu.dk
IT University of Copenhagen
Denmark

Olga Iarygina
olgl@itu.dk
IT University of Copenhagen & University of Copenhagen
Denmark

Kavous Salehzadeh Niksirat
kavous.salehzadehniksirat@unil.ch
EPFL & University of Lausanne
Switzerland

Lonni Besançon
lonni.besancon@gmail.com
Linköping University
Sweden

Pierre Dragicevic
pierre.dragicevic@inria.fr
Inria, Univ. Bordeaux, CNRS, LaBRI
France

Julien Gori
gori@isir.upmc.fr
Sorbonne Université, CNRS, Institut des Systèmes Intelligents et de Robotique, ISIR
France

Chat Wacharamanotham
chat@ifi.uzh.ch
University of Zurich
Switzerland

ABSTRACT

Research transparency has become a common topic of discussion in many fields, including human-computer interaction (HCI). However, constructive discussions require a shared understanding, and the diversity of contribution types and ways of doing research in HCI have made dialog about research transparency difficult. With this paper, we aim to facilitate such dialog by proposing a definition of research transparency that is broadly encompassing to diverse types of HCI research: *Research transparency refers to honesty and clarity in all communications about the research processes and outcomes—to the extent possible.* We unpack this definition to highlight the different facets of research transparency and offer examples of how transparency can be practiced across different HCI contribution types, including non-empirical contributions. With this article, we argue that research transparency does not have to be inflexible and that transparency in HCI research can be achieved in many ways depending on one's methodology or contribution type. Supplementary material is available on https://osf.io/gs4fy/.

KEYWORDS

research transparency, meta-transparency

1 INTRODUCTION

Research transparency is increasingly becoming a focal point of discussion across research areas. Within the field of human-computer interaction (HCI)[1], the importance of the topic can be seen both bottom-up—through a growing number of events [23, 63, 65, 111] and research papers that have discussed or studied transparent research practices [25, 26, 102, 117, 119]—and top-down through guides for authors and reviewers. For example, the submission guide for CHI[2], the biggest conference in HCI, states that *"research transparency is of utmost importance in a CHI paper"* [22], while the call for papers for the CSCW[3] conference states that, *"reviewers are encouraged to support evolving approaches to supporting open and transparent research practices"* [29].

However, for many researchers it remains unclear what research transparency is and how to achieve it. The general absence of clarity and consensus is exemplified by the differences between the author guidelines of different publication outlets. For example, the journal *Computers In Human Behavior* requires authors to declare their contributions according to a specific taxonomy, to detail financial support and the potential involvement of one of the sponsors in the research, and to provide a data availability statement [32]. Meanwhile, the CSCW conference encourages authors to make their work more reproducible, for example by submitting links to preregistrations and depositing data and supplementary material in public repositories, "when possible and when aligned with their methods" [29]. As for the CHI conference, its submission guidelines [22] provide recommendations that differ based on whether the study is quantitative (in which case the focus is on making sure methods and results are reproducible) or qualitative (in which case the focus is on making sure methods are properly motivated and results are contextualized, including by providing positionality statements). Notably, none of the guidelines *explains what research transparency is*; instead, they define it only implicitly by listing criteria for transparency and transparent practices. Admittedly, such checklists are useful due to them being actionable, but they are necessarily incomplete, and thus can exclude research practices. Besides, checklists for evaluating paper quality in general have been criticized on several grounds [83].

[1] "Human-computer interaction is a discipline concerned with the design, evaluation and implementation of interactive computing systems for human use and with the study of major phenomena surrounding them." [54, pp. 5–8] HCI is an interdisciplinary area that draws support from computer science, psychology, sociology, industrial design, and several other fields of study.

[2] The ACM CHI conference on Human Factors in Computing Systems.

[3] The ACM Conference on Computer-Supported Cooperative Work and Social Computing.

Box 1: Positionality statement

The idea for this paper originated at a Dagstuhl seminar on research transparency[a]. The discussions taking place there made us realize that many of our disagreements may be due, at least in part, to not talking about the same thing. While the seminar initially focused on research transparency in the context of quantitative research methods, we realized quickly that research transparency is relevant no matter one's methods or type of contribution. We, the authors, come from diverse backgrounds and are primarily experienced in quantitative empirical research and systems research, which we conduct mostly within a post-positivist framework. We have attempted to remedy this lack of representativeness by challenging each others' assumptions throughout this project and by engaging with the literature outside our familiar methodological territories. For example, we randomly selected papers highlighted on the CHI website as being representative for each of the CHI 2024 subcommittees[b] and reflected on how research transparency may apply in the context of the methods and types of contributions of these papers. In this paper, we intentionally avoid normative statements for or against transparency, as we wanted to focus on what transparency *is* and how it can be achieved. However, we are generally overwhelmingly in favor of striving for research transparency, and many of us have been actively involved in its promotion.

[a]https://www.dagstuhl.de/seminars/seminar-calendar/seminar-details/22392
[b]https://chi2024.acm.org/subcommittees/selecting-a-subcommittee/ More details in the supplementary material.

To make the problem worse, for historical reasons, many existing interpretations of research transparency are overly narrow, often focusing on replicability or reproducibility. Looking back, the increase in calls for transparency in research originates as a response to the replication crises that arose in different domains [86]. This is reflected in many definitions of research transparency; for example, Lyon states that *"transparency can be considered as an outcome from a combination of different behaviours and practices associated with reproducibility"* [74, p.161].

The perception that research transparency serves to ensure reproducibility also seems common within HCI, possibly due to an interest in making replication more central at CHI. A series of so-called *RepliCHI* panels, SIGs and workshops organized with this objective in mind took place at CHI between 2011 and 2014 [120–123]. After the RepliCHI initiative wound down, a separate movement that promoted research transparency took shape, initially with a focus on statistical practices [64]. Adding to the confusion, the ACM published around the same time a guide for Artifact Review and Badging with their own terminology, including replicability[4].

This stream of events might explain why research transparency is often only considered as a means to achieve replicability. This is potentially problematic because it not only reduces research transparency to a single limited goal, but also excludes a range of research practices and contribution types [124] in HCI. For example, replicability is widely seen as incompatible with studies using interpretative inquiry paradigms [49], theory or position papers, and literature reviews, for which transparency can also be desirable.

In this paper, we contend that transparency in research can be relevant to anyone, and that the different transparency practices called for by different research methods can be reconciled by an overarching conceptualization of research transparency, that is, by an *intensional definition* [16] that specifies what research transparency is in general, in contrast to current *extensional definitions* that are based on laundry lists of transparent practices. Such a definition would help achieve, first and foremost, a more homogeneous engagement with research transparency in HCI as a whole; in fact we believe many people already adopt some transparent research practices without labeling or even seeing them that way. We hope that a methodologically-inclusive definition can foster conversations in each methodological subcommunity or even be innovative in their methodological approach of transparency. In addition, such a definition may facilitate conversations and discussions about manuscripts during the reviewing process for both reviewers and authors, and may help redefine research assessment such that scientists can argue for having the work they put in to make their research transparent be recognized for their career advancement. Finally, such a definition can serve as a concrete starting point for further discussions and iterations within the HCI community.

Therefore, this article proposes a compact, methodologically-inclusive, and intensional definition of research transparency, unpacked in the next section, followed by three example situations where the definition can be useful (section 3). We then review previous definitions of research transparency in other fields (section 4), and finally illustrate how it can be applied within a wide range of research practices in HCI (section 5). The paper concludes with remarks about research transparency and points out potential limitations of this work.

2 DEFINING RESEARCH TRANSPARENCY

We propose the following:

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

We unpack the different components of this definition in the next subsections.

2.1 ... refers to honesty and clarity

Honesty is a central component in our definition of research transparency, reflecting the fact that transparency needs to be assessed at least in part based on the intent of the researchers who are the source of the communication,[5] even if it is often very hard to assess.

[4]In the first version of the ACM policy on artifact review badging [1], the terms "replicability" and "reproducibility" were defined opposite to the definitions that are widely accepted in other fields of research, such as psychological and physical sciences [97, Table 1]. Eventually, the ACM revised, in 2020, the definition to be consistent with others: Replicability refers to "Different team, different experimental setup" obtaining the same results [2].

[5]Our definition is consistent with the ACM Code of Ethics which explains how an honest researcher should behave. The contained recommendations are broader but include research transparency as we define it: "A computing professional should be

For example, if a group of researchers *forgets* to mention crucial information in their paper, or if they report false information as a result of a *honest mistake*, this should have some effect on how we judge the paper's (and the researchers') transparency; But the judgment should be more severe for omissions or mistakes that are *deliberate*. While previous definitions of research transparency rarely emphasize intent and rely instead on objective properties of the research work such as its replicability, the notion of honesty is central to research transparency and echoes previous conceptualizations, such as Feynman's [37] vision of scientific integrity that refers to an "utter honesty" mindset where researchers disclose all information that they anticipate may be used by others to criticize their research and question their findings (see section 4 for a review of previous definitions and conceptualizations).

Clarity[6] is another central component of research transparency, as honesty alone is insufficient to achieve a high level of transparency. For example, consider a paper written by researchers who are well-intended but unskilled at explaining their process and at deciding what information is important to report. Such a paper would be less transparent than a clearly-explained paper. Similarly, irrespective of the authors' intent to be transparent, a paper can lack transparency if it is poorly-written or accompanied by a confusing documentation that makes it difficult to understand the information and thus results in misinterpretations. Conversely, a paper that is very clear and reads very well but deliberately misleads or obfuscates information cannot be qualified as transparent either. Thus both honesty and clarity are important.

There can be a tension between honesty and clarity, and often it is not easy to strike the right balance between the two in order to maximize transparency. As an example, well-intended researchers who are striving to be as transparent as possible can end up reporting too much information in their paper, so much so that the key information ends up being buried among a host of unimportant details. A common solution is to only keep the key information in the paper and move all the rest to supplementary material. However, knowing that only few readers have the time to look at the supplementary material, it is not always easy to decide which information is important enough to deserve its place in the paper. Once again, Feynman's notion of utter honesty [37] can provide rough guidance: all the information that is the most inconvenient in the sense that it poses the largest threat to the papers' conclusions needs to be at least mentioned in the paper, which can invite readers to examine the supplementary material for more details.

2.2 ... in all communications

Communications refer to all instances in which researchers convey their work to others. They do this through academic publishing, but also during peer review and through various media such as conference presentations, press releases, or social media posts. Much literature on transparency focuses on communication between researchers, often in the form of scientific articles, with the goal to facilitate peer scrutiny and independent replication of research findings. However, research communication can target many other types of audiences, such as study participants, institutions, policy makers, or the lay public (directly or by way of journalists) [34]. Our definition highlights that research transparency concerns all types of research communications and audiences.

Depending on the audience, research transparency may take different forms. Transparency towards other researchers typically implies that rich technical information is shared in order to facilitate independent verification or evaluation, and—in some cases—replication. Meanwhile, transparency towards the public and journalists often entails that results and conclusions are carefully contextualized and sufficiently hedged, that is, limitations are included to prevent misinterpretation. While researchers are not fully responsible for the media coverage done of their research, those who strive to be transparent try to make sure that their findings are always accurately represented by the people interviewing them or contacting them about their results. Similarly, when talking to policy makers—or directly arguing for policies—research transparency implies clarifying the evidence on which the recommendations are made, as well as the political beliefs and the financial stakes that are linked to them.

2.3 ... about the research process

The research process refers to everything from the conception of the initial research idea to the initial research outcome and revisions during the peer review process. Some aspects of the research process are already commonly disclosed, such as details of the methodology, funding sources and conflicts of interest, or ethics approvals. The specifics of a research process can vary quite a bit depending on what kind of research one does and the methods one uses. Section 5 looks at different methods and provides more specific pointers. Generally speaking, being transparent about one's research process involves first documenting and later reporting one's methods, why those were chosen, and, when applicable, if and why these were adjusted over the course of the research. While not every single decision needs to be reported in an article, documenting decisions and their rationales generally increases transparency, in light of our imperfect memory, which tends to misremember our original predictions in hindsight [38]. Of course, one can change direction in the middle of a research project; being transparent about the process involves being transparent about such changes. Since peer reviewing is also part of the research process, disclosing submission history and (when authorized) reviewing history can also increase process transparency. Finally, the research process does not necessarily stop at publication: authors can publish corrections, post additional material, participate in public discussions, or seek open reviews, even after their paper has been published (see [93]).

2.4 ... and research outcomes

Research outcomes include everything that is claimed—either implicitly or explicitly—as a contribution. Within in HCI, many types of contributions exist [124], and many articles claim multiple types of contributions, including sets of design recommendations, toolkits, research prototypes, conceptual frameworks, or novel user interface ideas. For many empirical research contributions, the major

transparent and provide full disclosure of all pertinent system capabilities, limitations, and potential problems to the appropriate parties."

[6]We use this word in the context of "clarity in all communications" in a way consistent with Bischof & Eppler [9, Table 2]. They reviewed the literature on definitions of clarity in communication and synthesized five aspects: concise content, logical structure, making relevant context explicit, low ambiguity, and in the form that fits the needs.

research outcomes are findings and conclusions. Pieces of research material (e.g., data, software, videos) that are shared for the sake of process transparency are not research outcomes, but may become so if authors choose to claim them as contributions.

When research outcomes are digital artifacts, being transparent about the outcomes generally implies sharing the files, ideally by archiving them in persistent repositories that guarantee their availability for the foreseeable future[7].

Importantly, being transparent about one's research outcomes also implies being thoughtful and truthful about the *limitations* of one's research contributions—for example, being honest and explicit about the limitations in the usability of a new interaction technique which may be inappropriate for some usage contexts or for some user groups. Being transparent about the limitations of the findings and conclusions of a study includes acknowledging the inherent uncertainty of empirical findings, discussing potential threats to validity, and explicitly disclosing the assumptions on which one's findings rest and limits in their generalizability.

How clearly and visibly limitations of research outcomes are stated greatly impacts transparency. If limitations are mentioned inside a long discussion section without even an explicit header saying "Limitations", readers may not notice them. Much more transparency can be achieved if important limitations—e.g., those concerning the scope of one's claims—are stated in a place where they are unlikely to be missed such as the paper's introduction, its abstract, or even its title. For example, it has been suggested that describing findings in present tense implicitly generalizes to whole populations, which may oversell one's findings [30]. Using past tense would be a more transparent wording, for example: "Complex infographics *were* judged as more informative than simple ones" is more transparent than "*People find* complex infographics more informative than simple ones". Additionally, describing the results in terms of the actual measurements (e.g., completion time) is also more transparent than referring to them with abstract constructs (e.g., efficiency) [42].

2.5 ... to the extent possible.

