Towards AI Accountability Infrastructure: Gaps and Opportunities in AI Audit Tooling

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ABSTRACT

Audits are critical mechanisms for identifying the risks and limitations of deployed artificial intelligence (AI) systems. However, the effective execution of AI audits remains incredibly difficult. As a result, practitioners make use of various tools to support their efforts. Drawing on interviews with 35 AI audit practitioners and a landscape analysis of 390 tools, we map the current ecosystem of available AI audit tools. While there are many tools designed to assist practitioners with setting standards and evaluating AI systems, these tools often fell short of supporting the accountability goals of AI auditing in practice. We thus highlight areas for future tool development beyond evaluation—from harms discovery to advocacy—and outline challenges practitioners faced in their efforts to use AI audit tools. We conclude that resources are lacking to adequately support the full scope of needs for many AI audit practitioners and recommend that the field move beyond tools for just evaluation, towards more comprehensive infrastructure for AI accountability.

KEYWORDS

auditing, evaluation, audit tools, accountability

1 INTRODUCTION

A common thread weaving through most AI policy proposals—from the E.U. Digital Services Act to a municipal hiring bill passed in New York City [26]—is the now-familiar call for AI audits. Often defined as independent evaluations of the performance, fairness, or safety of deployed AI systems, AI audits have now been featured in several U.S. congressional bills [23, 59] and state efforts [66, 74], and the practice is regularly mentioned in AI governance proposals internationally [39].

Despite this increasing policy enthusiasm, the execution of effective *AI audits* remains practically difficult. The maturity of the audit ecosystem in the technology sector still lags far behind audit practices common in other industries, such as finance and health-care [80, 81]. A dearth of generalized AI audit guidance is remedied only partially by recent efforts from government advisory bodies like the U.K.'s Information Commissioner's Office (ICO) [49], the U.S. National Institute of Standards and Technology [99] and others [72]. In actuality, these evaluations remain inconsistent and unreliable [83], and the lack of access and visibility to many AI products

leaves external auditors without the information needed to make adequate, truly legitimate independent assessments [48].

In the face of these challenges, practitioners often rely on tools—software, frameworks, and other resources—to support their AI audit work. Past research in human-computer interaction (HCI) and social computing has developed and studied a host of fairness, explainability, and other toolkits that inform such evaluations [5, 9, 12, 17, 29, 30, 32, 35, 48, 51, 58, 65, 95, 111, 112], and governments across the world are developing similar tools for AI governance [52]. Studies of these evaluation toolkits are crucial for ensuring that AI systems are evaluated thoroughly and that stakeholders are included in the process. However, evaluation alone is not sufficient to hold AI builders and operators responsible and answerable for system behavior [44, 81]—auditors also need tools that support key components of accountability such as auditor independence, data access, peer review, standardization, and advocacy [24].

In this study, we survey the landscape of AI audit tooling to understand the challenges to accountability and potential opportunities for tool development and research. We taxonomized 390 audit tools and interviewed 35 audit practitioners employed at 24 different tech companies, startups, government agencies, non-profits, consulting firms, and academic institutions to explore the following questions:

- (1) RQ1: What AI audit tooling is available to support AI audit work?
- (2) RQ2: Which AI audit tools are actually used and how?
- (3) RQ3: What do AI audit practitioners actually need?

To investigate RQ1, we identified a landscape of audit tools that maps into seven key stages of tool-supported AI auditing—including both tools for evaluation and tools for other important aspects of auditing, such as harms discovery or advocacy. To investigate RQ2-3, we interviewed AI audit practitioners directly about their experience with AI audit tooling and which gaps they could identify.

We find that while there there are many tools to support audit work, particularly for evaluating AI systems and managing standards, these tools often fell short of helping auditors achieve accountability in practice. Some tools were empowering—but tools to help with tasks outside evaluation, such as discovering harms, communicating audit results, and advocating for subsequent changes, were much less common. Instead, the practitioners we interviewed often adapted existing tools or built their own from scratch to relieve the tedious or difficult tasks in their particular audit workflows.

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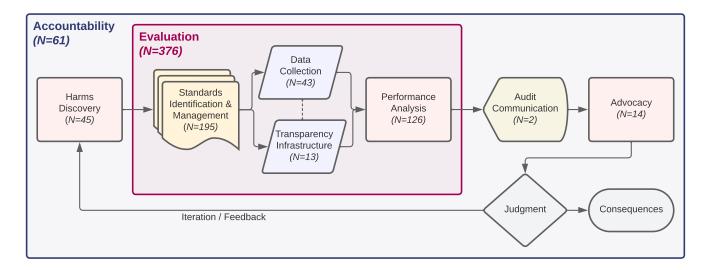


Figure 1: Stages of the tool-supported audit process surfaced in our survey of AI audit tooling. We taxonomize tools by the stage of the AI audit process in which they are meant to be used.

Auditors struggled to find tools, obtain high-quality, uncompromised data, apply consistent and holistic standards and methods, and ensure audit integrity—key challenges in ensuring that audits are effective and impactful.

Our results identify challenges in every stage of tool-supported AI auditing, but we also include suggestions for researchers, policymakers, and practitioners that may provide an alternative vision for tool development that supports accountability, inclusion, and independence. We conclude with a summary of broad lessons for the HCI community and other stakeholders that could help push the landscape of AI audit tools beyond evaluation and towards infrastructure for meaningful accountability.

2 RELATED WORK

AI audits involve the independent evaluation of the performance, risk and safety of deployed AI systems [76, 81]. These evaluations are required in order to make consequential judgements about the suitability of an AI product for widespread or context-specific use, and assess how well deployed systems match stakeholder claims and expectations. In this case we use the term artificial intelligence (AI) broadly, to refer to any AI-advertised product or model, including automated decision systems (ADS), algorithmic recommendation systems, large machine learning base models and more.

Past work on AI audit tools. Recent research in human-computer interaction (HCI), social computing, and cooperative design documents the experiences of practitioners evaluating AI and the challenges they face [17, 24, 32, 48, 58, 65]. For example, Holstein et al. [48] documents the practical and technical difficulties faced by internal auditors of ML systems trying to identify and improve fairness, while other studies have examined the organizational challenges and barriers these practitioners face [24, 65, 82, 86, 109]. Several HCI studies have since specifically examined the ways AI audit practitioners make use of various tools to address these issues [5, 30, 48, 58]. In this study, we extend these analyses to lay out a more

complete view on the utility of such tools, which we designate as AI audit tools: any software, services, frameworks, and other artifacts used to conduct audits of AI systems.

While some studies of AI audit tools focus on performance analysis [5] or user-driven grassroots auditing [29, 32], most HCI studies focus specifically on tools for assessing fairness. Lee and Singh [58], for example, compare six prominent open source fairness toolkits along various criteria related to practitioners' needs. Deng et al. [30] documented the ways practitioners learn about and use two prominent fairness toolkits, AI Fairness 360 and Fairlearn. And a survey of 152 audit practitioners, Costanza-Chock et al. [24] found that 62% of practitioners used existing tools like AI Fairness 360, Scikit Fairness, or Parity, though only 7% of respondents used a standardized framework for their overall audit protocol.

Accountable auditing. Our study aims to expand HCI research by looking beyond fairness toolkits to examine the broader array of AI audit tools available to practitioners. Evaluation represents only one phase in a broader process. In addition to evaluation, an effective audit both identifies harms and formulates effective strategies for either addressing them or for holding relevant stakeholders accountable for the audit result [24, 78, 80].

The practice of AI auditing, or algorithm auditing—a term first formally proposed by Sandvig et al. [84] to describe methods for detecting discrimination in online platforms—has expanded over the last decade [104]. Researchers have since used the term to encompass not just field studies for detecting discrimination with causal estimation[67] but also any kind of independent assessment of an automated or data-defined system [33, 80]. Early audit studies—of facial recognition systems and criminal risk assessment [6, 18], for example—by *external* journalists, academics, and civil advocates fueled advocacy that resulted in advocacy and, at times, even changes

¹We use the term "accountability" in the legal-political sense, meaning to face consequential judgement for a systems' behaviors and impacts [16, 31].

to the deployed systems [78, 88, 91, 96]. However, not all audits succeed in holding system builders and operators accountable [44, 108]. While these key studies define the practice of AI auditing and some of the components of accountability, no study yet examines the full range of tools used to support AI auditing and accountability. Most notably, Wong et al. [111] examine documentation from 27 toolkits for "AI Ethics", finding that these resources employ a narrow technical framing that fails to involve more diverse stakeholders or reckon with the non-technical dimensions of AI ethics work, Kaye and Dixon [52] survey and critique the tools currently used for AI governance by governments across the globe, and Berman et al. [11] call for more evaluations of the effectiveness of these tools. We build on these critical studies with a survey of the broader landscape of audit tooling, including some non-technical resources and several previously overlooked areas of tooling necessary for accountability.

Internal vs. external audits. More recently, corporations and policymakers have focused on what we refer to as internal AI audits² [36, 92]. These audits—afforded better access and cooperation than external audits—may enable accountability if designed properly [31, 80], but they may also result in false assurances ("audit washing") [44, 81], or foreclose on key remedies such as abolition or disgorgement [61, 94]. As a result, there is an equally important role for external AI audits, investigations conducted by civil society, journalists, lawyers, regulators, and other third-party actors. These external audits are typically voluntary research studies and investigations into the deployed AI systems. Past HCI work has not primarily focused on the experiences and challenges of those doing external audit work, and so we have few references for understanding their tooling and resource needs [7].

3 METHODOLOGY

To understand the tools available to audit practitioners, we collated a dataset of 390 tools used or intended for AI audit work and developed a taxonomy of the audit tool landscape based on our findings. To understand exactly which tools auditors use in their everyday work—and where those tools fall short—we also conducted 27 semi-structured interviews with 35 auditors across 24 organizations employing internal and external AI auditors.