This final part of our definition refers to the balance that needs to be struck between research transparency and other considerations, some of which may be as important and in some cases even more important than transparency. In particular, transparent research practices need to operate within ethical and legal constraints.

While transparency is desirable, in practice, the desire to be transparent has to be constantly weighed against other values. As a concrete example, anonymizing a dataset removes information and may therefore reduce research transparency, but disclosing the identity of research participants has in many cases undesirable ethical and legal implications (see [96]).

Sometimes, even data that is thought to be anonymized can pose a substantial risk of identification of participants, which is particularly problematic for studies that involve participants from vulnerable populations [115]. For sensitive research datasets, researchers can be transparent by stating what information were withheld, why, and describe their characteristics—e.g., volume, granularity, modality. Researchers might use alternative data sharing schemes.[8]

Resources—in particular, researchers' time and effort—are also in finite supply in any research project, and they often need to be weighted against considerations of transparency. While promoters of research transparency rarely consider time constraints as an excuse for not being transparent, it is unreasonable to require researchers to spend enormous amounts of time and effort documenting the smallest details of their research process before sharing any findings. The increased workload that comes from sharing research artifacts competes with many other tasks researchers have to get done—as detailed by Hostler [57]—and those may vary considerably across researchers, raising fairness considerations. Another example is how requirements of clarity can put a higher burden on non-native English speakers, who already have to spend considerably more time on reading and writing in English [3].

Finally, Nguyen [87] raised the concern that *"by forcing reasoning into the explicit and public sphere, transparency roots out corruption—but it also inhibits the full application of expert skill, sensitivity, and subtle shared understandings"*[87, p.1]. Although Nguyen's argument is mainly about the transparency of organizations, it applies to research transparency: increased process transparency implies more emphasis on systematic methods and clear documentation, which in turn implies a renouncement to fully exploit researchers' skills that cannot be easily systematized or documented. Worse even, a desire for increased process transparency can encourage researchers to oversimplify or misrepresent their research process [87]. Therefore, in some cases, researchers may choose not to document certain aspects of their research that are hard to capture—the more transparent approach in that case would be being forthright about it rather than misrepresenting the research methodology.

In summary, because there are other values and constraints in research than transparency, not only is it impossible to fully achieve research transparency, but transparency can also come at the cost of other important considerations. Researchers can nonetheless be transparent by explaining what they are transparent about and what they are less transparent about, and the trade-offs involved in their choices. We propose to refer to this flavor of transparency as *meta-transparency*:

Meta-transparency is transparency about which aspects of the research are made transparent and not, and why.

3 SITUATIONS WHERE THE DEFINITION CAN BE USEFUL

We proposed a definition of "research transparency" that is compact and multifaceted. Here are examples of situations that could benefit from these properties.

Facilitating conversations in the reviewing process: The definition is short and thus easily quotable in a review, rebuttal, or other discussions to ensure that all sides are grounding their arguments on the same basis. Instead of thinking about specific practices,

[7]A university or lab website, for example, is not a persistent repository as universities can reorganize their websites at any time and links are likely to go dead in the years following publication. See *FAIR* principles in Box 9 (page 20) for more pointers.

[8]There are ways of giving limited access to data through licenses and controlled-access data repositories, see Box 12 (page 22)

such as, "Are the data shared?", reviewers can use the definition to shift the focus to questions such as, "What did the authors do to demonstrate honesty and clarity about their research process and outcomes?" or "What could they do better within the constraints they face?". Such holistic assessments recognize the situations that require a balancing act, e.g., between honesty and clarity or between transparency and research ethics. From the authors' perspective, a potential transparency issue could be addressed in more ways than complying with a request or fighting back in their rebuttal. Depending on the case, the authors may choose meta-transparency and disclose their choice and reasoning.

Developing practices of research transparency specific to research communities: Across research communities, a mention of the term "research transparency" might invoke different understandings, such as replicability, data sharing, or being clear to study participants about the purpose of the study. Disagreements might erupt simply because each discussant thinks of different things. A concise definition can provide a shared understanding and prepare a common ground for constructive methodological discourses. Such discussions might take place top-down—among editors or steering committees of journals or conferences—or from the grassroots—e.g., in Special Interest Group meetings or a series of opinion papers. Furthermore, a clear definition enables research communities to develop new ways to be transparent, recognize existing practices that contribute to transparency (see also section 5), or—especially for HCI—develop tools to support transparency efforts that are complex or labor-intensive.

Preparing and evaluating proposals: A concise definition lends itself to be easily quoted in proposals for research projects. Researchers could quote the definition to highlight their efforts in their CVs or dossiers for career advancement. Conversely, having an agreed definition could allow researchers to convince research funding agencies and employers to recognize and encourage transparency methods in fields where data sharing is not applicable. Such recognition could let research funding agencies and employers include the definition of research transparency in their call for proposals and evaluation guides. These inclusions allow institutions to more precisely incentivize practices that contribute to a well-rounded approach to *Open Science* beyond just making papers *Open Access* or just *Open Data*. These usages could unlock resources necessary to conduct transparent practices, addressing a prevailing barrier to research transparency.

4 PREVIOUS DEFINITIONS OF TRANSPARENCY

We surveyed previous definitions and conceptualizations of research transparency to answer the question *Why do we need a new definition of research transparency?* Box 2 summarizes our findings.

We first looked at how English-language dictionaries define "transparency" in common language (see section "Dictionary definitions" of Box 2). We then searched for definitions from the academic literature. Several academic fields use the term "transparency" to refer to domain-specific concepts, such as "AI transparency" which refers to the characteristics of an algorithmic system [50], the structure and communication mechanisms of an institution [5, 118], a writing style in ethnography that claims to give readers an objective view to the phenomenon [27, p. 96] [24, p. 61], or as a journalistic value to enable processes that are open for monitoring and criticism [28]. Although all these concepts use the same word, they are quite different and are not the topic of this paper.

Instead, this paper is about the cross-disciplinary concept of *research transparency*. We found six explicit definitions published in various academic disciplines,[9] reported in the section "Definitions from academia" in Box 2. We note that some of these definitions are specific to experimental research or conflate transparency with reproducibility, which does not apply to some epistemologies in HCI. Other definitions are too narrow in their focus, for example, by solely focusing on transparency about the research process. Overall, none of these definitions appears to encompass the diverse types of research methods and contributions in HCI.

Instead of (or in addition to) defining research transparency, some papers offer a conceptualization of the term—for example a typology of *practices* that increase transparency, or a typology of *facets* of research transparency. These are summarized in the section "Conceptualizations" of Box 2. Once again, many of these conceptualizations adhere strictly to traditional notions of transparency, such as data sharing, and fail to capture the diverse methods of achieving transparency in HCI. In addition, while many papers break down transparency into discrete categories, several sources (e.g., [39]) insist that transparency lies on a continuum.

Previous conceptualizations of research transparency are useful in that they provide detailed explanations of the concept and implicitly define the term by explaining what it means and what it covers. However, a compact textual definition, as provided in this paper, is easier to recall, write down, and discuss. It is concise, provides a high-level overview of the concept, and can be unpacked into more detailed explanations of the multiple facets of transparency.

Finally, several terms used in the academic literature are closely related to and often brought up together with the term "transparency". Early on, the physicist Richard Feynman [37] advocated a vision of *scientific integrity* that closely resembles what is broadly understood today as research transparency, and which involves disclosing all relevant information about one's research, including (and especially) inconvenient information. We list some of the terms commonly associated with transparency in the section "Related terms" of Box 2. The delineation between these terms and the term "transparency" is often fuzzy and they are sometimes used interchangeably, which may account for some of the confusion and disagreement concerning the scope of transparency. There have been some efforts in trying to decouple the notion of transparency from its associated concepts. For example, in HCI, Niksirat et al. [102] point out that "*a transparent practice does not guarantee openness and vice versa*"[102, p.2], citing the example of a detailed statistical report behind a paywall, which is transparent but not open.

Bundling research transparency with other concepts could impede conversations in HCI because some associated concepts such

[9] We searched for the terms "research transparency is", "definition of research transparency", "define research transparency" and "define transparency" on Google Scholar, limiting ourselves to the first two pages of results, and also included articles the authors were already aware of. Our supplementary material on OSF includes an annotated bibliography and complete notes.

Box 2: Previous definitions of research transparency and related terms

Domain	Term	Definition or description	Refs
Dictionary definitions (paraphrased)			
English dictionaries	Transparency	That which is easy to understand.	[112, 113]
English dictionaries	Transparency	That which is free from deceit.	[113, 114]
English dictionaries	Transparency	That whose deception is easy to detect.	[112–114]
English dictionaries	Transparency	That which is open to public scrutiny.	[113, 114]
Definitions from academia			
Experimental biology	Transparency	"The reporting of experimental materials and methods in a manner that provides enough information for others to independently assess and/or reproduce experimental findings."	[90, p.3]
Information sciences	Transparency	"Outcome from a combination of different behaviours and practices associated with reproducibility which are implemented by the various actors and stakeholders in the research process."	[74, p.161]
Social & behavioral sciences	Research transparency	"Making the materials and procedures underlying research available to the extent that is possible and responsible."	[39, p.3]
Political science	Research transparency	"The degree to which the process used by scholars to produce a research product is made clear and open to others."	[18]
Political science	Research transparency	"The obligation to make data, analysis, methods, and interpretive choices underlying their claims visible in a way that allows others to evaluate them."	[81, p.2]
HCI	Transparent research practices	"Researchers' actions in disclosing details of methods, data, and other research artifacts."	[102, p.2]
Conceptualizations			
Political science	Research transparency	Three categories: *1. data transparency* or data access (researchers make available or reference the data on which they base their claims), *2. production transparency* (researchers describe their data-generation or data-selection processes), and *3. analytic transparency* (researchers describe how the data maps to their conclusions).	[73, 79, 81]
Social science	Research transparency	Increased by three practices: *1. disclosure* (reporting all details of the experiment design), *2. registration and analysis plans* (reporting intentions prior to data collection), and *3. open data and materials.*	[77]
Social & behavioral sciences	Research transparency	Consists of eight practices (TOP guidelines): *1. citation standards* (for material); *2. data transparency*; *3. analytic methods (code) transparency*; *4. research materials transparency*; *5. design and analysis transparency*; *6. preregistration of studies*; *7. preregistration of analysis plans*; *8. replication.*	[88]
Philosophy	Research transparency	Has four main facets: *1. why* be transparent, *2. who* is the audience, *3. what* is the disclosed content, and *4. how* is transparency achieved – plus many subcategories (see paper).	[34]
HCI	Shareable research artifacts	Consist in *1. study materials*, *2. raw data*, *3. data processing procedures*, and *4. prototypes.*	[119]
Related terms			
Physics	Scientific integrity		[37]
Social & behav. sc.	Openness, reproducibility		[88]
Library & inform. sc.	Openness, reproducibility, access ("the ability to (freely) locate and retrieve articles")		[74]
NGO	Openness, reproducibility, scrutiny, critique, open science		[116]

as replicability are incompatible with certain epistemologies. We hope the definition we presented in section 2 is sharp enough to distinguish it from related terms, and simultaneously inviting many ways to be transparent in HCI research—as shall be shown in the next section.

5 TRANSPARENCY ACROSS HCI CONTRIBUTION TYPES AND METHODS

In this section we will go through the different HCI research contribution types as described by Wobbrock and Kientz [124] and reflect on relevant transparency practices, tools, and educational materials for each of those[10]. The goal of this section is not to comprehensively list all practices, materials, and resources for research transparency, but rather to offer pointers, examples, and sources of inspiration, and to illustrate that there are many different ways in which one can practice research transparency across the variety of research methods and contributions possible within HCI. While the types and target audiences of communications can be diverse (subsection 2.2), this section focuses primarily on communication between researchers.

In many cases, a single HCI paper covers multiple contribution types or methods. We illustrate this explicitly using one example where this would frequently occur, a hypothetical article using participatory design (see Box 8 at the end of this section). Finally, the conversation about research transparency is evolving at different stages in each contribution type and research method. Consequently, some subsections below may have more materials than others. The amount of details under each subsection below should not be seen as correlated to the merit or importance of each practice. Practices with less transparency-promoting materials are those with ample room for future discussion and development. For convenience, we provide a glossary of terms and abbreviations related to research transparency in Box 9 in the appendix (page 20). Finally, we provide at-a-glance summaries for each subsection in Boxes 3–7.

[10]For an overview of the contribution types, see Box 10 in the appendix (page 21).

5.1 Artifact contributions

Artifacts in HCI can take many forms, including functional implementations, early prototypes, or design mockups of input devices, systems, hardware toolkits, interaction techniques, or new user interface concepts [124].

Insights into the *research process* could be gleaned from intermediate artifacts created at different project stages—such as sketches, prototypes, and collages of design inspirations [40, 126]. A research project might have a large number of these artifacts. Sharing all of them might maximize honesty but hurt clarity. Instead, a balance between honesty and clarity might better be achieved by curating and annotating a subset of materials that show key decisions and turning points in the process [e.g., 61]. While this curation would potentially add considerably to researchers' workload when done post-hoc, integrating such practices into the research process could additionally facilitate communications within the research team.

Artifact *research outcomes* can be achieved by sharing source files. *Source files* are specifications that enable people with a reasonable skill set and hardware infrastructure to reproduce the artifact to the level of fidelity as the authors developed it as part of their research. Examples of source files are software code, hardware schemata, or fabrication instructions. There are different ways to share source files, all with different levels of transparency. Partial transparency might be achieved by sharing pseudocode, sharing the source files only with reviewers, or sharing parts of the source files. A high level of transparency can be achieved by making all materials open source—that is, depositing them in a public repository and assigning an appropriate open-source license permitting reuse and redistribution [91]. (This practice is an example on how how transparency interacts with openness. See also the discussion in section 6.) Complex artifacts might require combining several methods to be transparent, e.g., providing pseudocode to show an overview and providing software code for implementation details.

A common issue is that artifacts might be challenging to build from their source. For example, a piece of software may require a specific operating system or hardware to compile, or a sizable machine-learning model may need an expensive set of hardware to train. In such situations, clarity in research communication could be better achieved by providing access to a working version of the artifact, such as a compiled version, a trained machine learning model, or a small version with fewer system requirements. Artifacts with high setup or maintenance costs (e.g., immersive spaces or real-time crowdsourcing systems) are not always feasible or ethical to keep running. In these cases, demos and exhibitions (and the recordings of such) can constitute transparency "to the extent possible".