3.1 Interview methodology

To explore the ways audit practitioners are using tools—and what challenges they face—we conducted 27 interviews with a total of 35 audit tool builders and practitioners, representing diverse backgrounds such as engineering, law, journalism, advocacy, policy, and academia in North America (N=22) and Europe (N=5) (Table 1). Participants for the interviews were recruited with convenience sampling and snowball sampling—we began by contacting practitioners in our professional networks who had conducted notable AI audit work and were active in AI audit communities. Occasionally, participants were referred us to by a colleague or professional contact at another organization. Our sample encompassed both *internal* and *external* auditors employed by for-profit tech companies,

AI startups, research & civil society non-profits, universities, and government agencies.

Interviews followed a semi-structured format and lasted 30-60 minutes. Our questions centered on the specific tools and methods practitioners built or employed and 2) common obstacles and unmet needs encountered in their development and use. (The full interview protocol is included in Appendix B.) Participants had the option to remain anonymous and skip questions at their discretion, though none skipped a question. Our protocol was approved by three university IRBs. To analyze the interview data, we transcribed each interview and annotated the transcripts with manual codes. Our coding approach followed an inductive methodology, allowing patterns and themes to emerge from the data [43, 110]. We employed a combination of descriptive coding, which captured the content of the interviews, and values coding, which captured the attitudes and beliefs expressed by participants. Through collaborative sessions and memo writing, we organized these codes and related quotes into key insights, presented in §4.

3.2 Tool Taxonomy

Initial search. To taxonomize the landscape of available audit tools, we first developed an initial list of tools and tool-building organizations by searching for tools mentioned in academic audit studies, news articles, government reports and frameworks, white papers from civil society organizations, law firm reports, case files, and existing lists of tools such as [46] (see Appendix A.1 for details). Our initial search was conducted in August 2022. We also included specific tools and sources that were mentioned in our interviews with practitioners. After we had collected an initial list of 148 tools, we developed an initial taxonomy by clustering tools into 21 initial categories based on their intended or actual uses in AI audit work.

Theoretical sampling. Next, we expanded our initial set of tools with two kinds of additional theoretical sampling. With targeted keyword searches on English Google and GitHub, we searched explicitly for additional tools in areas where we had fewer examples until theoretically fresh examples of tools ceased to arise.³ Our search queries were the category descriptors—either from our initial categories or from descriptors used by tools already collected alone or combined with terms like "audit tool" or "responsible AI" (see Appendix A.2). We also expanded our list of sources based on our initial taxonomy (e.g., for our initial "participatory" category, searching for tools mentioned in the Participatory Approaches to Machine Learning Workshop). We also followed links and references in our initial sample of tools to identify additional, similar tools (snowball sampling). Between August and October 2022, we added 181 tools with these methods, and we continued to update the database with 61 more examples through September 2023.

These searches surfaced new examples that forced us to expand and re-define our categories or create new ones. We iteratively revised our taxonomy twice more to accommodate new examples and to clarify or expand our categories, grouping clusters as more general themes appeared. Our final taxonomy groups tools into 30 main categories with 27 subcategories, sorted into a final set of 7 "stages" of the tool-assisted audit process (Fig. 1). The resulting

²Here, the auditors are still considered independent, as they are separate from the development process (i.e., product and engineering teams), even though they remain within the scrutinized organization.

 $^{^3}$ In this stage, we aimed for theoretical saturation, in the style of grounded theory [21].

Table 1: Participants' organizations and titles at the time of interview. Some titles are summarized for anonymity. Participants in the same interview are grouped in parentheses.

Employer	Roles of Interviewees	Participants
Large tech for-profit	Director of Policy Research, VP of Research, Data Science Mgr., Research Eng.,	P5, P8, P11, P14, P19, P27
	Researcher	
Tech startup	Co-Founder, CEO, Chief Scientist	P4, P12
Government agency	Tech Policy Principal/Mgr./Assoc./Advisor, Research Fellow	(P21, P28-35), P25
University	Assoc./Asst. Professor, Postdoc. Fellow, Data Scientist	P3, P10, P13, P17, P20
Research non-profit	Co-Founder, Director, Research Scientist	P9, P16, P18
Civil society non-profit	Director, Head of Analytics, Statistician, Researcher, Policy Fellow	P1, P2, P6, P22, P24
Non-profit news org.	Opinion Writer, Data Journalist	P7, P15
Law/consulting for-profit	Policy Director, Mgr., Consultant	(P23, P28), P27

taxonomy⁴ is grounded in the properties of the tools we found and shaped by our interviews with and our own experiences as AI audit practitioners.

3.3 Landscape analysis

To analyze the qualities of tools across our taxonomy,⁵ we also manually labeled each tool with several tags describing the tool's documentation and function: license (open-source or proprietary); organization type (for-profit, non-profit, government, or academic); intended audit target (automated decision system, online platforms, large pre-trained online platforms autonomous vehicles, and/or other); intended user (internal and/or external); and format (e.g. API, software product, code/data repository, white paper, and/or other). One author created the labels and at least one other author reviewed each label for agreement.

We also supplemented our dataset with data from Crunchbase [25], a platform for tracking funding, employment, revenue and other data for technology ventures, and Github [42], a platform for hosting and developing software. From Github, we scraped repository activity—primarily the number of forks, stars, and issues—for the 98 tools with Github repositories in our dataset. 187 of the 312 organizations in our dataset (accounting for 247 tools) have Crunchbase entries, which we manually identified using fuzzy matching and the Crunchbase search feature; 171 include estimated employee counts. Of the 129 entries that are not for universities or government agencies, 88 include revenue estimates. We also collected total venture funding (adjusted to U.S. dollars) for 47 firms out of the 110 firms that are still private (i.e., have not undertaken an initial public offering). Additionally, we used the Google Scholar API to annotate each academic reference of an identified tool with the most recent available citation count.

We analyzed the distribution of these supplemental variables across our taxonomy and include our findings in §4. Detailed results, including all figures summarizing all our quantiative analysis, can be found in Appendix C.

3.4 Reflections

We consider our own cultural and professional perspectives throughout the interviews and our analysis [21]. In particular, we view our position as both external to prominent AI developers and deployments, but still situated within the Western AI industry—our project was financially supported by a prominent U.S.-based foundation, all the authors are either graduate students or graduates of well-funded universities in the U.S. and Europe. Three have some experience studying or developing AI systems at U.S. tech companies. Because we drew our initial sources from our own fieldwork as audit practitioners and used English search engines for theoretical sampling, our dataset consists primarily of English language tools from from Western organizations, and our taxonomy reflects our own particular position⁶.

While analyzing our data and presenting the results, we considered how our positions might impose certain framings on the data or close off possible lines of inquiry. For example, we recognize that our analysis is primarily scoped to the U.S. and the E.U. and may not be representative of the global AI auditing landscape or appropriate for or informed by other contexts. We wrote this paper with the goal of promoting holistic accountability for algorithm-enabled harms. In particular, we struggled to avoid a techno-solutionist framing in our conclusions, given that our project focuses on toolkits that often fail to address non-technical dimensions of audit work [111]. We intentionally defined tools as resources more broadly and attempted to leave space for non-technical solutions in our analysis and discussion, and we hope that future work will expand and look outside of the mostly technical, Western solutions analyzed in our work.

4 RESULTS

Our survey of AI audit tools revealed a wide-ranging landscape of resources built by a variety of academic, for-profit, non-profit, and government organizations for a variety of purposes. A full

⁴Readers can view and contribute to a full interactive version of our taxonomy and dataset at tools.auditing-ai.com.

⁵All the code for our analysis and resulting plots—as well as instructions for obtaining supplemental data—can be accessed at github.com/ryansteed/oat-analysis.

⁶We also attempted to run translated queries in non-English search engines (e.g., Baidu) and to add regional keywords (e.g., African) to our searches, but we were unable to find any additional tools with initial tests of these methods. It thus seems likely that non-English, non-Western tools exist that our theoretical sampling was unable to identify.

Table 2: High-level description of the tool taxonomy categories (visit tools.auditing-ai.com for an interactive visualization).

Stage	Categories (Subcategories)	N	Purpose	Examples
Harms Discovery	Education / Awareness (community education, visioning), Incident Reporting (incident databases, intake forms, bug bounties, hotlines), Target Identification (algorithm visibility)	45	Help auditors identify and prioritize audit targets and harms to investigate.	ACLU Wa's Algorithm Equity Toolkit, AI Incident Database, Algorithm Tips
Standards Id. & Mgmt.	Goal Articulation (principle statements, standards formulation), Self-Assessment (checklists, grading), Documentation (single stage, continuous, licenses), Regulatory Awareness (discovery, monitoring), Methods Design, Participatory Standards-Setting	194	Help auditors identify and formulate principles and norms to guide their investigations.	AI-RFX Procurement Framework, Microsoft's AI Fairness Checklist, Model Cards [68], Queensland's Community Engagement Toolkit [77], Community Jury
Transparency Infrastruc- ture	Structured/API Access, Secure & Private Sharing (federated learning), Model/Data Exchange	13	Help auditors interact with and analyze proprietary information about the data or model with centralized infrastructure.	NIST's Face Recognition Vendor Test [71], Google AI Test Kitchen [107], Airbnb's Project Lighthouse [3]
Data Collection	Field Data Collection (scrap- ing, donation, interviews/surveys, compelled disclosure), Bot De- ployment, Simulation	43	Help auditors collect information about a model's interactions with its subjects.	Mozilla's YouTube Regrets [69], Tracking Exposed, Selenium, Meta's Web-Enabled Simulation [2]
Performance Analysis	Accuracy Evaluation (A/B test- ing, benchmarks, adversarial test- ing, monitoring), Explainability (models, training data), Fairness, Qualitative Analysis	126	Help auditors evaluate and explain model behavior through the calculation of performance metrics.	Weights & Biases, Meta's DynaBench, Foolbox, Fairlearn, IBM's AI Fair- ness 360, Hugging Face's ROOTS [75], Google PAIR's Language Interpretabil- ity Tool
Advocacy	Resistance, Community Spaces, Legal Search, Organizing	14	Help organize community action and other accountability measures in response to discovered harms.	Gigbox, Para, Adnauseam, Benefits Tech Advocacy Hub
Audit Com- munication	Dataset Visualization	2	Help auditors communicate the results of an audit to a broader audience.	Google PAIR's FACETS

interactive version of our dataset can be found at tools.auditingai.com, and further details about our analysis can be found at github.com/ryansteed/oat-analysis.

We identified seven main stages of tool-assisted auditing, depicted in Figure 1 and summarized in Table 2. Our survey surfaced many tools similar to those traditionally studied and developed in academic work—such as tools for Performance Analysis (particularly fairness evaluation) and Standards Identification & Management (such as principle statements or checklists). However, we also surfaced tools designed to support with other less-studied elements of AI auditing—such as Harms Discovery, Data Collection, and Transparency Infrastructure. For example, a few tools are uniquely focused on ensuring that audits result in accountability through facilitating Audit Communication and Advocacy. In part because our survey included only publicly listed tools, many of these tools (77.9%) were freely available and open-source, though we do include many proprietary or internal tools that are publicly advertised or publicly listed.

Our interviews with practitioners told a more complicated story. While many tools exist to aid in AI auditing, practitioners found the current array of resources inadequate in many ways. In particular, though many tools existed to aid in the evaluation of AI systems, current tooling did not always contribute to the ultimate aim of accountability. Despite the numerous tools available, practitioners still struggled to involve affected stakeholders, apply consistent and holistic standards and methods, access high-quality data about system behavior, ensure audit integrity, and collaborate across disciplines. And despite theoretical sampling, our survey of AI audit tools (N = 390) revealed mostly tools for evaluation—particularly tools for Standards Identification & Management (N = 184) and Performance Analysis (N = 116). Tools for stages of the audit process crucial to accountability—Audit Communication (N = 2), Harms Discovery (N = 43), Advocacy (N = 13), and model/data transparency (N = 12)—are much less common. Figure 2 depicts the number of tools in each stage and category of our taxonomy.

In this section, we detail the main tool-related challenges practitioners faced related to each stage in tool-assisted AI auditing,

and discuss the implications of our findings for the practice and study of AI auditing. Note that we did not explicitly ask interview participants about the tool-assisted AI audit stages, but after interviews, categorize their interview responses within the format of our existing AI audit tool taxonomy, arranged by the seven stages (Fig. 1).

4.1 Harms Discovery

A central task for AI auditing is identifying AI systems that should be subject to scrutiny and identifying their potential harms. This task can be especially difficult for external auditors who may not know where AI systems are in use or what their impacts might be. Tools for Harms Discovery (N=43) help identify and select targets for audits and support the identification, characterization, and prioritization of potential harms to investigate. This category includes tools for Education & Awareness (to engage affected stakeholders in articulating harms), Incident Reporting (to gather reports of algorithmic harms from users and the public, e.g., through bug bounties), and Target Identification (e.g., the Algorithm Tips database contains a list of deployed systems in the U.S. that could be investigated).

Compared to other stages of our taxonomy (Fig. 2), nonprofits contributed especially to creating and maintaining tools for Harms Discovery (e.g., databases for documenting AI incidents [20]) and Data Collection (e.g., scraping or data donation [32]).

Facilitating more participatory audits. Auditors recognized that to comprehensively identify AI-related harm, they must engage with those directly impacted by the AI deployments—though they did not necessarily have the tools to do so. Many participants recognized the importance of ongoing user engagement, collaborative feedback, and a focus on community representation in performing thorough and representative audits. Participation in harms discovery had two main benefits for auditors. First, participation helps auditors anticipate a broader range of possible harms: "Different types of biases are going to manifest, and accordingly it requires ... diverse groups from society, to understand their experiences and expectations in these settings and how they can be impacted" (P20). Second, participation helped make auditing more "context-dependent" and inclusive by providing thorough understanding of how an AI system intersects with impacted groups. Participation could also help instill confidence in the audit process among these groups and foster engagement with subsequent accountability efforts. Our tool survey did surface quite a few tools for participatory incident reportingsuch as the bug bounty platform HackerOne, which Twitter used to crowd audit its image cropping algorithm [102], or the AI Incident Database, a collection of reports of AI harms. However, fewer tools were designed specifically for identifying and collaborating with affected users, such as the American Civil Liberties Union (ACLU) of Washington's Algorithmic Equity Toolkit [8].

Avoiding participation washing. However, participants also recognized the challenge of designing methodologies and tools without exploitation, tokenization, or other forms of "participation washing" [93], highlighting the need for fair compensation and participatory algorithmic development, in addition to participatory auditing. One participant, for example, emphasized the importance of "an iterative process of doing longer-term, ongoing auditing or

observation of algorithmic behavior, and then using that to feed into tweaks, or changes, or even big shifts in where and how [audit] outcomes are used" (P17).

Implications. Limited access to information about AI systems poses a fundamental barrier to conducting comprehensive audits. Without a clear understanding of which AI systems require auditing, there is a risk of overlooking critical systems that have significant societal implications. While we did find multiple popular databases for recording and collating incidents of harm (such as the AI Incident Database), these databases mostly only record harms after they have already occurred, often rely on second-hand reports, and may not delve deeply into harms or impacts [101].

Several participants proposed mandating that corporations disclose AI systems, including information about model versions, anticipated use cases, expected users, and past audit results. Policy-makers may also explore mechanisms for centralized, proactive documentation and mandatory, standardized incident reporting for both private firms and government agencies [101]—and ensure that current federal AI transparency requirements are actually implemented [57]. Additionally, enabling mechanisms such as Freedom of Information Act (FOIA) requests could facilitate access to information held by public institutions or government agencies regarding the use of AI systems in decision-making processes. Future work could also develop and study systems for fair, inclusive community participation in auditing, the path most often suggested by practitioners for identifying systems and their harms.

4.2 Standards Identification & Management

Auditors also used tools to formulate the principles and norms to guide their investigations. This stage, Standards Identification & Management (N=184), includes tools for Goal Articulation (e.g., broad principles statements), Self-Assessment (more specific procedural assessment tools, such as Microsoft's AI Fairness Checklist [65]), Documentation (e.g., Model Cards [68]), Regulatory Awareness (tools, often paid services, for discovering and monitoring relevant regulations), Methods Design (standards for audit methodology), and Participatory Standard-Setting (methods for developing standards in collaboration with affected groups, such as Microsoft's Community Jury [19]).

Standards Identification & Management comprised the largest collection of tools in our database. In particular, this stage includes the "principle statements" and similar documents (N=75) that many organizations—particularly nonprofits and government agencies (77.2% not-for-profit)—have created to articulate their broad goals for AI systems and AI procurement. Checklists and other forms of procedural self-assessment, intended for developers and researchers, were also common (N=41), while methods for participatory standard-setting (N=6) were comparatively rare. We also noted the format of each tool we found, annotating when the tool included software (either a software product or an API), a code repository, a data repository, a white paper/report, or a guidebook (Fig. C.6). While every other category has more tools involving code or data than without, only 8% of Standards Identification tools included code or data.

Need for more standardized, context-specific, and holistic evaluation frameworks. Despite the large number of standards

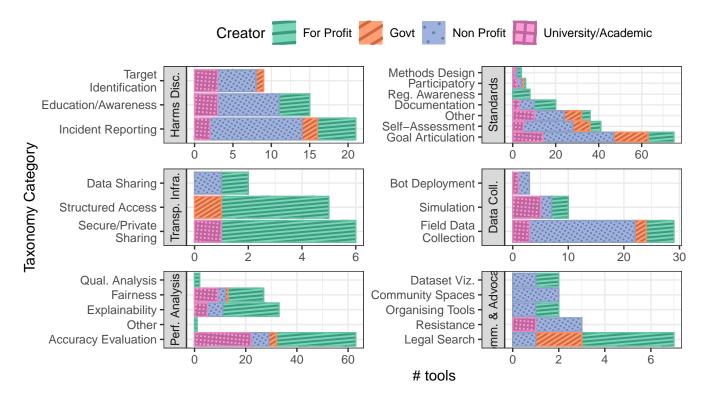


Figure 2: Number of tools in each category of our taxonomy, grouped by type of organization.

and evaluation frameworks surfaced in our landscape analysis, auditors still felt that evaluation frameworks needed refinement. Auditors emphasized the importance of standardized evaluation frameworks that provide clarity and consistency: "I think standardization is a big [concern]..." (P23) Many expressed a vision to streamline the auditing process by offering predefined structures and templates for assessment, which are essential for conducting audits effectively and facilitating communication.

Auditors wished that standards were both more context-specific and more holistic. Standards identification tools were particularly general in their applications, compared to other categories of tools—principle statements, checklists, and similar resources were usually intended for multiple kinds of audit targets (Fig. C.5). Some participants found these tools too vague:

I think what I've seen is that companies and institutions... really, really struggle to understand, 'What should we even do when it comes to auditing or evaluating the use of machine learning in our organizations?' And while a template or a checklist is not the right answer, a lot of them don't even know where to start... And so, (it helps) when you have a tool that...has some built in frameworks, and maybe there's some big ones in there, so like maybe the NIST framework [99] is in there. (P8)

Despite generality in application, though, some participants thought that assessments templates and checklists were focused too narrowly on fairness assessment. One civil society auditor said, "I would love some guidance on audits generally and tools that describe the non-fairness components of an audit..." (P6) Another described collating multiple standards themselves, wishing for a resource that covered criteria such as explainability, privacy, and transparency: "Currently we have to.. find open source tools and put them together ourselves, and you need to have expertise to know what to look for" (P21).