5.2 Methodological contributions

Methodological contributions are contributions meant to *"improve how we discover things, measure things, analyze things, create things, or build things"* [124, p.41]. Examples include new applications of existing methods, development of new methods, adaptations of methods, new measurements, and new measuring instruments. New methods may produce output deterministically (e.g., measurements of text entry efficiency [107]), while others' execution and output may be influenced by the context in which the method is executed (e.g., the Human-Centered Design Process [58] or the Reflexive Thematic Analysis [12]). Regardless of the nature of the method's output, methodological contributions can be transparent in their outcomes (the method itself) and their processes (in developing or evaluating the method).

Being transparent about the method itself includes sharing information relevant to the conditions under which a method can be used and those were it cannot. For example, the authors could describe the method's assumptions and limitations. If these conditions are not yet known at the time of publication, then it would be relevant to disclose that fact, for example, in the limitations section. Relatedly, such an article could be explicit that the method was so far only tested under specific circumstances or using specific datasets. In this case, a clear description of the circumstances or

Box 3: Summary of example practices I

Contribution	Phase	Examples of transparency practices and relevant tools
Any	Research outcome	• Limitations section • Meta-transparency statement
Artifact	Research process	• Sharing of sketches, photos, prototypes, collages of design inspirations, etc
	Research outcome	• Software code, hardware schemata, fabrication instructions, good documentation ⟶ Version-controlled repositories (e.g., git), documentation templates (Research Data Alliance, Project Tier • Release under open licenses ⟶ see glossary in Box 9 of the appendix (page 20) • Participation in demos and exhibits • Disclosure of limitations and drawbacks of generated artifacts, including wrt pre-existing artifacts ⟶ limitation section
Methods	Research process	• Positionality statements • Preconditions, assumptions, limitations • Data on which the method was tested
	Research outcome	• Code/algorithm to use the method ⟶ FAIR repositories (e.g., OSF, Zenodo), version-controlled repositories for methods operationalized with code (e.g., git) • Disclosing limitations and drawbacks of the methods, including with respect to other methods ⟶ limitations section

Box 4: What is a (good) positionality statement?

Positionality Statements are *"the recognition and declaration of one's own position in a piece of academic work"* [60, p. 323]. They aim to make researchers' backgrounds, socialization, and practices explicit in order to disrupt privilege, reduce bias, and increase research quality [75]. This is done by performing *reflexivity*, a process in which researchers explore their own position and how it may affect their work [8]. It has been widely adopted and argued for in qualitative research [e.g., 8, 15]. There are no universally agreed upon guidelines or quality markers for positionality statements (see [75]), but several comprehensive examples have been published in HCI. For example, Chen et al. includes a comprehensive positionality statement on their own experiences, identities, and the literature they have been influenced by [21, p. 4]. By comparison, the positionality statement in Erete et al. [35, p. 4] places particular focus on the researchers' relation to the community they studied and explicitly acknowledge harm similar prior research has done. In general, positionality statements can be most often found in opinion/argument contributions as well as in papers working with marginalized groups. However, they can be added and potentially benefit all kinds of contributions. While we are not aware of a singular, comprehensive resource on how to write a positionality statement (particularly in HCI), a brief introduction to writing positionality statements can be found in Holmes [56], but we also recommend readers to look at the specific HCI examples discussed above.

datasets used would provide transparency about the process of the method contribution, but also inform readers about properties of the method itself.

Several practices contribute to the clarity of a method. Clear instructions for each step are essential. Methods that may be executed non-linearly or recursively could also benefit from instructions that explicitly permit them and guidance for researchers to decide on when to choose a different path and how to choose them. For a computational method, method authors could provide both an executable software as well as the algorithm it uses—to establish immediate and long-term clarity, respectively. Clarity could be further increased by lowering the barrier for people to use and test the method, e.g., by providing software tools, example datasets, or test cases. If the method has been empirically compared to others, the authors should strive to be fair in their comparison setup.

5.3 Theoretical contributions

Theoretical contributions include diverse research outcomes such as thought frameworks, design spaces, conceptual models, design criteria, and quantitative models [124] spanning a wide variety of goals: a theory may aim to be descriptive (providing terminology and concepts), explanatory (of relationships and process), predictive, prescriptive (by guiding designs), generative (of ideas and inventions), or critical (arguing what should be done based on ethical or moral considerations) [7, 48, 101]. Some theories might be based on speculation of possible future designs [109] or how the world should be [48].

Transparency about the research *outcome* of this type of contribution is tightly linked to demonstrating the validity of a theory, and clarifying the boundaries of its validity. For example, it includes practices such as clearly stating the theory's goal(s), assumptions, and limitations. For theories which could be compared against others—e.g., a predictive model on interactions—choosing a strong and contextually appropriate baseline can be considered a form of research transparency.

Transparency concerning the research *process* aids in demonstrating the rigor with which a theory was developed and includes disclosing a theory's foundations—be it empirical studies, prior theories, or informal observations—and appraising their quality. For example, a design space may be built upon the analysis of a corpus of examples collected using a systematic or organic approach. Disclosing the approach used increases the contribution's transparency concerning the research process. Even more transparent would be to share the corpus—which would also allow authors to claim the corpus as an additional contribution (see subsection 5.5). In cases where the data of a corpus is too sensitive to share publicly, a *protected-access data repository* may be an option (see Box 9 (page 20)). Transparency can further be improved by detailing how the corpus was curated and analyzed.

However, process transparency is not always possible, and sometimes, it is more transparent to simply acknowledge that an organic and improvised process was used rather than reflecting post-hoc on justifications for the used process.

5.4 Opinion/argument contributions

Opinion contributions aim to *"persuade, not just inform [...] compel reflection, discussion, and debate"* [124, p.42]. To support their opinion, authors might draw evidence or arguments from works in any contribution type, prior opinion papers, or public discourses. Transparency can be increased by presenting these pieces of evidence at the level of strength and certainty warranted by the source. For example, authors can take care to not present evidence from correlational research as causal, or a consensus in a Western society should not be generalized as a global consensus. Further contributing to transparency are clear explanations of key inferential steps, assumptions, and scope qualification.

Although the purpose of opinion/argument contributions is generally to persuade, such contributions can be transparent by honestly acknowledging and addressing opposing opinions, and list possible counterarguments to their claims, even if no one has explicitly made them yet. Transparency in this area implies refraining from straw-manning valid opposing views, and to the contrary giving them the most charitable interpretation possible, a practice called steelmanning (see also the glossary (page 20)).

Being transparent about the research process of opinion contributions is less straightforward. Potential practices include providing materials documenting major iterations in writing as well as discussions, for example, such a practice could document which parts of the opinion piece are the least consensual among the authors. In addition, documenting the literature search backing up the claims can increase transparency and reduce the likelihood of cherry picking

Box 5: Summary of example practices II

Contribution Types	Phase	Examples of transparency practices and relevant tools
Theory	Research process	• Disclosing foundations, e.g., empirical studies, prior theories, observations, on which the theory builds • Sharing corpus (for theories derived from corpus analyses) ⟶ FAIR repositories (e.g., OSF, Zenodo)
	Research outcome	• Exploring boundaries of a theory's validity and comparing it against strong baselines ⟶ limitations section
Opinions & arguments	Research process	• Documenting inception and development of arguments & opinions • Positionality statements
	Research outcome	• Avoiding cherry-picking of supporting evidence • Disclosing limitations of the opinions and arguments, including wrt other positions. • Discussing counter-arguments, representing rival arguments in a charitable way, "steelmanning".
Datasets	Research process	• Documenting origins of dataset (how was it collected) • Positionality statements
	Research outcome	• Making datasets FAIR ⟶ FAIR repositories (e.g., OSF, Zenodo), release under open licenses (see glossary in Box 9 of the appendix (page 20)) • Documenting how to use the data • Providing examples of uses
Surveys	Research process	• Documenting search process and inclusion/exclusion criteria ⟶ PRISMA guidelines (see glossary in Box 9 of the appendix (page 20)) • Disclosing level of engagement with each article reviewed • Documenting rigor and strength of evidence for each article reviewed • Preregistering the survey method ⟶ Preregistration (see glossary in Box 9 of the appendix (page 20))
	Research outcome	• Being clear about scope and type of review and sharing the surveyed corpus ⟶ FAIR repositories (e.g., OSF, Zenodo)

and confirmation bias. A practice from political science is to provide extensive hyperlinked appendices showing excerpts of articles cited in—as well as those excluded from—the arguments [80][11].

5.5 Dataset contributions

Dataset contributions provide a new corpus, detail its characteristics, and usually enable the evaluation of algorithms, methods, or systems [124]. While few HCI papers have a dataset as their *sole* contribution, empirical papers can present the data collected during a study as a contribution in itself, if they choose to share that data in some form.

Such datasets are generally expected to be findable and obtainable for a long time (long-term preservation[12]) without a request to the principal investigator.[13] There are exceptions to that, and there may be legitimate reasons why researchers might not share data *publicly* and instead upload datasets in a protected-access data repository[14]; being transparent about such a choice includes a meta-transparency statement to explain why an exception is warranted. Possible reasons could be that making datasets publicly accessible invalidates their usefulness. For example, a case such as the IAPS[15] [66], which consists of thousands of pictures with their affective ratings, depends on participants not being familiar with the stimuli. Making the corpus public risks invalidating it. However, such special cases need to be justified with a transparent procedure in place for researchers to acquire the dataset, if they want to use it in their research, and ideally instructions for these authors how they in turn can be transparent without making the original dataset available, for example, by curating a small subset or dummy dataset with similar properties that can serve to illustrate the dataset contribution.

Concerning the sharing of data, a good overview of different levels of transparency is Tim Berners-Lee 5-star open data[16] initiative. It summarizes different levels of openness concerning data: (1) making data publicly available with a license, (2) in a structured format than can be read by a machine, (3) using an open format, (4) with a persistent URI (such as a DOI), and (5) interlinked with other related datasets. Communication can be improved by adopting data formats that are open and widely used, as does minimizing the software requirement to access the corpus. For example, for a relational database shared in an SQL format, one could provide additionally an alternative format as CSV(s) of joined tables. The latter format allows reviewers and readers to inspect the data without requiring them to set up a database engine. Another opportunity to increase the transparency of a dataset contribution is to provide additional files that explain how to use the data—this may be example code to load the data, a README file that explains what the columns of a table mean.

[11] This practice is called *active citation*. See the glossary (page 20) for a definition.
[12] e.g., https://nips.cc/Conferences/2023/CallForDatasetsBenchmarks
[13] e.g., https://www.nsf.gov/eng/general/ENG_DMP_Policy.pdf
[14] See https://osf.io/tvyxz/wiki/8.%20Approved%20Protected%20Access%20Repositories/
[15] International Affective Picture System
[16] See https://5stardata.info and https://www.w3.org/DesignIssues/LinkedData.html

Transparency concerning the *origins* of a dataset is another relevant component covered in other subsections. For datasets stemming from computational processes, see subsection 5.7.1, whereas datasets collected through studies with human participants are covered in the remaining subsections of subsection 5.7.

5.6 Survey contributions

Survey contributions refer to literature surveys.[17] Their purpose is to search, appraise, analyze, and synthesize knowledge from publications or other materials on techniques, emerging topics, tools, domains, or technologies [124]. Examples in this category are systematic literature reviews, narrative reviews, meta-analyses, and analyses of corpora of texts or visualizations. Being clear about the search process and the inclusion/exclusion criteria greatly contributes to transparency [108, sections 5.5–5.6]. Since the purpose of a survey often dictates the kind of survey conducted, it is more transparent to make this purpose clear early on in the manuscript. There exist many survey types [46], and some of them sometimes overlap [46, 85], therefore it is recommended to clearly state the analysis strategy employed (e.g., chronological, conceptual, numerical) and their appraisal (or quality assessment) method. More transparency is achieved if authors convey their sincere assessment of each piece of work while being respectful of its original authors. Although etiquette advises against being harsh towards published papers, it would be less transparent to present papers that happen to be extremely poor in terms of rigor or clarity in the same way as strong research contributions.

In some cases, it can make sense for authors to preregister all methodological information to establish that their literature survey has not been manipulated to obtain a specific finding [82]. Providing intermediate output from each stage (e.g., the results of the initial search) in supplementary materials not only increases transparency but also enables future surveys to update with new results. Finally, although it is not commonplace, it can greatly benefit transparency if authors choose to be transparent about their level of engagement with each paper, ranging from just reading the abstract, to selective reading, to reading the entire paper in-depth.

As for the research outcomes, authors of literature surveys can achieve more transparency by clearly portraying the scope and limitations of their survey—for example, by being clear about the type of the survey in the paper title (as recommended by item 1 of the PRISMA statement [70]).

5.7 Empirical contributions

Empirical research in HCI uses a wide range of research methods which have different sets of constraints and opportunities for transparency practices. Before going into different methodological approaches, we provide a few pointers to a set of tools, guidelines, and educational materials which have been developed to facilitate research transparency in HCI. Some are action oriented, such as a guide compiled by Haroz et al. [51], which summarizes ways to make data and their analysis transparent and which comes with some pointers to platforms and services useful to do so. Similarly, Goswami et al. [45] compiled a cheat sheet that attempts to break down a typical research process in terms of tasks to be done to ensure transparency throughout the project. It is also accompanied by resources to support each of these steps. Then there is more scholarly work, like Vornhagen et al. [117] who analyzed statistical reporting practices at CHI PLAY and based on this analysis offers a template to build transparency into one's research process. Salehzadeh Niksirat et al. [102] proposed a screening tool to analyze PDF documents in terms of research ethics, openness, and transparency (https://github.com/petlab-unil/replica).

While certainly useful, these resources do not completely cover the diversity of methods that one can find in HCI research. Therefore, we make here an attempt to provide more nuances by discussing different types of empirical contributions in a finer granularity. Specifically, we use a classification of empirical research methods based on the *degree of control* that researchers can exert over their research environment [69]. (Further discussion and rationale for this classification is available in Box 11 (page 21).)

5.7.1 *Transparency when doing Computational Studies.*

Computational studies are studies with the highest level of control; as a result, research transparency for this kind of contribution has the potential to result in full reproducibility [95, 98, 103]. Enhancing transparency involves not only making code and relevant data accessible, but also ensuring code is legible (e.g., with READMEs or comments). Some computational work relies on specific state-of-the-art software or libraries which may undergo significant changes over time. Thus, when applicable, the environment in which the computational study was conducted could also be made reproducible. This reproducibility can be achieved by means of a virtual environment or machine, or for smaller scale projects this can be achieved by files that specify library dependencies and their specific versions[18]. Stochastic (non deterministic) computational studies use pseudo random number generators to produce random outcomes. For these a seed can be set to guarantee that for each run the output of the generator is identical. Hence, the ability to fix the seed may ensure that the results are perfectly reproducible even in a setting with randomness. Transparent reporting also includes unaddressed errors [72] or warnings, so that they can be checked in subsequent replications.