Need for regulatory guidance. Despite some participants' desire for standardized frameworks like NIST's [99], multiple participants commented on the difficulty of harmonizing current or expected regulatory guidance with practical implementation. One civil society auditor said:

There's two different points...: What are we evaluating for? And the question of, even when we have some kind of legal or other benchmark in mind, what are the metrics, and what are the benchmarks and other ways in which to evaluate, technical and otherwise, which also remain quite unclear? We're seeing the ready adoption of audit language into policies, so that just kind of makes us nervous... What are we auditing for? (P2)

Several emphasized the necessity of regulatory entities being more forthcoming in defining best practices. Some sought the guidance of the regulatory bodies in the domains they operate to establish their own frameworks but often struggle to connect or translate industry expectations into meaningful standards for evaluation. Multiple participants felt there was a "culture or communications gap between

the legal and compliance people on one side and the engineers on the other" (P12). As a result, some hoped for more collaborative approaches instead of command-and-control prescriptions:

Half the time we reach out, and there's just no one to contact... and it's just a black hole... [Another way forward is] not regulation, but it's more like insurance liability and these sort of semi-regulatory structures that force you to engage... (P13)

Implications. Standards for evaluating AI systems must be simultaneously holistic, context-specific, and compatible with practice. Some of the tools we found made advances in one or more of these dimension, but few accomplished all three. Microsoft's AI Fairness checklist, for example, was co-designed with practitioners [65] in an effort to be more compatible with practical challenges, but many of the other standards frameworks we found did not obviously consult practitioners—and even fewer involved affected stakeholders. Likewise, while NIST's AI Risk Management Framework includes safety, security, reliability, transparency, explainability, and privacy, in addition to fairness, its guidance for specific evaluation techniques remains fairly broad [99].

Future work could further explore how resources and tools (such as templates and documentation workflows) can generally make standards management easier and more relevant for practitioners while also involving affected stakeholders to ensure that standards remain inclusive and impactful. Research could continue to explore how regulatory standards could be translated into concrete metrics or other expectations for industry [105], even as policymakers aim to provide more effective and feasible guidance [45]. One participant at a large tech company, for example, preferred a "must, could, should" (P14) structure for regulatory guidance: a non-technical legal minimum ("must") accompanied by more precise, technically feasible paths to compliance ("should") and a set of ideal best practices for high performers and innovators ("could"). Research on the organizational practice of responsible AI [47, 109] could help improve collaboration between standards-setting and practice.

4.3 Data Collection & Transparency Infrastructure

Gathering empirical evidence is a key step in AI auditing, but often posed a significant challenge—especially to independent auditors. When model operators were unwilling or unable to release relevant documentation and other evidence, auditors turned to two main classes of tools. First, tools for Transparency Infrastructure (N=12) are interfaces and databases hosted by model operators that allow controlled access to relevant data. This category includes tools for Structured or Application Programming Interface (API) Access (tools that allow auditors to interact with models and live systems in controlled ways, such as Google's AI Test Kitchen [107]), tools for Data Sharing (platforms or trusts for hosting models and related data, such as the Gig Economy Data Hub [41]), and tools for Secure & Private sharing (tools that help mitigate security and privacy concerns with sharing data, such as Airbnb's Project Lighthouse [3]).

More commonly, though, tools for Data Collection (N=42), helped auditors gather information *outside* these controlled interfaces. These tools help auditors gather data about model behavior,

including relevant information not routinely collected by model operators. This category includes tools for Field Data Collection, which collect data from real systems and real users—including tools for Data Donation (such as Mozilla's YouTube Regrets project [69]), Data Scraping (e.g., Tracking Exposed [1]), Interviews/Surveys, and Compelled Transparency (e.g. tools such as MuckRock that facilitate FOIA requests). We also found tools for Simulation (e.g. Meta's Web Enabled Simulation platform for simulating interactions on Facebook [2]) and Bot Deployment (tools used for sock puppet auditing [7], such as Selenium or Appium), both used to test systems in artificial or semi-artificial interactions.

Need for uncompromised data access. These tools have been used to help overcome one of the challenges most frequently mentioned by our participants: the difficulty of accessing data and other vital information required to conduct meaningful audits. While there are a few existing tools that provide external auditors with controlled access to models and data-especially for online platforms (Fig. C.5)—they require voluntary investment by model operators. One participant noted that key APIs used for auditing are becoming more costly and undependable: "There's a direct impact on shutting off the access to information that affects people doing audits... we saw that with Reddit charging for their API and shutting down... Twitter charging astronomical, now, amounts for their API. It's because everybody is scraping public Reddit and public Twitter to train large [AI] models..." (P24). They wished for "access to platform data, or like doing like a context under which people can do controlled experiments, using data that is provided by platforms directly" (P24). Another civil society auditor said, "I wish I had something to force people to give me their data... Part of the problem of auditing in general is that the only people who get let in are usually the people who are willing to say nice things about whatever the technology is being audited" (P6).

Auditors also said that corporate control over APIs created a lack of trust among investigators. Indeed, the tools for Transparency Infrastructure we found were disproportionately built by large, for-profit tool developers (75.0% built by for-profits), compared to tools for Data Collection (19.0% built by for-profits), which came more often from non-profits, government agencies and academics (Fig. C.7). In practice, participants reported that key details, such as data sampling methods, data provenance, model versioning, metrics, and design justifications, were often omitted or only partially disclosed.

Currently, the vetting process for API use often requires the auditor to disclose their intent for the evaluation in advance, which may compromise the integrity of the study. "I'm very much concerned that what's going to happen is.. [platforms have] given all this access, and there will actually be... more of a cover up than there is now... They have so much power in this conversation to just share whatever information they want" (P7). Instead, one participant's ideal was an "inspectability API" (P7), a required, standardized interface to allow researchers to interact with online platforms, including the ability to test different profiles, geographies, and other variables needed to evaluate disparate treatment, misinformation, and other algorithmic harms. Similarly, an auditor at a startup wished for centralized data archive available to the public:

If I really had to paint my perfect vision, it would be an independent database archive, or whatever, of all the relevant data. And then... different parts of society can tap into it... I think what you want is a lot of different innovative organizations and people and builders taking this data and building useful things with it, rather than a single one. (P12)

Challenges with independent data collection. Rather than rely on the model operator to provide access, auditors—especially external auditors—often turned to tools for Data Collection to obtain evidence themselves, sometimes developing and sharing their own tools and processes. Unlike tools for Transparency Infrastructure, which were mostly proprietary (25.0% open source), tools for Data Collection we found were much more likely to be available under an open source license (73.8% open source; see Figure 3). Tools for Data Collection also included the most popular Github repositories in our survey (Table 4)—for example, auditors used Selenium [87], a popular collection of open source tools for browser automation, to simulate user profiles while scraping data (known as a "sock puppet" audit [7]).

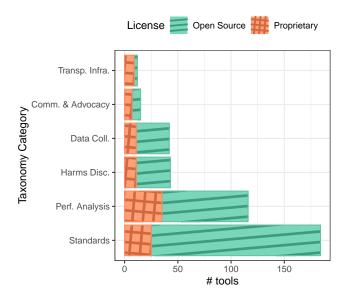
While this approach gave auditors more freedom, it could also take more effort. Some of the tools we found—such as the Markup's Citizen Browser [100], a data donation platform—were built from scratch to collect specific kinds of data for auditing. Existing tools for data scraping were helpful but often required extensive adaptation.

We almost always have to build custom scrapers to collect data... There's some templates right out there for these scrapers, and then you usually have to customize them. And then there's a huge amount of like work to keep them alive... They break all the time with all these edge cases. And so they're really a pain. I don't really know that there's a way to solve that. (P7)

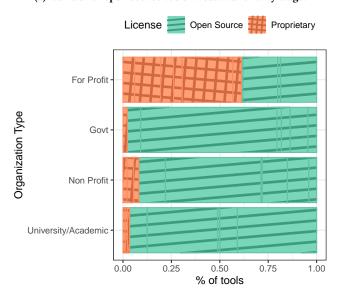
Despite these difficulties, external auditors—particularly the journalists in our sample—still saw advantages in independent data collection. One journalist noted:

There's a lot of requests for inside access, as if that's the only way to do this type of thing, but in reality inside access can actually be a trap... your view inside the room is actually really limited. And so I have come to believe... that actually doing analysis from the outside can often be way more revealing... I usually never have insight into the algorithm itself, but I can do analysis on the outputs. And to me, that's the right place for a journalist to operate, because the outputs are the real-life impact. (P7)

Challenges with understanding and processing data. Even when they had access to the data they wanted, auditors also struggled with the basic challenges involved with managing and analyzing data. Participants noted that this stage of auditing often necessitates more manual labor than any other. A government auditor said, "90% of the work is figuring out what different tables are, and what different columns are, and working out whether it makes sense to join certain things. And then figuring out some meaningful metrics that we can draw from that data..." (P25). In addition to typical data science tasks involved with processing large datasets, participants



(a) Number of open source tools in each taxonomy stage.



(b) Percentage of open source tools by organization type.

Figure 3: Tool licensing by taxonomy stage (left) and by organization type (right).

also reported spending lots of time reviewing documentation and requesting additional information about audit targets.

Our survey did not surface any tools designed to assist with data management or data processing for AI auditing, nor did the audit reports we read or our participants mention any specific tools used for this purpose. However, multiple participants wished for tools to help with these tasks. One auditor expressed that infrastructure may be most useful for more time-consuming steps in the auditing process, such as data collection and cleaning, stating, "most of the

value of data infrastructure is literally cleaning data" (P3). One auditor hoped for innovation in data quality management: "There are custom scrapers, a lot of human data quality work, and one thing that I have really wanted to do and never been able to do is try to figure out ways to get that data quality work done in more interesting ways" (P7). Participants repeatedly urged the development of standardized tooling and infrastructure to facilitate data collection and cleaning, in order to streamline the auditing process.