Transparency also applies to the modeling level. Modeling entails various choices and assumptions which a researcher can clearly explain and/or validate. For example, authors can be transparent about why they use a e.g., a Gaussian distribution and not an exponential one to describe a random variable. Even better would be to compare model predictions with competing assumptions [44, 100]. Communicating baseline comparisons, including implementation details, is also an essential component of transparent practices. Baselines can be weakly implemented (e.g., with less fine-tuning than the proposed original methods [36]). Concerning *honesty*, researchers can be transparent about the limitations of their study, for example, detailing the effort (or lack of) put into constructing a fair baseline—particularly if it has been implemented from scratch—enhances transparency.

[17] Survey questionnaires do not fall in this category as they are *empirical* contributions, which are covered later. Also excluded from this section are related work sections, assuming they only serve to contextualize contributions. In case a related work section is claimed as research contribution in themselves, this section would apply to them.

[18] For example, for those familiar with the Python ecosystem, this could be a `setup.py` and a `requirements.txt` with the exact module versions specified, such as those produced by `pip freeze`

Box 6: Summary of example practices III

Contribution Types	Phase	Examples of transparency practices and relevant tools
Empirical Computational	Research process	• Facilitating reproducibility of the research environment ⟶ Preregistration (see glossary in Box 9 of the appendix (page 20)) • Comparing against strong baselines • Document model choices
	Research outcome	• Sharing virtual environments⟶ FAIR repositories (e.g., OSF, Zenodo)
Standardized studies	Research process	• Document choice of materials ⟶ Preregistration
	Research outcome	• Report all standardized materials used and any potential deviations ⟶ FAIR repositories (e.g., OSF, Zenodo), Protected-access data repositories
Controlled experiments	Research process	• Pre-registering study design, data analysis and reporting methods
	Research outcome	• Sharing stimuli, data, code, analysis, and findings ⟶ FAIR repositories (e.g., OSF, Zenodo), Protected-access data repositories • Additional annotated figures in supplementary material

5.7.2 Transparency when doing Standardized Studies. Standardized studies refer to studies making use of standardized data collection, analysis, and reporting procedures [69]. A classical example of a standardized study in HCI is a Fitts's law experiment which obtained its own ISO standard in 2002 to provide a standardized testing procedure for pointing studies. Empirical studies in HCI are, however, rarely standardized studies. More common is to rely, partially or entirely, on *standardized instruments*, such as the SUS (Standard Usability Scale) [17]. Reusing a standardized method reduces the workload on researchers with respect to transparency: the details of the procedure are already documented in the standard itself, and the authors can simply refer to these through a citation in order to make their methodology transparent. Concerning *honesty*, researchers can be transparent by clearly stating any and all deviations from the standard (including partial adoption or translation of questionnaire items in another language). Some standardized test, methods, or stimuli might not be freely available to all. For example, some psychological tests might become unreliable in the population if laypeople become aware of their content (see also subsection 5.5). In such case, researchers could clearly indicate specifically which part they have used in their experiment, or provide a synthetic example.

5.7.3 Transparency when doing Controlled Experiments. A considerable part of HCI research contributes findings from controlled experiments [67, p. xxi] which refer to studies in which researchers manipulate a variable, or a factor, to observe the effect it has on other so called outcome variables. Controlled experiments are conducted under specific conditions derived to minimize noise and limit subjectivity on the measured outcome variables. Typical outcome variables include, but are not limited to, performance metrics (e.g., completion time or accuracy), or subjective assessments about newly developed techniques compared to a baseline control technique.

In controlled experiments, more transparency is achieved when the researchers share the reasoning behind every study design decision, such as their potential hypotheses about the study results (for confirmatory research), the choice of datasets or control group/technique, any adjustments they may have done after pilot testing and the reasoning behind it, etc. In doing so, researchers allow for a clear communication and assessment of the limitations of their studies and clearly report flexibility in data analysis or study design (see e.g., [26, 104]).

A high level of transparency can be achieved through preregistering study design, data analysis, and reporting methods prior to data collection. Preregistration is a frozen timestamped and publicly available record of research material (see the glossary (Box 9 (page 20)) and e.g., [25]). It requires researchers to state their plan and expectations before collecting any data and prevent researchers from cherry-picking their results [104] and post-hoc intent adjustments [26].

Clarity is achieved by sharing the stimuli, data, code, analysis, and findings in a reusable manner, minimizing the steps for reuse or reproduction. This includes providing well-commented and documented code and data. Also, offering annotated figures to support claims (as exemplified by Yang et al. [125]) further enhances clarity alongside preregistration and sharing of resources.[19]

Concerning *honesty*, researchers can be transparent about the limitations of their study and be clear about the limits to generalization that their study design permits.

5.7.4 Transparency when doing Field Experiments. Controlled field experiments [52] involve conducting experiments in real-world settings (i.e., "the field"), often using quasi-experimental designs [47][20]. Running experiments in real-world settings provides gains in ecological validity, but typically adds more noise in the data as factors outside the control of the researchers can vary, such as organic pre-existing group compositions, or external events, such as weather conditions which may vary across different days on which an (outside) experiment is run.

[19] For more information on transparency specific to controlled experiments, see [23, 25, 26, 63, 117].

[20] Quasi-experimental designs cannot randomly assign participants to groups to external constraints. For example, in an educational setting, a researcher would not be able to assign students to different classes and can only assign conditions randomly to pre-existing groups between which variability may exist that is outside the control of a researcher.

Box 7: Summary of example practices IV

Contribution Types	Phase	Examples of transparency practices and relevant tools
Field experiments	Research process	• Document field conditions under which experiment took place (also any variations across data cases) • Document data collection and analysis process ⟶ Preregistration (see glossary in Box 9 of the appendix (page 20)) • Design data collection such that it minimizes identifiable information of participants
	Research outcome	• Describe field settings and cultural, ethnic, and social dynamics among stakeholders • Share data to the extent possible ⟶ FAIR repositories (e.g., OSF, Zenodo) • Protected-access data repositories
Pre-structured	Research process	• Share the pre-defined structure that is used to collect data ⟶ preregistration • Document and report details of the data collection process and changes (if any)
	Research outcome	• If using predefined codebooks, publish the codebooks ⟶ FAIR repositories (e.g., OSF, Zenodo) • Protected-access data repositories • Reflect on assumptions and theoretical lenses used in the analysis • Share the data together with the assigned codes ⟶ FAIR repositories (e.g., OSF, Zenodo) • Protected-access data repositories
Open-ended	Research process	• Justify participant inclusion criteria • Show clear connections between categories and theories in Grounded Theory • Disclosing goals, theoretical position, and researchers' positionality • Disclose analytical focus (e.g., semantic or latent analyses)
	Research outcome	• Thick description • Balancing showing data descriptively and writing researchers analyses

To favor *clarity* in reporting, researchers can provide a detailed account of the conditions under which they conducted the study. This may include a full description of the field setting, such as the geographical location of the field. Explanation of relevant contextual factors that may have influenced the experiment can also enhance transparency. For example, it could be advisable to explain the cultural and ethnic characteristics of, and social dynamics among, key stakeholders (particularly participants, recruiters, and researchers). Also, unanticipated external events that may have influenced the results can be useful to mention.

Concerning *honesty*, researchers can be transparent about the limitations of a study, for example, they could discuss the limitations of conducting an experiment in a real-world setting (potential threats to external validity[21]) and possible limitations due to non-randomized condition assignment (potential threats to internal validity[22]) [47, 92].

Transparency concerning the *research process* can entail a detailed description of the data collection and analysis process, such as a description of the participant selection process, condition assignment, and participant tasks or instructions (e.g., [31]). As for *research outcomes*, researchers could share field notes about their observations and interactions with participants to provide additional insights. Researchers could also record and share multimedia evidence from the field (e.g., photos, videos), and, where appropriate, declare if they obtained approval from local authorities—beyond their institutional ethics approval.

[21] External validity of a study refers to the degree to which findings may generalize to other contexts than the one studied.

[22] Internal validity refers to the degree to which an experimental setup is able to determine causal relationships. Are measured outcomes due to the experimental manipulation or other external factors?

Transparency can be practiced *to the extent possible* if it conflicts with the privacy and vulnerability of participants. In some cases, this could be addressed already at the data collection stage. For example, researchers can devise strategies to not include any personally identifiable information about participants in their field notes, or they can position cameras so as not to capture participants' faces and document the study location without participants being visible. Such preparations can immensely reduce the need for later anonymization efforts, such as blurring faces and redacting names.

5.7.5 Transparency when doing Semi-structured Observations. Semi-structured observations can take many different forms including semi-structured interviews (e.g., [89]), diaries (e.g., [106]), think-aloud processes (e.g., [33]), or field observations with a predetermined observation grid to be filled out according to the observations (e.g., [4]). Unlike experiments, which offer a high degree of control, semi-structured observations follow some type of "script" that guides the data collection process. It facilitates to collect similar data across participants, or multiple experimenters to collect data in a similar way. Importantly, this process allows for deviations, and in the end, the specific observation situation determines the resulting data. For example, the participants' responses during an interview dictate the course of the conversation, and consequently, some questions may lose relevance, while others require further clarification. In diaries, even with predefined questions, participants may highlight what they find important.

A straightforward way of being transparent about the research process in semi-structured observations is to share the pre-defined structure that guides the observation and explaining the rationale behind choosing that specific structure. Since observations are not controlled and many external and unique factors influence the data

Box 8: Research transparency for participatory design

There are many approaches to participatory design, which address different purposes at different phases of a design project [84, Table 1]. Research transparency can be established within each phase according to the methods deployed. Researchers could choose to focus their transparency efforts proportional to how pertinent the knowledge of each phase to the overall knowledge generated. For example, a final evaluation might deserve more transparency than an early preliminary study.

In addition to individual phases, overall transparency could be established by showing how different stakeholders "actively" [84, sec. 11.1.2] participated and in which stages—which is not necessarily the entire process [11]. Transparency in research *outcomes* could be established by documenting the tangible design artifacts (see also subsection 5.1). Some projects might results in intangible changes (e.g., making the people's voice heard, impacting an organization's policy, or enabling future projects) [11]. Such changes might lend themselves to be empirically measured (and transparently reported as described in subsection 5.7).

Some projects might be successful in their participatory process but not yield participatory outcomes [10, 11]—possibly due to external constraints (e.g., institutional constraints [71]). In such a situation, transparency could be increased by an honest reflection on the "arenas" of the impact of the outcome [11]. Examples on opinion/argument contributions in subsection 5.4 might be applicable.

obtained, researchers can be transparent about relevant details of the observation process, as well as about iterations and potential changes made to the script during the study [78]. However, reporting such deviations requires to first document them, which may require having mechanisms in place to do so during data collection. A preregistration template for semi-structured observations is also available [53].

Data gathered from semi-structured observations typically yield qualitative information and is commonly analyzed through a process known as coding. This can take various forms, including using codebooks which can be pre-defined or developed bottom-up from themes emerging from the data. There are numerous ways to foster transparency, such as detailing how a codebook was developed (e.g., [62]), providing predefined codebooks (e.g., [68])—if available and suitable for the research methodology [76]—or detailing the frameworks and milestones employed in the coding process. Reflecting on assumptions and theoretical lenses that researchers have prior to analyzing the data adds transparency to how researchers reach certain conclusions from the data (see the term *reflectivity* in the glossary (page 20) as well as Box 4). Where ethically appropriate, sharing research artifacts generated in the analysis process—e.g., a transcript file together with the assigned codes—could allow others to understand the coding process and the specificity of the authors' analytical lens (e.g., as done in [89][23]). Some datasets might require additional processing (e.g., anonymization) before sharing. If sharing the full dataset is infeasible, authors might consider focusing their efforts on sharing parts of data that are pertinent to the major claims [59, p. 180]. Finally, when researchers face constraints preventing transparency, they could outline what aspects are transparent, which are not, and why in a meta-transparency statement (subsection 2.5).

5.7.6 Transparency when doing Open-Ended Data Collection. Open-ended data collection does not or only loosely make use of pre-existing structures during data collection and may employ interpretative data analysis approaches. Research in this category embraces the influence of context and subjectivity on its outcome and plays important roles, such as providing a rich understanding of complex research settings, insights into beliefs and meanings from the perspectives of underrepresented people, or discovering new research questions [6, 49]. This category spans various epistemologies, methodologies, methods, and positions.

This diversity regularly poses challenges during the reviewing process [105]: Material that may make sense to accompany an article reporting on a controlled experiment, may not be relevant or not even be appropriate for the methodology and epistemology of an interpretative research paper. Soden and colleagues [105] discuss this problem and include a discussion of typical critiques interpretative research papers may receive from reviewers together with suggestions how those could be addressed or rebutted by authors. We reproduce some of the suggestions made in that article as they are also excellent examples of research transparency in the context of interpretative research. The recommendations follow the basic principle to provide additional information that helps the reader better understand the paper, such as, *"Instead of asking for the interview script, ask authors what topics were covered in interviews and how these related to the overall goals of the research and the specific contributions of the paper"* [105, p. 41]. Since research in this category uses interview scripts only loosely or not at all, they would not give a good picture of the questions actually asked.

Another example mentioned by Soden et al. is reviewers asking for interrater reliability scores, which do not always make sense, as detailed by McDonald in their review of 251 qualitative papers describing reliability [76, p. 72:13]: *"Many papers in our dataset demonstrated that coding takes place over multiple meetings to discuss disagreements and refine codes (descriptive text attached to a unit of analysis), the primary goal of which is not agreement, but to eventually yield concepts and themes (recurrent topics or meanings that represent a phenomena). Even if coders agree on codes, they may interpret the meaning of those codes differently, and those differences may be valuable."* Soden et al. suggest a range of alternative practices all of which would also increase the process transparency of the research reported: *"Instead, data-analysis descriptions should provide a description of how authors consulted others using approaches as varied as peer debriefing, group discussions, or member checking, how they iterated on their claims throughout the process, and how they settled on their final arguments."* [105, p. 42].

Similarly, some practices that are already called for by methodological papers contribute directly to research transparency. Some of these practices are similar to other types of empirical research,

[23]The shared analysis artifacts are comprehensive, but in a proprietary format. See also the discussion "Transparency vs. openness" in section 6

e.g., being clear about and justifying how study participants are selected [110, Ch. 16]. However, some methodologies call for specific practices that demonstrate transparency in data analysis: For example, both versions of Grounded Theory call for researchers to clearly show connections between concepts (categories and theories) that are formed in each stage of data analysis [20, point 5] [110, Ch.16]. Reflexive Thematic Analysis and Feminist methodology emphasize the importance of disclosing researchers' goal, theoretical position, and their position (intellectually, socioeconomically, politically) in relation to the phenomena or their study participants [6, 14]. This is commonly done in the form of a positionality statement (see the glossary (page 20) and Box 4) which contributes to being transparent about the research process.