Data quality concerns intersected with concerns about audit integrity. "I think we often have to worry about... [whether] what we see is what we think it is" (P15). With recent datasets scaling up to staggering sizes, this concern has become more acute and auditors commented on how manual analysis was no longer feasible: "Given how much data we are able to process, we need new methods to analyze the data curation process and what kind of problems data comes with. And then we need tools to detect what is synthetic, what is real" (P20).

Risk of retaliation. Some external auditors also worried that external data collection tools—particularly tools for data scraping or data donation—may violate terms of service set by platforms and result in legal liability or retaliation. In 2021, for example, Facebook disabled the accounts of a group of researchers auditing its advertising algorithm using a data donation tool called Ad Observer [34]. Facebook initially insinuated that disabling the researchers' accounts was required by an Federal Trade Commission (FTC) consent decree related to privacy, backtracking only after the FTC called the statement inaccurate [60].

In particular, auditors expressed concern about the broad and ambiguous language in existing laws and regulations-particularly the Computer Fraud and Abuse Act (CFAA), but also the General Data Protection Regulation (GDPR) and other privacy laws-that could expose them to legal risk. Under the CFAA, for example, an auditor who violates a platforms' terms of service may be held criminally liable. As it stands, the CFAA does not include a list of clear exemptions for auditors doing research for the public interest. And it is difficult for auditors to determine what methods—such as public data scraping or even data donation—may be deemed "unauthorized" and criminal under the CFAA unless the audited organization grants explicit authorization. In Sandvig v. Barr (2019) the ACLU sued to allow researchers to set up false accounts (sock puppets) to audit computer algorithms [85], arguing that this provision exerts a chilling effect on auditing research [4]. Indeed, Facebook used exactly this term of art-"unauthorized"-several times in its explanation for shutting the Ad Observer project accounts [22]. As one civil society auditor said, "Even if the legal risks have not been acted upon as much, there's cases everyone points to in terms of attacks against researchers. It's a matter of time before it ramps up. As soon as our work becomes threatening enough, that's when it all really starts" (P24).

As a result, auditors engaged in external data collection had to take great steps to guard against legal liability and retaliation. One journalist said, "[The CFAA] is an incredible legal hangover for the type of work I do... how much lawyering I need to even get one tool off the ground is insane" (P7). Auditors also expressed hesitation about reforms that give platforms more control over what data is released. The same journalist continued,

Exemption from [the CFAA] would honestly be more helpful than these platform access roles that the E.U. is claiming that they're going to offer [e.g., in the Digital Services Act], which I am very skeptical about... I just feel like the history of these things is that when platforms have been required to provide API access, they have somehow always made it impossible to do real accountability. (P7)

Even auditors hired internally may assume some degree of personal risk. One civil society auditor noted, for example:

Another really frequent sort of question that I get [from organizations]... is what is my liability around doing this kind of [audit work]? And frankly, to your earlier question about building in-house versus contracting, that's another main [reason to contract]... it's like, okay, we're still going to do this thing, but just sort of outsource it. So I think that just remains like a really open question that people doing this kind of work are carrying a lot of legal risk in doing so. (P24)

Implications. Given that data access and integrity is critical for auditing and for accountability, future research could explore tools and processes for not only facilitating access to data—especially independently, through scraping or simulation—but also for ensuring data quality and integrity. Participants specifically wished for more tooling for data donation and user-driven auditing—a nascent area of research in human-computer interaction [29, 32, 56]. Auditors also faced challenges common to data work in general, and research on practices surrounding data quality and data integrity may be applied specifically to discrimination testing and AI auditing methods.

Other challenges were more particular to auditing work. Future work could explore, for example how auditors request information and interact with model operators. Transparency Infrastructure in particular is a nascent area of tooling that may become more common to auditing as AI regulation develops and as barriers to external data collection mount; independent research may help guide these tools into more trustworthy mechanisms for disclosure, even as policymakers can ensure platform-controlled tools are not the only avenue for scrutiny.

4.4 Performance Analysis

Tools for Performance Analysis (N=116) are designed to help auditors evaluate and explain model behavior, usually through the calculation of quantiative metrics related to accuracy/safety (N=63), explainability (N=33), or fairness (N=27). This category includes tools for Fairness Evaluation and Accuracy Evaluation (including tools for A/B testing, benchmarking, and model monitoring, such as Meta's Dynabench or the Linux Foundation's Adversarial Robustness Toolbox) as well as Explainability (tools for explaining the behavior of a model, such as IBM's AI Explainability 360, or for exploring training data, such as Hugging Face's ROOTS search tool [75]) and some tools specifically for Qualitative Analysis.

Despite the many tools developed for these purposes—the most popular AI-specific Github repositories (e.g., OpenAI Evals [73]) in our survey were for Performance Analysis (Table 4)—practitioners

expressed a need for more robust, well-vetted tools and methodologies.

Concerns about methodological integrity. Practitioners had concerns about the validity, reproducibility, transparency, and trustworthiness of the methods used in popular Performance Analysis tools. One auditor at a tech startup said, "I'm still not convinced of the validity, even, of some of those methods" (P4) used in "auditing tools for monitoring and validation. For example, the most popular Performance Analysis tool we found on Github was SHAP (SHapley Additive exPlanations), a game-theoretic method for measuring feature importance in a model [64] (see Table 4). But as Kumar et al. [55] argue, Shapley values are prone to misuse and may be unsuitable for procedural justice, recourse, or normative evaluation. Interpretability and explainability methods promoted by popular tools vary widely in their goals [63] and may encourage false confidence in their users [40], like many "snake oil" AI products [50, 70, 97]—yet explainability tools such as SHAP are often suggested in official regulatory guidance [52].

Some participants put methodological deficiencies down to differences in the rigor employed by the various disciplines involved with auditing. An auditor in civil society said, "The bar of the kind of threshold of... validity of findings and novelty of findings is much higher in academia than it is for civil society" (P24). Other concerns stemmed from observations about the lack of maintenance of existing tools, the effectiveness of automated monitoring processes, and the efficacy of simulated data for representing real users instead of functioning as "an academic exercise" (P4). As another put it, "you can perturb all the different inputs you want. But they might not be realistic combinations of features for people who are actually using the system" (P25).

Need for inspectable, reproducible methods. To allay methodological concerns, several participants emphasized the importance of open-sourcing data and tools for others in the community to inspect. Some of our participants had reproducibility in mind when designing evaluation procedures in industry: "You want to iterate... but you know that also makes the results less reproducible. And are you being deceptive then, if you [refer in published evaluations] to a model that's different from the one that people analyze?" (P5) However, in our tool survey, Performance Analysis tools were disproportionately proprietary (30.1%), especially tools for Explainability (42.4%), compared to other tools (22.1% overall; Fig. C.4).

Need for more expansive evaluations. Similar to Standards Identification & Management, our participants wished for tools to help evaluate a broader spectrum of criteria beyond explainability and fairness. Performance Analysis tools—the most popular of which are built by disproportionately disproportionately large (> 10,000 employees), for-profit firms (Figures C.7)—often focused on a narrow set of technical fairness definitions and explainability methods popularized in academic literature. The tools we surveyed in this category often overlooked entire other areas of concern, including the basic functionality of the model [79] as well as other methods of evaluation. For example, tools specifically devoted to qualitative—as opposed to quantitative—analysis were much harder to find (N=2) and rarely mentioned by our participants.

Implications. While there are multiple studies on the use of tools for fairness evaluation [30, 48, 58] and explainability [12, 51, 53, 62, 95, 106], fewer studies examine how practitioners evaluate

other criteria such as basic functionality [79], safety, privacy, or recourse, just as fewer tools exist for this purpose. Future work should develop and investigate tools for a broader range of evaluation criteria. Also, although our study surfaced many performance analysis tools, practitioners expressed concerns about methodological integrity. Future work should explore practitioners' standards for audit tooling [52], and policymakers may develop standards that require academic peer review or vetting by regulatory bodies for audit tooling.

Moreover, research must examine further how tools may contribute to "audit washing," the use of auditing procedures to legitimize unethical practices [76]. A tool for accuracy evaluation, for example, may be used to analyze the accuracy of dubious technology for predicting "criminality" or "trustworthiness" without questioning underlying ethical issues with these applications [97]. In general, tools may claim to provide auditing capabilities—using terms such as fairness, safety, or explainability—while failing to conduct meaningful evaluations. Wong et al. [111], for example, show that AI ethics toolkits frame ethics work as primarily technical work for individual practitioners while failing to contend with power dynamics and institutional barriers to accountability.

4.5 Audit Communication & Advocacy

Some of the most crucial work of an AI audit comes after empirical evaluation is complete. We found two emerging sets of tools that begin to address this important stage of AI auditing: tools for Audit Communication, to effectively translate audit results to a broader audience, and tools for Advocacy, for reporting and campaigning for consequential outcomes in response to audit results. Tools to facilitate Audit Communication were rare in our dataset (N = 2), all tools for Dataset Visualization (for communicating results in a more accessible way; Google's FACETS [37], for example). Tools for Advocacy were more common (N = 13) but still fewer than other stages of our taxonomy, including Community Spaces (e.g., the Benefits Tech Advocacy Hub [10], which facilitates collaboration and shared resources between advocates who fight algorithm-based cuts to public benefits), tools for Organizing (e.g., the Algorithmic Ecology framework [98], a tool for mapping the non-technical dimensions of algorithmic impact), tools for Legal Search (e.g., the generic case database Westlaw can be used to identify relevant precedent for legal redress), and tools for Resistance (e.g., the gig work app Para, which helps drivers avoid bad algorithmic offers).

These tools were also mentioned less often in our interviews, compared to preceding stages of our taxonomy. Still, auditors were concerned with following through on their evaluation work. As one put it, "in the business of designing audits, it should be as important to design the consequences and penalties that accompany these audits" (P2). Auditors identified many barriers unrelated to tooling that could hinder the impact of audit results, particularly lack of funding. For the auditors we spoke to, tooling in this stage of auditing was mostly aspirational.

Tools and resources for community building. Auditors especially wished for resources that would bring together the diverse, interdisciplinary groups involved in auditing, similar to the few tools for Community Spaces we found in our tool survey. Auditors hoped greater communication could help unite the profession

around policy developments, shared language, standards, and goals that could improve the impact of their work. As one auditor put it, "We have to have people in the accountability business" (P7). Another asked, "How do we bring these interdisciplinary communities together so that we can use tools together?" (P20)

Participants also emphasized the importance of establishing guidance and facilitating education about auditing tools. One auditor at a tech startup said, "[NIST] has like AI guidelines that come out, and we work with them... we send in comments, we give talks, all that kind of stuff. I think that's an important part of the auditing community" (P4). Another described a workshop attended by civil society, academics, and consulting firms to help prepare for legislation in the European Union (P23).

Implications. Communicating audit findings, lessons, and insights learned can help build trust and validate audit findings, recommendations, and subsequent interventions. Published audit reports expand the forum holding model operators accountable, allowing policymakers, journalists, and other public stakeholders to engage with and analyze the outcomes without performing evaluations themselves. Embracing public evaluation results also helps to foster and expedite a culture of continuous learning, enabling audit practitioners to learn from each other's experiences, and critiques.

Despite these benefits, tooling to support these stages in our taxonomy was rare. While we found some domain-specific spaces where auditors can interact—the Benefits Tech Advocacy Hub [10], for example—we did not find any audit report registries or other platforms for hosting audit results and facilitating communication between auditors, journalists, and activists. Following calls for toolkits to embrace the non-technical dimensions of AI ethics work [111], future design work and research could explore these emergent categories of tooling.

Future audit work should also consider publishing concrete recommendations or demands to facilitate public pressure and accountability, which prior work shows is incredibly impactful in determining the effectiveness of audit target responses [78]. Demands could include calls for recalls, product updates, or adjustments to communication in marketing materials or terms of service. Academic research could explore in more detail the specific mechanisms of audit communication that are most likely to result in meaningful change, either through voluntary self-correction or through the influence of a regulator or other authority.

5 OVERALL OBSERVATIONS & DISCUSSION

In this section, we discuss potential paths forward to address the concerns and challenges raised by the current AI audit tool ecosystem. We specifically discuss the important takeaways for the HCI community—which has historically played a key role in the design and development of *AI audit tools* [48, 58, 84, 111]—and broader lessons for other stakeholders, including policymakers, audit practitioners, and funders.

5.1 Moving beyond evaluation, towards accountability

In interviews, accountability was mentioned repeatedly as a major priority for many AI auditors, but is also seemingly one of the most difficult goals to achieve. This aligns with a past survey of AI

audit practitioners [24], in which over 65% felt that "accountability" (defined as a "commitment from auditee to address problems covered by audit within set time") was an unmet need in their AI auditing work. However, this translation of AI audit results towards accountability outcomes has been under-prioritized for some time. When it comes to the work on AI audit tooling, our tool survey suggests that the focus of audit tool developers has narrowed in on resources for only a subset of the process outlined in Figure 1-we identified six times as many tools in the evaluation stages of our generalized AI audit process as we did tools for harms discovery, audit communication, or advocacy. And understandably so-these are the stages of the audit process that participants expressed as simultaneously being the least resourced and the least understood, requiring contextual awareness and typically under-studied participatory and community engagement methods (see §4.1, §4.5). Here, we identify several key ways HCI researchers and other stakeholders can help expand AI audit tooling beyond evaluation and towards accountability, particularly by studying and developing tools to support other stages of auditing other than evaluation, by continuing to develop tools that facilitate stakeholder participation, and by encouraging and protecting open source tool development.

5.1.1 Implications for HCI.

- Studying and developing tools for harms discovery, audit communication, and advocacy. Most research on AI audit tools focuses on the toolkits used to evaluate AI systems, particularly with respect to fairness and explainability [9, 12, 48, 51, 58, 65, 95, 112]. This research is important, but future work should also explore other kinds of tools that could help AI auditors produce effective audit reports. Our tool survey identifies several categories of tools-particularly tools for Incident Reporting, Education/Awareness, Target Identification, Audit Communication, Resistance, Organizing, and Community Spaces-that are also worthy subjects of research. Feffer et al. [38], for example, explore how the AI Incident Database can be used as an educational tool in the classroom. Future research should also explore some of the other challenges practitioners raised, such as toolkits for evaluating basic functionality or privacy, in addition to fairness and explainability, or the process of translating regulatory requirements into specific evaluation criteria.
- Developing participatory methods for audit work. Participatory processes can be leveraged throughout the AI audit process-when drafting AI principles and conduct standards, when collecting data for AI audits, when defining metrics for performance analysis, and more. Community participation provides the benefit of revealing potential harms, test cases, and mitigation strategies that may be overlooked by auditors and other stakeholders. Directly engaging the community also fosters widespread awareness and efforts towards mobilization and accountability, therefore defining and strengthening what actions constitute meaningful and accountable organizational expectations. Our external audit participants, in particular, embraced collaborative and participatory approaches that involve outside communities in the audit process. Given the broader calls for a participatory turn in AI development [13, 27, 54], it is no surprise that this

is an increasing focus for AI audit practitioners and audit tool developers as well. Recent HCI work on user auditing [29], such as the "WeAudit" tool [32], exemplifies this shift and highlights the upcoming challenge of designing for a more participatory AI audit process [28, 89, 90].

5.1.2 Broader Implications.

- Open sourcing AI audit tools. Some participants were concerned about the efficacy of many tools for Performance Analysis-particularly tools whose methods were not made public. Unlike standards and identification tools, which were mainly open source (Fig. 3), tools for performance analysis were more likely to be proprietary. Making AI audit tools publicly available enables external collaboration as well as third-party validation of the tools' processes and findings. Open source tools enable outside organizations, researchers, and other stakeholders to access, assess, and benefit from an organization's internal tools, leading to a collective understanding of current practices and the improvement of otherwise inaccessible methods. By inviting external scrutiny, AI audit tool developers demonstrate a commitment to transparency and accessibility, fostering trust and participation among themselves, AI auditors and other stakeholders. The benefit of knowledge-sharing that occurs when especially internal tools are made available not only leads to tool improvement but enables the replications required to validate the audit results derived from the use of such tools. Policymakers, foundations, and other stakeholders pursuing audit tool development should prioritize open source licensing, and at the least, make their methods public. Policymakers could also consider legislation that requires the publication of not only audit reports and artifacts but also clear explanations of auditors' methods and tools.
- Protecting auditors and audit tool builders. Multiple participants expressed concerns about disparate power dynamics between auditors and the organization being audited severely limiting the impact of audit results. Interviewees mentioned experiencing audit results being blocked from publication (P1) or unduly restricted in scope (P13) due to interventions from audit targets. Audit target retaliation and censorship was raised as a risk to both internal auditors (P5), who face the threat of firings, social dismissal or professional demotion [15, 109], and external auditors (P7), who face the threat of legal action under existing privacy and anti-hacking laws [81, 103]. For example, the creators of Ad Observer, one of the Data Collection tools surfaced in our survey, were suspended from Facebook because of their tool [34]. In addition to encouraging tool development, policymakers and other influential stakeholders should also take steps to protect auditors. In addition to legal reforms, stakeholders could offer legal funds or services to provide an opportunity for even less-resourced AI auditors experiencing corporate legal retaliation following the publication of an audit report.

5.2 Moving beyond *ad hoc* toolkits, towards common infrastructure

Throughout our results, auditors highlighted the context-specific, custom-built nature of their auditing tools. As one participant noted, "Many approaches were not necessarily principled. They were quite ad hoc" (P20). While many open source tools existed, auditors often preferred to build their own tooling solutions: "it's mostly stuff we just doing ourselves because... if we tried to use the existing stuff, it would just complicate that process, I think" (P25). For some, existing tools were inadequate for the complexity and scale of the systems being evaluated: "Most often we try to use open source tools, but that's very different than a data pipeline that... curates data on millions of [users] every day" (P3). But auditors often also preferred to build their own tools not only because existing tools didn't fit their needs, but also to give their evaluations more legitimacy. As one internal auditor noted,

Our determination of the performance of the algorithm carries a lot of weight within the organization. It's not like somebody else could just throw it and be like "Oh, we'll go ask somebody else"... because we built the infrastructure [to test algorithms], so we have that lever. So I almost feel like, if you can control the data sources or the ways to integrate algorithms into the data sources, that gives you power. (P3)

Toolkits currently dominating the audit tooling landscape are devoted mostly to performance evaluation and were built mostly by large, for-profit tech companies (Figures 2 & C.7). Especially the external auditors interviewed seemed to be either skeptical of the data provided from these tools or aware of their unreliability, naming the shutdowns of Reddit and Twitter's APIs (P24) as well as Facebook's CrowdTangle tool (P12) (see Section 4.3). Open-source tools can often fill the gap, however, due to the frequent context-specific customizations required for such a varied and multi-disciplinary user base, many tools end up suitable only for a constrained set of methods or targets. As one government official noted, "Some methods might be appropriate for real-time systems. Some methods might be appropriate for after-the-case assessment, as some might need caseby-case analysis, and some might be applicable to the entire training or assessment data" (P21). There are also very few resources to guide the end-to-end audit process, with most practitioners making use of a custom curated toolkit of often independently developed resources [80].

However, our participants' aspirations for tooling suggest another path may be possible—a path towards lasting infrastructure that gives auditors additional levers to hold model operators accountable. In the remainder of this section, we suggest several ways that researchers, practitioners, policymakers and other stakeholders can bridge the gap between available tooling and practice, including the development of educational resources and tool selection frameworks, greater commitments to audit tool maintenance, centralized resource repositories, and funding commitments.

5.2.1 Implications for HCI.

• Shared educational resources. HCI practitioners are particularly well equipped to develop the education-first practices and training resources that may be helpful to facilitate a shift

towards more informed and nuanced decision-making. Because stakeholders involved in auditing come from various backgrounds, tools and practices are likely to require some degree of education and training for those who come from non-engineering backgrounds in order to use and embrace emerging best practices. Also, education-first tooling can help lower the barrier for participation for affected communities.