There are many ways to be transparent about research outcomes. Some methodologies place importance on describing the findings in vivid details so *"that readers actually can see, taste, smell, and hear what is going on in a scene"* [110, Ch.2] [19, p. 293]. Others call for a *Thick Description* of the context surrounding the data—including thoughts and feelings of participants that might be shown nonverbally during data collection [41, 99]. Researchers might need to determine how to balance showing data excerpts to illustrate the situation versus describing researchers' analysis. In Reflexive Thematic Analysis, this balance is determined by whether researchers focus on surface meanings or underlying ideas—which is a choice to disclose in the research process [13, p. 252].

In the field of HCI, many open-ended data collection methods are deployed in research sites that are sensitive or involve participants from vulnerable populations; we would like to re-emphasize that disclosing data at all levels—including quoting participants in the paper—must be done with care of participants' safety and privacy, as discussed in subsection 2.5.

6 ADDITIONAL CONSIDERATIONS

This paper is a reflection on research transparency and how this concept may be applied across the diverse types of contributions and methods one can find in HCI research. We proposed a definition of *research transparency* as a starting point and illustrated possible ways to operationalize it across different contribution types and research methods. We hope that these materials will enable authors to consider transparency throughout the research process, sensitize reviewers to judge a paper fairly, weighing benefits, dangers, and competing interests of transparency, and benefit readers by facilitating better communication, enabling reuse, and improving rigor. Before concluding, we discuss here a few aspects of transparency which are not specific to contributions or methods.

6.1 Research transparency is not equally easy for everyone

Adopting transparent practices might be easier in some environments than others. For example, some institutions or funding agencies might provide resources and infrastructure; some labs may have people who can advise and educate. Not all HCI researchers start at the same point on the research transparency continuum. We hope the HCI community considers this fact when critiquing the research transparency of a paper. Should transparent practices be recognized institutionally in the HCI community (e.g., a research transparency award or badges), it would be more appropriate to consider a trajectory of improvement over time—i.e., the current paper is more transparent than previous papers from the same authors—rather than focusing on a single paper. By giving more ideas on how to be transparent, we hope this paper will help researchers who wish to be more transparent to improve their transparency incrementally.

6.2 Research transparency is dynamic

In the current publication process, practices that contribute to research transparency usually end when the paper is published. However, research transparency is not inherently static. With the availability of version-controlled research material repositories (such as Open Science Foundation or Zenodo), it is possible to increase research transparency even for papers that are already published by providing additional materials or fleshing out the existing ones over time. However, the bottleneck of this evolving process is that the improvements in supplementary materials are not reflected in the paper, and changing the paper content is a long process. A potential solution could be for the ACM Digital Library to provide a prominent section on the paper's landing page where the authors can point the readers to updates in their supplementary materials. On a more global level, existing infrastructure such as the Crossmark mechanism,[24] could be used to point readers to repositories containing post-review supplementary material.

6.3 Embracing research transparency is embracing imperfection

We refrained from advocating for transparency and making normative statements such as "researchers *should* ...". We instead tried to provide guidance and ideas to researchers who wish to be transparent. We believe that transparency is a mindset that needs to be adopted willingly and included in one's research practices. Nonetheless, if we as a community want to promote a culture of honesty and clarity in the way our research is reported, it is important that, as reviewers, we do not reject too easily papers that are transparent about their methods and honest about their limitations. This implies embracing the idea that *research is necessarily imperfect* [43, 55]. Often limitations are not necessarily threats to research quality but rather opportunities to continue and deepen our understanding and exploration of a research question in future work—as long as they are clearly and honestly disclosed in a paper.

6.4 Research transparency is a continuum

We believe that research transparency cannot be judged simply by ticking boxes on a checklist (e.g., is the data shared? is the study preregistered?), but needs a holistic assessment of the entire research communication. The reasons are: (1) A research project might make multiple types of contributions (Box 10 (page 21)); (2) Each type of contribution has many ways to bolster research transparency (section 5), and (3) these efforts vary in their workload (subsection 2.5); (4) researchers themselves are in the most informed position to make trade-off decisions. These trade-offs and decisions can also

[24] See https://www.crossref.org/services/crossmark/

transparently be reported in the form of a meta-transparency statement. Relatedly, the transparency of research practices should be judged on a continuum (more transparent or less) instead of a dichotomy (transparent or not). Improving transparency can unfold along multiple paths—each with a different cost to the authors. We hope this mental image of continuum and paths will allow more nuances in discussion within research teams and in the reviewing process.

6.5 Research transparency vs. openness

Like previous work [102], we chose to consider openness (ease of access to information) as distinct from transparency, and thus did not discuss openness in much detail. This distinction allowed us to keep our definition straightforward, and we also believe that not conflating the two concepts can help discussions. However, the two concepts are tightly linked, and in particular, transparency relies on openness. As an example, authors may choose to make rich data available but in a way that makes it difficult to access—requiring to contact the authors or to acquire an expensive proprietary software. If the information shared about the research process or outcome is very low on the openness continuum, then it is fair to argue that in practice, transparency has not been fully achieved.

6.6 Limitations

The definition we presented in section 2 is not meant to be authoritative; we see it as a starting point for reflection and discussion. Researchers are free to use it, but also improve it, or criticize it. We tried to make our definition as broadly applicable as possible, by only referring to research process and outcomes, but we collectively only have a limited understanding and knowledge of the entire HCI field, and it is possible that we left out important considerations. Our definition could therefore benefit from a broader critique in the field. Future work could conduct a survey or interviews to reveal potential blind-spots and concerns that could lead to further refinements. The examples of research transparency we discuss in section 5 are also not meant to be exhaustive. There are likely many methodologies and specific types of contributions we have not captured. In addition, our examples only target researchers as the audience of communication. We did not elaborate on other audiences such as study participants, policy makers, or the general public. These are all important audiences, as emphasized by our own definition of research transparency in the part "in all communications". Beyond the scholarly community, transparent communication might require approaches that differ across sub-fields, application domains, and cultures. We relegate to the expertise of researchers and stakeholders specialized in each subdomain to continue this discourse. We structured section 5 according to research contribution types. Sometimes, predicting which types of research contribution a project will yield could be challenging (for example, see the discussion on participatory design in Box 8). Future pedagogical materials for research transparency could organize transparent research practices in a more approachable structure.

7 CONCLUSION

Although research transparency has been frequently discussed in the field of HCI, the term has been inconsistently conceptualized and many interpretations were not broadly applicable to diverse ways of knowing in HCI. In this paper, we defined research transparency as *honesty and clarity in all communication about the research processes and outcomes—to the extent possible*, and unpacked the different components of this definition. We explained with concrete examples from the HCI community how this definition can translate to specific practices that can individually increase research transparency. We hope this work can serve authors, reviewers and editors as a framework to think about and communicate about research transparency. We also hope that the definition and examples inspire authors who wish to be more transparent, provide a set of vocabulary for appraising papers, and provoke HCI researchers to think about how transparency could manifest in their specific subfields. We believe it to be an important step in continued conversation on research transparency and we hope other HCI scholars will help critiquing and refining it.

ACKNOWLEDGMENTS

This work benefited from the Dagstuhl Seminar 22392. We thank Sophia Crüwell for her participation at the early stage of this work.

REFERENCES

[1] ACM. 2016. Artifact Review and Badging version 1.0. https://www.acm.org/publications/policies/artifact-review-badging [Cited in section 4.]

[2] ACM. 2016. Artifact Review and Badging version 1.1. https://www.acm.org/publications/policies/artifact-review-and-badging-current [Cited in section 4.]

[3] Tatsuya Amano, Valeria Ramírez-Castañeda, Violeta Berdejo-Espinola, Israel Borokini, Shawan Chowdhury, Marina Golivets, Juan David González-Trujillo, Flavia Montaño-Centellas, Kumar Paudel, Rachel Louise White, and Diogo Veríssimo. 2023. The manifold costs of being a non-native English speaker in science. *PLOS Biology* 21, 7 (July 2023), e3002184. https://doi.org/10.1371/journal.pbio.3002184 Publisher: Public Library of Science. [Cited in section 2.5.]

[4] Ignacio Avellino, Sheida Nozari, Geoffroy Canlorbe, and Yvonne Jansen. 2021. Surgical Video Summarization: Multifarious Uses, Summarization Process and Ad-Hoc Coordination. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW1, Article 140 (apr 2021), 23 pages. https://doi.org/10.1145/3449214 [Cited in section 5.7.5.]

[5] Carolyn Ball. 2009. What is transparency? *Public Integrity* 11, 4 (2009), 293–308. https://doi.org/10.2753/PIN1099-9922110400 [Cited in section 4.]

[6] Shaowen Bardzell and Jeffrey Bardzell. 2011. Towards a Feminist HCI Methodology: Social Science, Feminism, and HCI. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 675–684. https://doi.org/10.1145/1978942.1979041 [Cited in section 5.7.6.]

[7] Benjamin B Bederson and Ben Shneiderman. 2003. Theories for understanding information visualization. In *The craft of information visualization: Readings and reflections*. Morgan Kaufmann, Chapter 8, 349–351. [Cited in section 5.3.]

[8] Roni Berger. 2015. Now I see it, now I don't: researcher's position and reflexivity in qualitative research. *Qualitative Research* 15, 2 (April 2015), 219–234. https://doi.org/10.1177/1468794112468475 [Cited in section 4.]

[9] Nicole Bischof and Martin J. Eppler. 2011. Caring for Clarity in Knowledge Communication. *JUCS - Journal of Universal Computer Science* 17, 10 (2011), 1455–1473. https://doi.org/10.3217/jucs-017-10-1455 [Cited in section 6.]

[10] Susanne Bødker and Morten Kyng. 2018. Participatory Design that Matters—Facing the Big Issues. *ACM Trans. Comput.-Hum. Interact.* 25, 1, Article 4 (feb 2018), 31 pages. https://doi.org/10.1145/3152421 [Cited in section 8.]

[11] Tone Bratteteig and Ina Wagner. 2016. What is a participatory design result? *(PDC '16)*. ACM, New York, NY, USA, 141–150. https://doi.org/10.1145/2940299.2940316 [Cited in section 8.]

[12] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative Research in Psychology* 3, 2 (2006), 77–101. [Cited in section 5.2.]

[13] Virginia Braun and Victoria Clarke. 2013. *Successful Qualitative Research: A Practical Guide for Beginners*. Sage Publications. [Cited in section 5.7.6.]

[14] Virginia Braun and Victoria Clarke. 2019. Reflecting on reflexive thematic analysis. *Qualitative Research in Sport, Exercise and Health* 11, 4 (2019), 589–597. [Cited in section 5.7.6.]

[15] Virginia Braun and Victoria Clarke. 2022. *Thematic analysis: a practical guide.* SAGE, London ; Thousand Oaks, California. OCLC: on1247204005. [Cited in sections 4 and 11.]

[16] Encyclopaedia Britannica. 2020. Intension and extension. https://www.britannica.com/topic/intension. Accessed: 2023-12-15. [Cited in section 1.]

[17] John Brooke. 1996. SUS: a 'quick and dirty' usability scale. In *Usability Evaluation In Industry*, Patrick W. Jordan, B. Thomas, Ian Lyall McClelland, and Bernard Weerdmeester (Eds.). Taylor & Francis, 189–194. [Cited in section 5.7.2.]

[18] Thomas M Carsey. 2014. Making DA-RT a reality. *PS: Political Science & Politics* 47, 1 (2014), 72–77. [Cited in section 2.]

[19] Kathy Charmaz. 2014. *Constructing grounded theory.* Sage Publications. [Cited in section 5.7.6.]

[20] Kathy Charmaz and Robert Thornberg. 2021. The pursuit of quality in grounded theory. *Qualitative Research in Psychology* 18, 3 (2021), 305–327. [Cited in section 5.7.6.]

[21] Janet X. Chen, Allison McDonald, Yixin Zou, Emily Tseng, Kevin A Roundy, Acar Tamersoy, Florian Schaub, Thomas Ristenpart, and Nicola Dell. 2022. Trauma-Informed Computing: Towards Safer Technology Experiences for All. In *CHI Conference on Human Factors in Computing Systems.* ACM, New York, NY, USA, 1–20. https://doi.org/10.1145/3491102.3517475 [Cited in section 4.]

[22] CHI 2023 Paper Chairs. 2023. Guide to a Successful Submission - CHI 2024 conference. https://chi2024.acm.org/submission-guides/guide-to-a-successful-submission/ [Cited in section 1.]

[23] Lewis L. Chuang and Ulrike Pfeil. 2018. Transparency and Openness Promotion Guidelines for HCI. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems (CHI EA '18).* ACM, New York, NY, USA, 1–4. https://doi.org/10.1145/3170427.3185377 [Cited in sections 1 and 19.]

[24] James Clifford. 1990. Notes on (field) notes. In *Fieldnotes: The makings of anthropology*, Roger Sanjek (Ed.). Vol. 1990. Cornell University Press, Chapter 3, 47–70. [Cited in section 4.]

[25] Andy Cockburn, Pierre Dragicevic, Lonni Besançon, and Carl Gutwin. 2020. Threats of a replication crisis in empirical computer science. *Commun. ACM* 63, 8 (2020), 70–79. https://doi.org/10.1145/3360311 [Cited in sections 1, 5.7.3, and 19.]

[26] Andy Cockburn, Carl Gutwin, and Alan Dix. 2018. HARK No More: On the Preregistration of CHI Experiments. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18).* ACM, New York, NY, USA, 1–12. https://doi.org/10.1145/3173574.3173715 [Cited in sections 1, 5.7.3, and 19.]

[27] Nancy Cook. 1999. The Thin Within the Thick: Social History, Postmodern Ethnography, and Textual Practice. *Histoire sociale / Social history* 32, 63 (1999). [Cited in section 4.]

[28] Stephanie Craft and Tim P. Vos. 2021. The ethics of transparency. *The Routledge Companion to Journalism Ethics* (2021), 175–183. [Cited in section 4.]

[29] CSCW 2024 Paper Co-chairs. 2023. Call for Papers - CSCW 2024 conference. https://cscw.acm.org/2024/index.php/submit-papers/#open-and-transparent-science [Cited in section 1.]

[30] Jasmine M. DeJesus, Maureen A. Callanan, Graciela Solis, and Susan A. Gelman. 2019. Generic language in scientific communication. *Proceedings of the National Academy of Sciences* 116, 37 (2019), 18370–18377. https://doi.org/10.1073/pnas.1817706116 [Cited in section 2.4.]