- Decision-support frameworks for AI audit tool selection. Auditors sought more than just a plethora of auditing tools; they also wished for robust frameworks to aid practitioners in choosing the right tool for the specific problem they encounter. Tool selection was a major source of uncertainty for practitioners; as one expert suggested, "it's not just about creating a multitude of auditing tools but also about fostering decision support frameworks that empower practitioners to make informed choices based on the context they are dealing with" (P25). Future research could explore frameworks that assist audit practitioners in identifying and choosing between tools at each stage in an audit.
- Institutionalized AI audit tool maintenance. Currently, the burden of building and maintaining tools to address technical debt falls on the auditors, raising concerns about the sustainability of auditing efforts. This maintenance challenge leads to questions about responsibility—who should develop and sustain the necessary tools and infrastructure to support auditing activities effectively? One participant suggested putting expiration dates on tools to avoid future inaccuracies (P7). Researchers and practitioners should ensure that newly developed tools are accompanied with long-term maintenance plans, possibly through collaborations with civil society organizations such as the Linux Foundation, which hosts several of the open source tools we found (IBM's AI Fairness 360 [9], IBM's AI Explainability 360, and the Adversarial Robustness Toolbox).

5.2.2 Broader Implications.

• Centralized AI audit resources. Participants unanimously agreed on the need for shared infrastructure that supports the auditing process. One participant commented that tools are "a superpower for journalists, and something that really is the future of accountability... There really needs to be some sort of public infrastructure [for auditing online platforms]" (P7). As it stands, the audit tooling landscape is widely decentralized, which makes it difficult for auditors to find and use multiple audit tools to develop more end-to-end methodologies. A centralized repository-accompanying regulatory guidance, for example-could house a set of various tools, guidelines, and procedures tailored to the auditing process. Such a repository would provide multiple benefits: easier tool discovery and selection, ultimately leading to increased awareness, accessibility, and language sharing; enhanced collaboration between AI audit tool practitioners and tool developers by informing auditors of existing tools, which may deter unnecessary tool duplication; and coordination between audit standards and audit tool standards, which could help mitigate concerns about audit integrity.

• Funding. Multiple participants noted the value of long-term funding to support tool development and maintenance: "We need more funding for this space... especially when it comes to infrastructure" (P20). One participant hoped to find "funders who are on board for longer tool maintenance projects" (P7). Another suggested that funders may be incentivized to address infrastructure gaps by connecting "performance issues and ML to downstream business KPIs," (P4) but noted the difficulty of doing so when talking about "nebulous things, like fairness and bias" (P4). Developing high quality audit tools-even when adapting existing open source tools-took resources. Authors of audit legislation—as well as other policymakers and foundations-should set aside funding and resources for these kinds of long-term projects to ensure that audit tools are high quality, long-lasting, and address the wide range of auditor needs identified in this study.

6 CONCLUSION

Ideally, AI audit studies will translate into tangible outcomes of accountability, but this outcome is far from a given reality. In order for the audit process to truly be feasible and effective, we—researchers, policymakers, regulators, and audit practitioners—need to invest in the infrastructure required for accountability. This will require a full effort on multiple fronts, including everything from the design and development of new tools; to new community infrastructure, communication standard-setting; to considering advocacy for certain policy positions. In the end, we cannot just accept the minimum expectation when it comes to auditing, and must push the boundaries of this work until it becomes the meaningful mechanism of accountability it promises to be.

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A METHODS

A.1 Initial Sources

We drew our initial list of tools from:

- tools mentioned by our interviewees;
- tools mentioned in previous surveys of fairness and other toolkits [30, 46, 58]
- academic papers presenting new tools surfaced in a recent literature review of audit studies [14], including
 - the last five years of conference proceedings from: FAccT, AIES, EAAMO, AAAI, CVPR, ICWSM, WWW, WACV, EECV, and the ACL Anthology; also, the ACM Digital Library (including CHI and IC2S2) with the terms "audit", "accountability", "case study", "bias", "fairness", or "assurance" in the title or abstract;
 - reports from the government agencies ICO and NIST;
- a convenience seeding (accounting for 79 of the initial 148 tools) of other prominent audit tooling projects, academic papers, and tool-building organizations that we had encountered in our work as researchers and practitioners.

A.2 Theoretical Sampling

Category descriptors from the initial taxonomy that were sourced either from our labels or from descriptors used by tools already collected were then searched in combination with general keywords we identified that were commonly used in the algorithmic auditing domain. These keywords include the following: "tool", "audit",

"algorithm", "accountability", "responsible AI", "fairness", "discrimination", and "AI". For each of our categories, we conducted English Google searches using each keyword combined with each of our initial category descriptors (e.g., "participatory audit", "participatory tool", etc.). In order to determine a point of saturation for each search, we examined each Google search page of 30 results at a time until two pages in a row contained no references to specific audit tools. It is important to note that we conducted searches for all categories in our initial taxonomy, but focused on less saturated categories (for example, harms discovery and tools using participatory methods) in order to provide well-rounded definitions of categories that were less common and/or visible. Categories with a more saturated set of examples were not given an equal amount of additional sourcing.

In addition to these targeted Google searches, we also added several new sources of tools to our initial list:

- News articles and reports by new organizations and civil society organizations including ProPublica, The Markup, the Pulitzer Center, the ACLU, and AlgorithmWatch;
- the Participatory ML Workshop at ICML [54];
- an additional Google search for startups working on "reg tech" (regulatory tech).

B INTERVIEW PROTOCOL

We used the following protocol in each of our interviews. Because the interviews were semi-structured, not all participants answered every question in the same order. Bolded questions, however, were prioritized—we asked all these questions of nearly all participants. The rest were optional follow-ups.

Thanks so much for taking the time to share your expertise. We really appreciate it and are looking forward to hearing your thoughts! [Briefly introduce the project.] [Confirm participant has completed consent form, remind participant of confidentiality, and confirm optional permissions.]

BACKGROUND

- How did you get involved in auditing to begin with?
- What do you hope to achieve?
 - Would you describe yourself as an internal or external auditor?
 - What system was the target of your audit?
 - What was the motivation behind your audit work?
 - What are some notable successes?
 - Notable failures?
 - What were the most difficult aspects of the audit? How were those challenges overcome?
 - What were the easiest aspects of the audit?
- Who do you consider to be stakeholders and why?
- Tell me about the people who have a role in designing and executing the audits you're involved with.

Tool Usage and Development

- Is there a specific tool or method (or set of tools and methods) that you employ? How do you choose these tools? What parts of the audits did they assist with?
 - What pain points did you encounter while using the tools?

- Who made the decision to use this tool?\Why do you use this tool and not others?
- What prompted you to use/develop a tool? What are the system behaviors that you worry about?
- When do you know when to develop a tool vs. use an existing one?
- Can you help me understand why these tools are helpful, from an ethical perspective?
- What is the intent of the tool/method used? Do you find that the way you've used the tools/methods aligns with those intents?
- Some people are trying to build more open-source audit methodologies and tools that are freely available to the community. Is this an important goal for your audit practice? Why or why not?

Exploring Gaps & Challenges in Tools

- What common obstacles do you encounter while designing, building, performing, and communicating about audits/tooling? For tools, are there particular challenges (i.e., around adoption, maintenance, and distribution) that we should be aware of?
- Do you find that there are needs that are unmet with existing auditing tools? What are they? / Is there any tool you wish you had but didn't? Have the tools/frameworks you've developed/used revealed any of the system behaviors that you are worried about? If yes, which ones (and to what extent)? If not, why do you think it did not uncover anything?
- In your experience, what are common properties that existing auditing tools/methods try to assess?
 - Do you think existing tools/methods are successful at measuring them?
 - Are there things it would be good to measure that current tools don't capture?
- To what degree do you find that existing auditing formats & methodologies are useful and impactful? Are there formats/methodologies that you would like to see or see more of?
- We'd like to get a sense of how resource-intensive your tool(s)/methods are. Would you be willing to talk about how much it cost to perform audits or develop tools? How many people were involved? And how long does it take? How hard was it to do the audit and how much did it cost you?

Wrap-up

- Is there anything else you'd like to talk about? Do you have any questions for me?
- [Confirm optional permissions again.]

C ADDITIONAL FIGURES

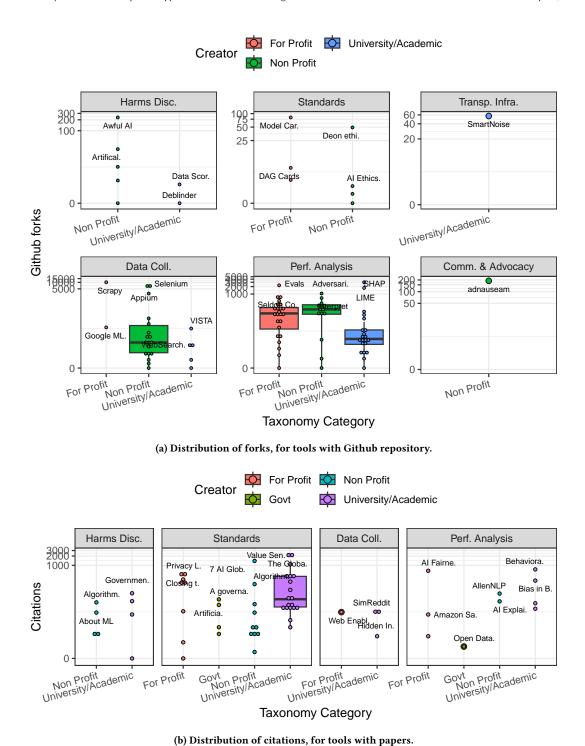


Figure C.1: Usage statistics by taxonomy category. Sorted by type of organization (our classification). Box-and-whisker plots included for categories with more than 10 points.