[31] Tawanna R. Dillahunt, Sylvia Simioni, and Xuecong Xu. 2019. Online Grocery Delivery Services: An Opportunity to Address Food Disparities in Transportation-Scarce Areas. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19).* ACM, New York, NY, USA, 1–15. https://doi.org/10.1145/3290605.3300879 [Cited in section 5.7.4.]

[32] Editorial Board of Computers in Human Behavior Journal. 2024. Guide for Authors. https://www.sciencedirect.com/journal/computers-in-human-behavior/publish/guide-for-authors [last checked 2024/01/24]. [Cited in section 1.]

[33] Sanne Elling, Leo Lentz, and Menno de Jong. 2011. Retrospective Think-Aloud Method: Using Eye Movements as an Extra Cue for Participants' Verbalizations. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11).* ACM, New York, NY, USA, 1161–1170. https://doi.org/10.1145/1978942.1979116 [Cited in section 5.7.5.]

[34] Kevin C. Elliott. 2022. A Taxonomy of Transparency in Science. *Canadian Journal of Philosophy* 52, 3 (April 2022), 342–355. https://doi.org/10.1017/can.2020.21 [Cited in sections 2.2 and 2.]

[35] Sheena Erete, Jessa Dickinson, Alejandra C. Gonzalez, and Yolanda A. Rankin. 2022. Unpacking the Complexities of Community-led Violence Prevention Work. In *CHI Conference on Human Factors in Computing Systems.* ACM, New Orleans LA USA, 1–15. https://doi.org/10.1145/3491102.3502122 [Cited in section 4.]

[36] Maurizio Ferrari Dacrema, Paolo Cremonesi, and Dietmar Jannach. 2019. Are We Really Making Much Progress? A Worrying Analysis of Recent Neural Recommendation Approaches. In *Proceedings of the 13th ACM Conference on Recommender Systems (RecSys '19).* ACM, New York, NY, USA, 101–109. https://doi.org/10.1145/3298689.3347058 [Cited in section 5.7.1.]

[37] Richard Feynman. 1974. Cargo cult science. Caltech commencement address. In *Surely You're Joking, Mr. Feynman.* Norton & Company, Inc., 341–343. A copy of this chapter is available publicly at https://calteches.library.caltech.edu/51/2/CargoCult.htm. [Cited in sections 2.1, 4, and 2.]

[38] Baruch Fischhoff and Ruth Beyth. 1975. I knew it would happen: Remembered probabilities of once—future things. *Organizational Behavior and Human Performance* 13, 1 (1975), 1–16. [Cited in section 2.3.]

[39] Lori Frohwirth, Sebastian Karcher, and Tamrin A Lever. 2023. A Transparency Checklist for Qualitative Research. https://doi.org/10.31235/osf.io/wc35g [Cited in sections 4 and 2.]

[40] William Gaver. 2011. Making Spaces: How Design Workbooks Work. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11).* ACM, New York, NY, USA, 1551–1560. https://doi.org/10.1145/1978942.1979169 [Cited in section 5.1.]

[41] Clifford Geertz. 1973. Thick Description: Toward an Interpretive Theory of Culture. In *The interpretation of cultures.* Basic books, 310–323. [Cited in section 5.7.6.]

[42] Andrew Gelman. 2022. Own your design choices: We should express findings in paper titles by referring to what was measured rather than the general construct that was being aimed for. Blog post. https://statmodeling.stat.columbia.edu/2022/03/07/own-your-design-choices-we-should-express-findings-in-paper-titles-by-referring-to-what-was-measured-rather-than-the-general-construct-that-was-measured/ [Cited in section 2.4.]

[43] Roger Giner-Sorolla. 2012. Science or Art? How Aesthetic Standards Grease the Way Through the Publication Bottleneck but Undermine Science. *Perspectives on Psychological Science* 7, 6 (2012), 562–571. https://doi.org/10.1177/1745691612457576 PMID: 26168113. [Cited in section 6.3.]

[44] Julien Gori, Olivier Rioul, Yves Guiard, and Michel Beaudouin-Lafon. 2018. The perils of confounding factors: How Fitts' law experiments can lead to false conclusions. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems.* 1–10. [Cited in section 5.7.1.]

[45] Lahari Goswami, Amelia McNamara, Viktorija Paneva, Jan Benjamin Vornhagen, and Erich Weichselgartner. 2022. A Cheat Sheet for a Transparent CHI paper. (Sept. 2022). https://doi.org/10.17605/OSF.IO/YHWUQ [Cited in section 5.7.]

[46] Maria J Grant and Andrew Booth. 2009. A typology of reviews: an analysis of 14 review types and associated methodologies. *Health information & libraries journal* 26, 2 (2009), 91–108. https://doi.org/10.1111/j.1471-1842.2009.00848.x [Cited in section 5.6.]

[47] Frederick J Gravetter and Lori-Ann B Forzano. 2018. *Research methods for the behavioral sciences.* Cengage learning. [Cited in section 5.7.4.]

[48] Shirley Gregor. 2006. The Nature of Theory in Information Systems. *MIS Quarterly* 30, 3 (2006), 611–642. https://doi.org/10.2307/25148742 [Cited in section 5.3.]

[49] Egon G Guba and Yvonna S Lincoln. 1994. Competing paradigms in qualitative research. *Handbook of qualitative research* 2, 163-194 (1994), 105. [Cited in sections 1 and 5.7.6.]

[50] Kashyap Haresamudram, Stefan Larsson, and Fredrik Heintz. 2023. Three Levels of AI Transparency. *Computer* 56, 2 (Feb. 2023), 93–100. https://doi.org/10.1109/MC.2022.3213181 [Cited in section 4.]

[51] Steve Haroz, Lewis Chuang, Matthew Kay, and Chat Wacharamanotham. 2020. A Reviewer Asked You to Make Your Materials Open. Now What? https://transparenthci.medium.com/a-reviewer-asked-you-to-make-your-materials-open-now-what-f4af38e44b86 Publication Title: Medium. [Cited in section 5.7.]

[52] Glenn W. Harrison and John A. List. 2004. Field Experiments. *Journal of Economic Literature* 42, 4 (December 2004), 1009–1055. https://doi.org/10.1257/0022051043004577 [Cited in section 5.7.4.]

[53] Tamarinde L. Haven, Timothy M. Errington, Kristian Skrede Gleditsch, Leonie van Grootel, Alan M. Jacobs, Florian G. Kern, Rafael Piñeiro, Fernando Rosenblatt, and Lidwine B. Mokkink. 2020. Preregistering Qualitative Research: A Delphi Study. *International Journal of Qualitative Methods* 19 (2020), 1609406920976417. https://doi.org/10.1177/1609406920976417 [Cited in section 5.7.5.]

[54] Thomas T. Hewett, Ronald Baecker, Stuart Card, Tom Carey, Jean Gasen, Marilyn Mantei, Gary Perlman, Gary Strong, and William Verplank. 1992. *ACM SIGCHI Curricula for Human-Computer Interaction.* Technical Report. New York, NY, USA. [Cited in section 1.]

[55] Ken Hinckley. 2015. *So you're a program committee member now: On excellence in reviews and meta-reviews and championing submitted work that has merit.* Technical Report. https://www.microsoft.com/en-us/research/wp-content/uploads/2016/10/Excellence-in-Reviews-MobileHCI-2015-Web-Site.pdf [Cited in section 6.3.]

[56] Andrew Gary Darwin Holmes. 2020. Researcher Positionality – A Consideration of Its Influence and Place in Qualitative Research – A New Researcher Guide. *Shanlax International Journal of Education* 8, 4 (Sept. 2020), 1–10. https://eric.ed.gov/?id=EJ1268044 Publisher: Shanlax International Journals ERIC Number: EJ1268044. [Cited in section 4.]

[57] Thomas J. Hostler. 2023. The Invisible Workload of Open Research. *Journal of Trial & Error* (may 4 2023). https://journal.trialanderror.org/pub/the-invisible-workload. [Cited in section 2.5.]

[58] IDEO.org. 2015. *The field guide to human-centered design: design kit.* IDEO. http://www.designkit.org [Cited in section 5.2.]

[59] Alan M. Jacobs, Tim Büthe, Ana Arjona, Leonardo R. Arriola, Eva Bellin, Andrew Bennett, Lisa Björkman, Erik Bleich, Zachary Elkins, Tasha Fairfield, and et al. 2021. The Qualitative Transparency Deliberations: Insights and Implications. *Perspectives on Politics* 19, 1 (2021), 171–208. https://doi.org/10.1017/S1537592720001164 [Cited in section 5.7.5.]

[60] Anisa J N Jafar. 2018. What is positionality and should it be expressed in quantitative studies? *Emergency Medicine Journal* (Jan. 2018), emermed–2017–207158. https://doi.org/10.1136/emermed-2017-207158 [Cited in section 4.]

[61] Nadine Jarvis, David Cameron, and Andy Boucher. 2012. Attention to Detail: Annotations of a Design Process. In *Proceedings of the 7th Nordic Conference on Human-Computer Interaction: Making Sense Through Design (NordiCHI '12).* ACM, New York, NY, USA, 11–20. https://doi.org/10.1145/2399016.2399019 [Cited in section 5.1.]

[62] Vaishnav Kameswaran, Lindsey Cameron, and Tawanna R. Dillahunt. 2018. Support for Social and Cultural Capital Development in Real-Time Ridesharing Services. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18).* ACM, New York, NY, USA, 1–12. https://doi.org/10.1145/3173574.3173916 [Cited in section 5.7.5.]

[63] Matthew Kay, Steve Haroz, Shion Guha, and Pierre Dragicevic. 2016. Special Interest Group on Transparent Statistics in HCI. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '16).* ACM, New York, NY, USA, 1081–1084. https://doi.org/10.1145/2851581.2886442 [Cited in sections 1 and 19.]

[64] Matthew Kay, Steve Haroz, Shion Guha, and Pierre Dragicevic. 2016. Special Interest Group on Transparent Statistics in HCI. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '16).* ACM, New York, NY, USA, 1081–1084. https://doi.org/10.1145/2851581.2886442 [Cited in section 1.]

[65] Matthew Kay, Steve Haroz, Shion Guha, Pierre Dragicevic, and Chat Wacharamanotham. 2017. Moving Transparent Statistics Forward at CHI. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '17).* ACM, New York, NY, USA, 534–541. https://doi.org/10.1145/3027063.3027084 [Cited in section 1.]

[66] Peter J Lang, Margaret M Bradley, Bruce N Cuthbert, et al. 2008. *International affective picture system (IAPS): Technical manual and affective ratings.* Technical Report A-8. [Cited in section 5.5.]

[67] Jonathan Lazar, Jinjuan Heidi Feng, and Harry Hochheiser. 2017. *Research Methods in Human-Computer Interaction - 2nd Edition.* Morgan Kaufmann, MA, USA. [Cited in section 5.7.3.]

[68] Lina Lee, Celine Latulipe, and Tonya Frevert. 2022. Using Discrimination Response Ideation to Uncover Student Attitudes about Diversity and Inclusion in Computer Science. *ACM Trans. Comput. Educ.* 22, 4, Article 52 (dec 2022), 32 pages. https://doi.org/10.1145/3550487 [Cited in section 5.7.5.]

[69] Sabina Leonelli. 2018. Rethinking Reproducibility as a Criterion for Research Quality. In *Including a Symposium on Mary Morgan: Curiosity, Imagination, and Surprise.* Research in the History of Economic Thought and Methodology, Vol. 36B. Emerald Publishing Limited, 129–146. https://doi.org/10.1108/S0743-41542018000036B009 [Cited in sections 5.7, 5.7.2, and 11.]

[70] Alessandro Liberati, Douglas G Altman, Jennifer Tetzlaff, Cynthia Mulrow, Peter C Gøtzsche, John PA Ioannidis, Mike Clarke, Philip J Devereaux, Jos Kleijnen, and David Moher. 2009. The PRISMA Statement for Reporting Systematic Reviews and Meta-Analyses of Studies That Evaluate Health Care Interventions: Explanation and Elaboration. *Annals of Internal Medicine* 151, 4 (2009), W–65–W–94. https://doi.org/10.7326/0003-4819-151-4-200908180-00136 PMID: 19622512. [Cited in section 5.6.]

[71] Thomas Lodato and Carl DiSalvo. 2018. Institutional constraints: the forms and limits of participatory design in the public realm. In *Proceedings of the 15th Participatory Design Conference: Full Papers - Volume 1 (PDC '18).* ACM, New York, NY, USA, Article 5, 12 pages. https://doi.org/10.1145/3210586.3210595 [Cited in section 8.]

[72] K. Luijken, A. Lohmann, U. Alter, J. Claramunt Gonzalez, F. J. Clouth, J. L. Fossum, L. Hesen, A. H. J. Huizing, J. Ketelaar, A. K. Montoya, L. Nab, R. C. C. Nijman, B. B. L. Penning de Vries, T. D. Tibbe, Y. A. Wang, and R. H. H. Groenwold. 2024. Replicability of simulation studies for the investigation of statistical methods: the RepliSims project. *Royal Society Open Science* 11, 1 (2024), 231003. https://doi.org/10.1098/rsos.231003 [Cited in section 5.7.1.]

[73] Arthur Lupia and Colin Elman. 2014. Openness in Political Science: Data Access and Research Transparency: Introduction. *PS: Political Science & Politics* 47, 1 (2014), 19–42. https://doi.org/10.1017/S1049096513001716 [Cited in section 2.]

[74] Liz Lyon. 2016. Transparency: the emerging third dimension of Open Science and Open Data. *LIBER Quarterly: The Journal of the Association of European Research Libraries* 25, 4 (Jun. 2016), 153–171. https://doi.org/10.18352/lq.10113 [Cited in sections 1 and 2.]

[75] Julie P. Martin, Renee Desing, and Maura Borrego. 2022. Positionality statements are just the tip of the iceberg: Moving towards a reflexive process. *Journal of Women and Minorities in Science and Engineering* 28, 4 (2022). https://doi.org/10.1615/JWomenMinorScienEng.2022044277 Publisher: Begel House Inc.. [Cited in section 4.]

[76] Nora McDonald, Sarita Schoenebeck, and Andrea Forte. 2019. Reliability and Inter-rater Reliability in Qualitative Research: Norms and Guidelines for CSCW and HCI Practice. *Proc. ACM Hum.-Comput. Interact.* 3, CSCW, Article 72 (nov 2019), 23 pages. https://doi.org/10.1145/3359174 [Cited in sections 5.7.5 and 5.7.6.]

[77] Edward Miguel, Colin Camerer, Katherine Casey, Joshua Cohen, Kevin M Esterling, Alan Gerber, Rachel Glennerster, Don P Green, Macartan Humphreys, Guido Imbens, et al. 2014. Promoting Transparency in Social Science Research. *Science* 343, 6166 (2014), 30–31. https://doi.org/10.1126/science.1245317 [Cited in section 2.]

[78] Sebastian Misztal and Jonas Schild. 2022. Visual Delegate Generalization Frame – Evaluating Impact of Visual Effects and Elements on Player and User Experiences in Video Games and Interactive Virtual Environments. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22).* ACM, New York, NY, USA, Article 191, 20 pages. https://doi.org/10.1145/3491102.3501885 [Cited in section 5.7.5.]

[79] Andrew Moravcsik. 2014. Transparency: The Revolution in Qualitative Research. *PS: Political Science & Politics* 47, 01 (Jan. 2014), 48–53. https://doi.org/10.1017/S1049096513001789 [Cited in section 2.]

[80] Andrew Moravcsik. 2014. Transparency: The revolution in qualitative research. *PS: Political Science & Politics* 47, 1 (2014), 48–53. [Cited in sections 5.4 and 9.]

[81] Andrew Moravcsik. 2019. Transparency in Qualitative Research. In *SAGE Research Methods Foundations*, Paul Atkins, Sara Delamont, Alexandru Cernat, Joseph W. Sakshaug, and Richard A. Williams (Eds.). SAGE Publications Ltd, 1 Oliver's Yard, 55 City Road, London EC1Y 1SP United Kingdom. https://doi.org/10.4135/9781526421036863782 [Cited in section 2.]

[82] David Moreau and Beau Gamble. 2022. Conducting a meta-analysis in the age of open science: Tools, tips, and practical recommendations. *Psychological Methods* 27, 3 (2022), 426. https://doi.org/10.1037/met0000351 [Cited in section 5.6.]

[83] Janice Morse. 2021. Why the Qualitative Health Research (QHR) Review Process Does Not Use Checklists. *Qualitative Health Research* 31, 5 (2021), 819–821. https://doi.org/10.1177/1049732321994114 [Cited in section 1.]

[84] Michael J. Muller, Jean Hallewell Haslwanter, and Tom Dayton. 1997. Chapter 11 - Participatory Practices in the Software Lifecycle. In *Handbook of Human-Computer Interaction (Second Edition)*, Marting G. Helander, Thomas K. Landauer, and Prasad V. Prabhu (Eds.). North-Holland, Amsterdam, 255–297. https://doi.org/10.1016/B978-044481862-1.50077-7 [Cited in section 8.]

[85] Zachary Munn, Micah DJ Peters, Cindy Stern, Catalin Tufanaru, Alexa McArthur, and Edoardo Aromataris. 2018. Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. *BMC medical research methodology* 18 (2018), 1–7. https://doi.org/10.1186/s12874-018-0611-x [Cited in section 5.6.]

[86] Leif D Nelson, Joseph Simmons, and Uri Simonsohn. 2018. Psychology's renaissance. *Annual review of psychology* 69 (2018), 511–534. [Cited in section 1.]

[87] C. Thi Nguyen. 2021. Transparency is Surveillance. *Philosophy and Phenomenological Research* (2021). https://doi.org/10.1111/phpr.12823 [Cited in section 2.5.]

[88] B. A. Nosek, G. Alter, G. C. Banks, D. Borsboom, S. D. Bowman, S. J. Breckler, S. Buck, C. D. Chambers, G. Chin, G. Christensen, M. Contestabile, A. Dafoe, E. Eich, J. Freese, R. Glennerster, D. Goroff, D. P. Green, B. Hesse, M. Humphreys, J. Ishiyama, D. Karlan, A. Kraut, A. Lupia, P. Mabry, T. Madon, N. Malhotra, E. Mayo-Wilson, M. McNutt, E. Miguel, E. Levy Paluck, U. Simonsohn, C. Soderberg, B. A. Spellman, J. Turitto, G. VandenBos, S. Vazire, E. J. Wagenmakers, R. Wilson, and T. Yarkoni. 2015. Promoting an Open Research Culture. *Science* 348, 6242 (June 2015), 1422–1425. https://doi.org/10.1126/science.aab2374 [Cited in section 2.]

[89] Sean Oesch, Scott Ruoti, James Simmons, and Anuj Gautam. 2022. "It Basically Started Using Me:" An Observational Study of Password Manager Usage. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22).* ACM, New York, NY, USA, Article 33, 23 pages. https://doi.org/10.1145/3491102.3517534 [Cited in section 5.7.5.]

[90] Federation of American Societies for Experimental Biology. 2016. *Enhancing research reproducibility: recommendations from the Federation of American Societies for Experimental Biology.* Technical Report. https://www.aai.org/AAISite/media/Public_Affairs/Policy_Issues/NIH_Peer_Review/FASEB_Enhancing-Research-Reproducibility.pdf [Cited in section 2.]

[91] Open Source Initiative. 2023. The Open Source Definition. https://opensource.org/osd/ [Cited in section 5.1.]

[92] Antti Oulasvirta. 2009. Field Experiments in HCI: Promises and Challenges. In *Future Interaction Design II*, Hannakaisa Isomäki and Pertti Saariluoma (Eds.). Springer London, London, 87–116. https://doi.org/10.1007/978-1-84800-385-9_5 [Cited in section 5.7.4.]

[93] Lydia O'Sullivan, Lai Ma, and Peter Doran. 2021. An overview of post-publication peer review. *Scholarly Assessment Reports* 3, 1 (2021). [Cited

in section 2.3.]

[94] Sam Parsons, Flávio Azevedo, Mahmoud M. Elsherif, Samuel Guay, Owen N. Shahim, Gisela H. Govaart, Emma Norris, Aoife O'Mahony, Adam J. Parker, Ana Todorovic, Charlotte R. Pennington, Elias Garcia-Pelegrin, Aleksandra Lazić, Olly Robertson, Sara L. Middleton, Beatrice Valentini, Joanne McCuaig, Bradley J. Baker, Elizabeth Collins, Adrien A. Fillon, Tina B. Lonsdorf, Michele C. Lim, Norbert Vanek, Marton Kovacs, Timo B. Roettger, Sonia Rishi, Jacob F. Miranda, Matt Jaquiery, Suzanne L. K. Stewart, Valeria Agostini, Andrew J. Stewart, Kamil Izydorczak, Sarah Ashcroft-Jones, Helena Hartmann, Madeleine Ingham, Yuki Yamada, Martin R. Vasilev, Filip Dechterenko, Nihan Albayrak-Aydemir, Yu-Fang Yang, Annalise A. LaPlume, Julia K. Wolska, Emma L. Henderson, Mirela Zaneva, Benjamin G. Farrar, Ross Mounce, Tamara Kalandadze, Wanyin Li, Qinyu Xiao, Robert M. Ross, Siu Kit Yeung, Meng Liu, Micah L. Vandegrift, Zoltan Kekecs, Marta K. Topor, Myriam A. Baum, Emily A. Williams, Asma A. Assaneea, Amélie Bret, Aidan G. Cashin, Nick Ballou, Tsvetomira Dumbalska, Bettina M. J. Kern, Claire R. Melia, Beatrix Arendt, Gerald H. Vineyard, Jade S. Pickering, Thomas R. Evans, Catherine Laverty, Eliza A. Woodward, David Moreau, Dominique G. Roche, Eike M. Rinke, Graham Reid, Eduardo Garcia-Garzon, Steven Verheyen, Halil E. Kocalar, Ashley R. Blake, Jamie P. Cockcroft, Leticia Micheli, Brice Beffara Bret, Zoe M. Flack, Barnabas Szaszi, Markus Weinmann, Oscar Lecuona, Birgit Schmidt, William X. Ngiam, Ana Barbosa Mendes, Shannon Francis, Brett J. Gall, Mariella Paul, Connor T. Keating, Magdalena Grose-Hodge, James E. Bartlett, Bethan J. Iley, Lisa Spitzer, Madeleine Pownall, Christopher J. Graham, Tobias Wingen, Jenny Terry, Catia Margarida F. Oliveira, Ryan A. Millager, Kerry J. Fox, Alaa AlDoh, Alexander Hart, Olmo R. van den Akker, Gilad Feldman, Dominik A. Kiersz, Christina Pomareda, Kai Krautter, Ali H. Al-Hoorie, and Balazs Aczel. 2022. A community-sourced glossary of open scholarship terms. *Nature Human Behaviour* 6, 3 (March 2022), 312–318. https://doi.org/10.1038/s41562-021-01269-4 Number: 3 Publisher: Nature Publishing Group. [Cited in section 9.]

[95] Roger D. Peng. 2011. Reproducible Research in Computational Science. *Science* 334, 6060 (2011), 1226–1227. https://doi.org/10.1126/science.1213847 [Cited in section 5.7.1.]

[96] Robin Levin Penslar and Joan P Porter. 1993. Institutional Review Board Guidebook. Chapter III Basic IRB Review, Section D Privacy and Confidentiality. http://web.archive.org/web/20080207010024/http://www.808multimedia.com/winnt/kernel.htm. Accessed: 2023-06-20. [Cited in section 2.5.]

[97] Hans E. Plesser. 2018. Reproducibility vs. Replicability: A Brief History of a Confused Terminology. *Frontiers in Neuroinformatics* 11 (2018), 76. [Cited in section 4.]

[98] Darya Pokutnaya, Bruce Childers, Alice E. Arcury-Quandt, Harry Hochheiser, and Willem G. Van Panhuis. 2023. An implementation framework to improve the transparency and reproducibility of computational models of infectious diseases. *PLOS Computational Biology* 19, 3 (March 2023), 1–9. https://doi.org/10.1371/journal.pcbi.1010856 Publisher: Public Library of Science. [Cited in section 5.7.1.]

[99] Joseph G Ponterotto. 2006. Brief note on the origins, evolution, and meaning of the qualitative research concept thick description. *The Qualitative Report* 11, 3 (2006), 538–549. https://doi.org/10.46743/2160-3715/2006.1666 [Cited in sections 5.7.6 and 9.]

[100] Seth Roberts and Harold Pashler. 2000. How persuasive is a good fit? A comment on theory testing. *Psychological review* 107, 2 (2000), 358. [Cited in section 5.7.1.]

[101] Yvonne Rogers. 2012. *HCI Theory: Classical, Modern, and Contemporary.* Morgan & Claypool Publishers. [Cited in section 5.3.]

[102] Kavous Salehzadeh Niksirat, Lahari Goswami, Pooja S. B. Rao, James Tyler, Alessandro Silacci, Sadiq Aliyu, Annika Aebli, Chat Wacharamanotham, and Mauro Cherubini. 2023. Changes in Research Ethics, Openness, and Transparency in Empirical Studies between CHI 2017 and CHI 2022. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23).* ACM, New York, NY, USA, 1–23. https://doi.org/10.1145/3544548.3580848 [Cited in sections 1, 4, 2, 5.7, and 6.5.]

[103] Geir Kjetil Sandve, Anton Nekrutenko, James Taylor, and Eivind Hovig. 2013. Ten Simple Rules for Reproducible Computational Research. *PLOS Computational Biology* 9, 10 (Oct. 2013), 1–4. https://doi.org/10.1371/journal.pcbi.1003285 Publisher: Public Library of Science. [Cited in section 5.7.1.]

[104] Joseph P Simmons, Leif D Nelson, and Uri Simonsohn. 2011. False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological science* 22, 11 (2011), 1359–1366. https://doi.org/10.1177/0956797611417632 [Cited in section 5.7.3.]

[105] Robert Soden, Austin Toombs, and Michaelanne Thomas. 2024. Evaluating Interpretive Research in HCI. *Interactions* 31, 1 (jan 2024), 38–42. https://doi.org/10.1145/3633200 [Cited in section 5.7.6.]

[106] Timothy Sohn, Kevin A. Li, William G. Griswold, and James D. Hollan. 2008. A Diary Study of Mobile Information Needs. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '08).* ACM, New York, NY, USA, 433–442. https://doi.org/10.1145/1357054.1357125 [Cited in section 5.7.5.]

[107] R. William Soukoreff and I. Scott MacKenzie. 2003. Metrics for Text Entry Research: An Evaluation of MSD and KSPC, and a New Unified Error Metric. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '03).* ACM, New York, NY, USA, 113–120. https://doi.org/10.1145/642611.642632 [Cited in section 5.2.]

[108] Evropi Stefanidi, Marit Bentvelzen, Paweł W. Woźniak, Thomas Kosch, Mikołaj P. Woźniak, Thomas Mildner, Stefan Schneegass, Heiko Müller, and Jasmin Niess. 2023. Literature Reviews in HCI: A Review of Reviews. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23).* ACM, New York, NY, USA, Article 509, 24 pages. https://doi.org/10.1145/3544548.3581332 [Cited in section 5.6.]

[109] Erik Stolterman and Mikael Wiberg. 2010. Concept-driven interaction design research. *Human–Computer Interaction* 25, 2 (2010), 95–118. https://doi.org/10.1080/07370020903586696 [Cited in section 5.3.]

[110] Anselm Strauss and Juliet Corbin. 1998. *Basics of qualitative research: Techniques and procedures for developing grounded theory, 2nd ed.* Sage Publications, Inc, Thousand Oaks, CA, US. Pages: xiii, 312. [Cited in section 5.7.6.]

[111] Poorna Talkad Sukumar, Ignacio Avellino, Christian Remy, Michael A. DeVito, Tawanna R. Dillahunt, Joanna McGrenere, and Max L. Wilson. 2020. Transparency in Qualitative Research: Increasing Fairness in the CHI Review Process. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems (CHI EA '20).* ACM, New York, NY, USA, 1–6. https://doi.org/10.1145/3334480.3381066 [Cited in section 1.]

[112] Transparency. 2023. In *The Oxford Advanced Learner's Dictionary.* https://www.oxfordlearnersdictionaries.com/definition/english/transparency?q=transparency [Cited in section 2.]

[113] Transparent. 2023. In *The Merriam-Webster Dictionary.* https://www.merriam-webster.com/dictionary/transparent [Cited in section 2.]

[114] Transparent. 2023. In *The American Heritage Dictionary.* https://ahdictionary.com/word/search.html?q=Transparent [Cited in section 2.]

[115] Alexander C. Tsai, Brandon A. Kohrt, Lynn T. Matthews, Theresa S. Betancourt, Jooyoung K. Lee, Andrew V. Papachristos, Sheri D. Weiser, and Shari L. Dworkin. 2016. Promises and pitfalls of data sharing in qualitative research. *Social Science & Medicine* 169 (Nov. 2016), 191–198. https://doi.org/10.1016/j.socscimed.2016.08.004 [Cited in section 2.5.]

[116] UNESCO. 2021. UNESCO Recommendation on Open Science. (2021). https://unesdoc.unesco.org/ark:/48223/pf0000379949.locale=en [Cited in section 2.]

[117] Jan B. Vornhagen, April Tyack, and Elisa D. Mekler. 2020. Statistical Significance Testing at CHI PLAY: Challenges and Opportunities for More Transparency. In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play (CHI PLAY '20).* ACM, New York, NY, USA, 4–18. https://doi.org/10.1145/3410404.3414229 [Cited in sections 1, 5.7, and 19.]

[118] Marina Vujnovic and Dean Kruckeberg. 2016. Pitfalls and promises of transparency in the digital age. *Public Relations Inquiry* 5, 2 (2016), 121–143. https://doi.org/10.1177/2046147X16635227 [Cited in section 4.]

[119] Chat Wacharamanotham, Lukas Eisenring, Steve Haroz, and Florian Echtler. 2020. Transparency of CHI Research Artifacts: Results of a Self-Reported Survey. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20).* ACM, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376448 [Cited in sections 1 and 2.]

[120] Max Wilson, Wendy Mackay, Ed Chi, Michael Bernstein, and Jeffrey Nichols. 2012. RepliCHI SIG: from a panel to a new submission venue for replication. In *CHI '12 Extended Abstracts on Human Factors in Computing Systems (CHI EA '12).* ACM, New York, NY, USA, 1185–1188. https://doi.org/10.1145/2212776.2212419 [Cited in section 1.]

[121] Max L. Wilson, Ed H. Chi, Stuart Reeves, and David Coyle. 2014. RepliCHI: the workshop II. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems (CHI EA '14).* ACM, New York, NY, USA, 33–36. https://doi.org/10.1145/2559206.2559233 [Not cited.]

[122] Max L. Wilson, Wendy Mackay, Ed Chi, Michael Bernstein, Dan Russell, and Harold Thimbleby. 2011. RepliCHI - CHI should be replicating and validating results more: discuss. In *CHI '11 Extended Abstracts on Human Factors in Computing Systems (CHI EA '11).* ACM, New York, NY, USA, 463–466. https://doi.org/10.1145/1979742.1979491 [Not cited.]

[123] Max L. L. Wilson, Paul Resnick, David Coyle, and Ed H. Chi. 2013. RepliCHI: the workshop. In *CHI '13 Extended Abstracts on Human Factors in Computing Systems (CHI EA '13).* ACM, New York, NY, USA, 3159–3162. https://doi.org/10.1145/2468356.2479636 [Cited in section 1.]

[124] Jacob O. Wobbrock and Julie A. Kientz. 2016. Research contributions in human-computer interaction. *Interactions* 23, 3 (April 2016), 38–44. https://doi.org/10.1145/2907069 [Cited in sections 1, 2.4, 5, 5.1, 5.2, 5.3, 5.4, 5.5, 5.6, and 10.]

[125] Fumeng Yang, Mandi Cai, Chloe Mortenson, Hoda Fakhari, Ayse Deniz Lokmanoglu, Jessica Hullman, Steven Franconeri, Nicholas Diakopoulos, Erik Nisbet, and Matthew Kay. 2023. Swaying the Public? Impacts of Election Forecast Visualizations on Emotion, Trust, and Intention in the 2022 US Midterms. *IEEE Transactions on Visualization and Computer Graphics* (2023). https://doi.org/10.31219/osf.io/qpyna in press. [Cited in section 5.7.3.]

[126] John Zimmerman, Jodi Forlizzi, and Shelley Evenson. 2007. Research through Design as a Method for Interaction Design Research in HCI. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '07).* ACM,

New York, NY, USA, 493–502. https://doi.org/10.1145/1240624.1240704 [Cited in section 5.1.]

Box 9: Glossary of terms

This article uses many terms which are not necessarily familiar to all. We summarize a subset of these terms in the table below and define each of them. Most of these definitions are reused from the *Framework of Open and Reproducible Research Teaching* (FORRT) community who curates an online glossary (https://forrt.org/glossary/) of hundreds of terms related to open and transparent research practices [94].

Practice	Definition
Active citation	*"Active citation envisages that any empirical citation be hyperlinked to an annotated excerpt from the original source, which appears in a "transparency appendix" at the end of the paper, article, or book chapter."* [80]
FAIR	*"Describes making scholarly materials **F**indable, **A**ccessible, **I**nteroperable and **R**eusable (FAIR). 'Findable' and 'Accessible' are concerned with where materials are stored (e.g. in data repositories), while 'Interoperable' and 'Reusable' focus on the importance of data formats and how such formats might change in the future."* https://forrt.org/glossary/fair-principles/
Open licenses	Open licenses specify what others are allowed to do with shared material. Two main types exist: copyleft and permissive licenses. Copyleft licenses, such as GNU GPL, require that any derivative reusing the shared material needs to be shared under a copyleft license as well. Permissive licenses, such as BSD, MIT, or Apache licenses, do not restrict reuse and allow distribution of derivatives under many different licenses. https://choosealicense.com/
Positionality	*"The contextualization of both the research environment and the researcher to define the boundaries within [which] the research was produced."* https://forrt.org/glossary/positionality/ See also Box 4
Preregistration	*"The practice of publishing the plan for a study, including research questions/hypotheses, research design, data analysis before the data has been collected or examined.[...] A preregistration document is time-stamped and typically registered with an independent party (e.g., a repository) so that it can be publicly shared with others (possibly after an embargo period)."* https://forrt.org/glossary/preregistration/
PRISMA	*"PRISMA is an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses."* It was initially designed to focus on the reporting of reviews evaluating the effects of interventions, but the general approach can be applied in a wide range of reviews http://www.prisma-statement.org
Protected-access data repository	A *"repository that manages access to data to qualified researchers through a documented process"* https://osf.io/tvyxz/wiki/8.%20Approved%20Protected%20Access%20Repositories/
Reflexivity	*"The process of reflexivity refers to critically considering the knowledge that we produce through research, how it is produced, and our own role as researchers in producing this knowledge. [...] Reflexivity aims to bring attention to underlying factors which may impact the research process, including development of research questions, data collection, and the analysis."* https://forrt.org/glossary/reflexivity/
Registered report	*"A scientific publishing format that includes an initial round of peer review of the background and methods (study design, measurement, and analysis plan); sufficiently high quality manuscripts are accepted for in-principle acceptance (IPA) at this stage. [...] This shifts the focus of the review to the study's proposed research question and methodology and away from the perceived interest in the study's results."* https://forrt.org/glossary/registered-report/
Replicability	*"The measurement can be obtained with stated precision by a different team, a different measuring system, in a different location on multiple trials. For computational experiments, this means that an independent group can obtain the same result using artifacts which they develop completely independently."* ACM Artifact Review and Badging v. 1.1 https://www.acm.org/publications/policies/artifact-review-and-badging-current
Reproducibility	*"The measurement can be obtained with stated precision by a different team using the same measurement procedure, the same measuring system, under the same operating conditions, in the same or a different location on multiple trials. For computational experiments, this means that an independent group can obtain the same result using the author's own artifacts."* ACM Artifact Review and Badging v. 1.1 https://www.acm.org/publications/policies/artifact-review-and-badging-current
Thick description	*"Thick description refers to the researcher's task of both describing and interpreting observed social action (or behavior) within its particular context."* [99]
TOP guidelines	*"Transparency and Openness Promotion Guidelines (PDF and HTML) include eight modular standards, each with three levels of increasing stringency. Journals select which of the eight transparency standards they wish to implement and select a level of implementation for each. These features provide flexibility for adoption depending on disciplinary variation, but simultaneously establish community standards."* https://www.cos.io/initiatives/top-guidelines
Version control	*"The practice of managing and recording changes to digital resources (e.g. files, websites, programmes, etc.) over time so that you can recall specific versions later. Version control systems are designed to record the history of changes (who, what and when), and help to avoid human errors (e.g. working on the wrong version)."* https://forrt.org/glossary/vbeta/version-control/

Box 10: Contribution types

Wobbrock and Kientz [124] list seven types of contributions to HCI, summarized below, and detail that the primary contribution keywords used at CHI since CHI 2016 follow the same structure with some added nuance dividing empirical contributions into studies that tell us about people and studies that tells us about how people use a system. We found that last distinction not sufficiently nuanced to inform our discussions in this article and thus additionally use a second framework that enables us to better distinguish different approaches within the rich space of empirical HCI contributions. The descriptions and examples provided in this table are taken from Wobbrock and Kientz [124].

Type	Description	Examples
Empirical	Empirical research aims to generate new knowledge through observations and data collection. It encompasses various methods such as experiments, user tests, field observations, interviews, and surveys.	Interview studies, diary studies, quantitative lab experiments, crowdsourced studies, qualitative field studies
Artifacts	Artifact contributions include creating interactive artifacts like prototypes, toolkits, architectures, and techniques. Artifacts can be the main contribution of a paper or a proof-of-concept implementation of a more general concept.	input devices, systems, hardware toolkits, interaction techniques, envisionment
Methods	These create new ways of conducting research or design work. They enhance the methods used in discovery, measurement, analysis, and creation.	method application, method innovation, method adaptation, new measures, new instruments
Theories	Theory contributions assume the introduction of new concepts, models, principles, or frameworks that can guide future HCI work. Theories explain and predict phenomena, and they should be testable and falsifiable.	thought frameworks, design spaces, conceptual models, design criteria, quantitative models
Opinions	These are papers that seek to change readers' minds by presenting well-argued viewpoints. While opinion contributions draw from various research types, their focus is on persuasion, reflection, discussion, and debate.	opinions on evaluation, prioritization; visions, definitions
Dataset	Dataset contributions provide new and useful datasets for HCI research, often with accompanying analyses and benchmarks. Datasets enable standardized evaluations and comparisons of algorithms, systems, or methods.	test corpora, benchmark test, corpus creations, repositories, global datasets
Surveys	Surveys review and synthesize existing work to identify trends and gaps. They organize knowledge, expose opportunities, and guide further research.	surveys on techniques, emerging topics, tools, domains, technologies

These types of contributions are not necessarily mutually exclusive: a single paper can make different kinds of contributions, as is reflected in the contribution statements often stated in the last paragraph of introductions in HCI papers. As keywords, declaring a primary contribution type is optional, and Wobrock and Kientz report in their article that, for the CHI 2016 submission cycle, only 5.6% of submissions chose not to do so.

Box 11: Leonelli's degrees of control

Leonelli argues to reconsider the use of reproducibility as a criterion to judge research and makes the point that research domains differ considerably concerning the *degree of control* over their research process [69]. The article introduces six levels of control, from computational studies, where e.g., models and associated parameters are fully controlled, to open-ended participant observations, where subjectivity and reflexivity are valued and the situatedness of knowledge is emphasized [15].

The table below summarizes these different types of (empirical) research following Leonelli [69], with their respective level of expected reproducibility and the level of control a researcher can exert. We illustrate each using generic examples from the HCI domain.

Type of research	Level of reproducibility	Level of control	Examples in HCI
Computational studies	Computational reproducibility	Fully specified methods and parameters in a set of files and written instructions whose execution result in the same key quantitative findings, tables, and figures.	Predictive modeling of task performances, simulation studies
Standardized studies	Direct experimental reproducibility	The use of strictly defined/standardized research methods which are expected to yield the same results.	ISO 9241-9 (Fitts's law tasks), NASA TLX, SUS
Controlled experiments	Scoping, Indirect and Conceptual Reproducibility	Methods, setup and materials used are well defined by the researcher and tailored to the research questions, but not every aspect of an experiment can be controlled.	controlled experiment comparing a new interaction technique with an established one
Field experiments	Reproducible Expertise	Very low control over environmental variability, but with the expectation that any skilled experimenter working with the same methods and the same type of materials at that particular time and place would produce similar results.	Field experiments exposing different groups to different designs
Semi-structured data collection	Reproducible Observation	Observational research with the expectation that any skilled researcher placed in the same time and place would pick out, if not the same data, at least similar patterns.	Structured interviews of people interacting with technology
Open-ended data collection	Irreproducible Research	Observational research which embraces the subjectivity and situatedness of research outcomes.	Ethnographic research of people interacting with technology

Box 12: Data licensing

There are licenses that exist for datasets, similar to licenses for software or other intellectual property. These licenses help define the terms and conditions under which the dataset can be used, shared, and modified. A few examples:

- Creative Commons licenses: Creative Commons (CC) offers a range of licenses that provide different levels of permissions and restrictions. For example, the CC BY license allows users to share, adapt, and build upon the dataset for any purpose, even commercially, as long as proper attribution is given to the original creator. Other CC licenses, such as CC BY-SA (ShareAlike) or CC BY-NC (NonCommercial), impose additional restrictions on the usage, derivative works, or commercial applications.
- Open Data Commons licenses: Open Data Commons (ODC) provides a set of licenses specifically designed for open data. The ODC licenses include the ODC Public Domain Dedication and License (PDDL), which allows for unrestricted use and redistribution of the dataset, and the ODC Open Database License (ODbL), which grants similar freedoms but also requires attribution and share-alike conditions.
- Community Data License Agreement (CDLA)

The website https://opendefinition.org/ provides a definition of licenses compatible with open data/open science. For a large set of licenses that conform to the site's definition of *open*, see https://opendefinition.org/licenses/. On the contrary, licenses that do not conform to the site's definition of "open" can be found at https://opendefinition.org/licenses/nonconformant/.

For more restrictions than the ones provided by one of the CC's and ODC's one can:

- write a custom license: one can create a custom license with specific terms and conditions that restrict the use of the data for purposes other than the specific data analysis conducted. This allows one to define the exact restrictions and permissions as per one's requirements. This may be challenging for a single researcher, but could be done by the legal team of an institution, for example a university, private company etc.
- Host data on a controlled/protected access data repository. Such repositories grant access to data under certain conditions, usually registration or application, but this is specified transparently. OSF provides a list of such acknowledged repositories at https://osf.io/tvyxz/wiki/8.%20Approved%20Protected%20Access%20Repositories/

For researchers in the European Union, additional notions of copyright and *sui generis* may apply, see https://europa.eu/youreurope/business/running-business/intellectual-property/database-protection/index_en.htm. In particular, copyright may be used to protect the structure of a database, but not its content. *Sui generis* may be invoked to protect content of a database, although that requires proving substantial investment (financial, material or and/or human) in either obtaining the verification or the presentation of the database content. The *sui generis* database right protects the content of the database, and may be used to prevent exctraction and/or reuse of the whole or a substantial part of the database's content for 15 years.