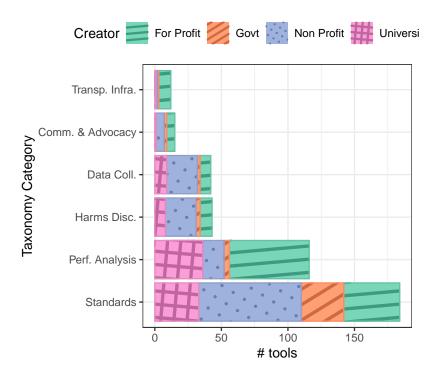


Figure C.2: Number of tools by taxonomy category, sorted by type of organization (our classification).

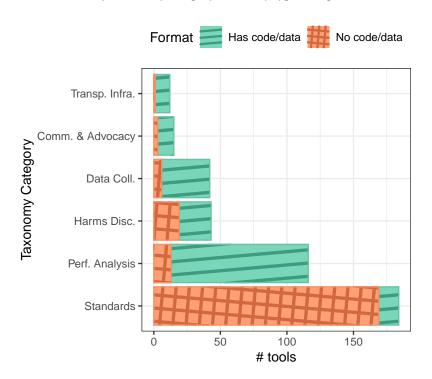


Figure C.3: Number of tools with code in each taxonomy stage.

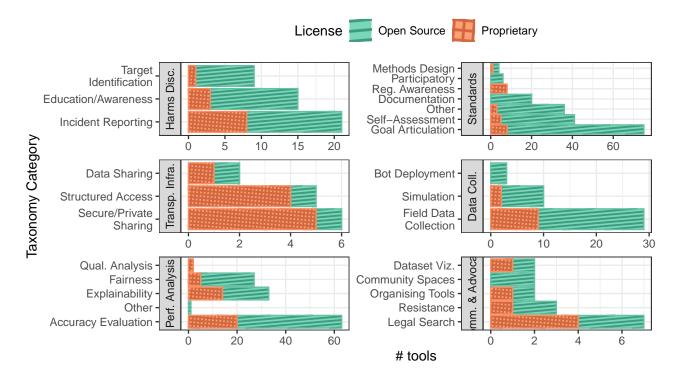


Figure C.4: Number of tools by taxonomy category sorted by license type.



Figure C.5: Number of tools by taxonomy category sorted by audit target.

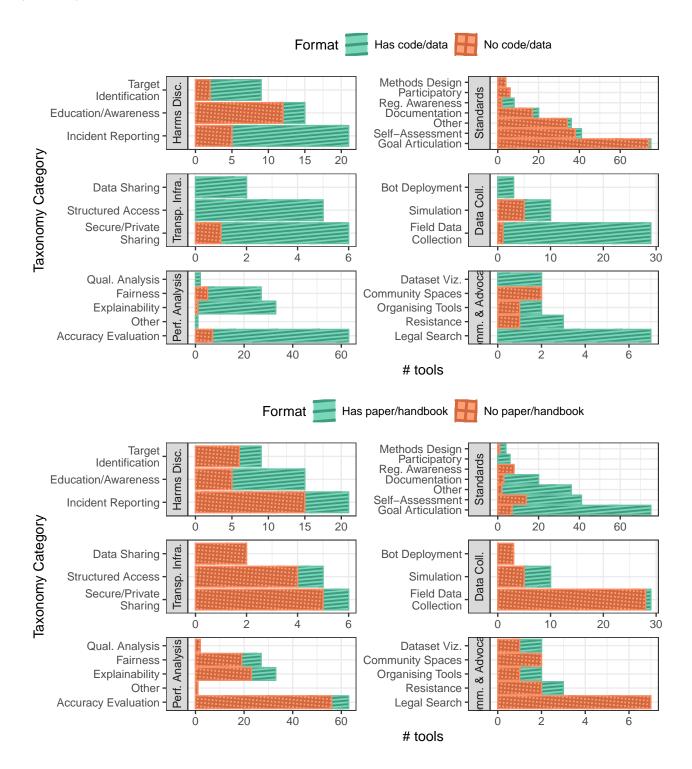


Figure C.6: Number of tools by taxonomy category sorted by format.

Table 3: Top-funded audit tool builders, per Crunchbase data. Includes only private (pre-IPO) organizations with Crunchbase entries.

Organization	Total funding (millions USD)	Estimated revenue	Employees	Stages	
OpenAI	11303.12	\$50M to \$100M	501-1000	Perf. Analysis, Trans. Infra., Standards	
Databricks	3497	\$500M to \$1B	5001-10000	Trans. Infra., Perf. Analysis	
OneTrust	1120	\$100M to \$500M	1001-5000	Harms Disc.	
DataRobot	1000.598	\$100M to \$500M	501-1000	Perf. Analysis	
Hugging Face	395.2		101-250	Perf. Analysis, Standards	
GitHub	350	\$100M to \$500M	1001-5000	Perf. Analysis	
H2O.ai	251.099999	\$10M to \$50M	251-500	Perf. Analysis	
Weights & Biases	250	\$10M to \$50M	251-500	Perf. Analysis	
HackerOne	159.4	\$10M to \$50M	1001-5000	Harms Disc.	
Bugcrowd	78.65	\$1M to \$10M	501-1000	Harms Disc.	
Arthur	60.3		51-100	Standards, Perf. Analysis	
Pymetrics	56.63	\$1M to \$10M	51-100	Perf. Analysis	
Fiddler AI	45.2	\$1M to \$10M	11-50	Perf. Analysis	
TruEra	42.284998		51-100	Perf. Analysis	
CognitiveScale	40	\$10M to \$50M	51-100	Perf. Analysis	
Calypso AI	38.2	\$500M to \$1B	11-50	Standards, Perf. Analysis	
Seldon	33.691771	\$1M to \$10M	51-100	Perf. Analysis	
Open Data Institute	32.835579	\$1M to \$10M	11-50	Standards	
LexisNexis	30	\$1B to \$10B	10001+	Advocacy	
The Markup	20	\$1M to \$10M	11-50	Data Coll.	

Table 4: 20 most popular Github repositories for tools in our database, sorted by number of forks.

Organization	Forks	Issues	Stars	Stages
Scrapy	10140	714	48351	Data Coll.
Selenium	7762	222	27630	Data Coll.
Appium	5916	211	16867	Data Coll.
CARLA	3013	858	9592	Data Coll.
SHAP	2993	1463	20021	Perf. Analysis
Evals	2242	107	11684	Perf. Analysis
LIME	1762	97	10813	Perf. Analysis
Adversarial Robustness Toolbox	1047	128	3930	Perf. Analysis
Seldon Core	780	103	3882	Perf. Analysis
AI Fairness 360	715	165	2116	Perf. Analysis
Interpret	686	65	5674	Perf. Analysis
Big Bench	529	79	2223	Perf. Analysis
Tensorflow Privacy	433	107	1802	Perf. Analysis
Foolbox	418	37	2539	Perf. Analysis
CodeSearchNet	369	14	1992	Perf. Analysis
Fairlearn	360	179	1635	Perf. Analysis
Language Interpretability Tool	336	82	3189	Perf. Analysis
AI Explainability 360	305	55	1389	Perf. Analysis
Tensorflow Model Analyzer	265	33	1213	Perf. Analysis
Error Analysis	254	86	944	Perf. Analysis
Responsible AI Toolbox	254	86	944	Perf. Analysis

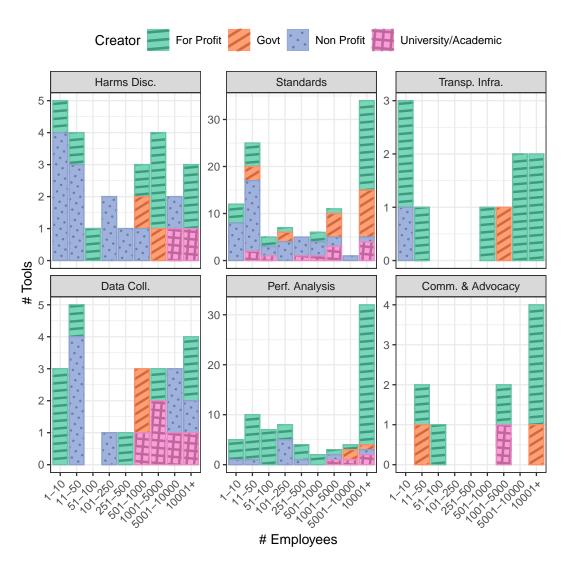


Figure C.7: Number of tools by taxonomy category. Workforce size of creating organization sourced from Crunchbase [25]. Sorted by type of organization (our classification). Tools from organizations without Crunchbase entries excluded.

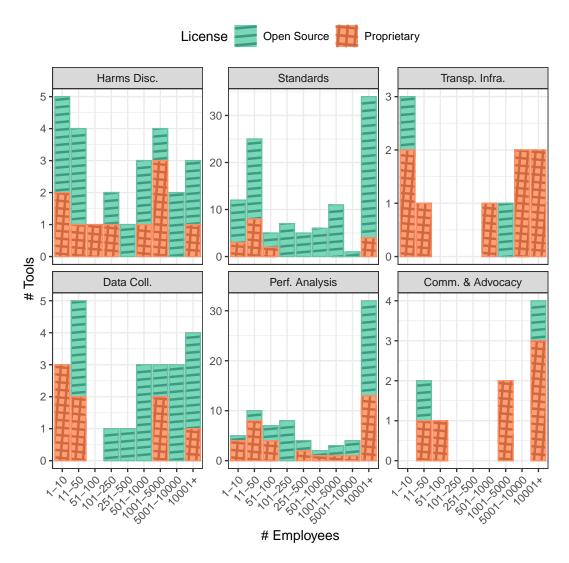


Figure C.8: Number of tools by taxonomy category. Workforce size of creating organization sourced from Crunchbase [25]. Tools from organizations without Crunchbase entries excluded.

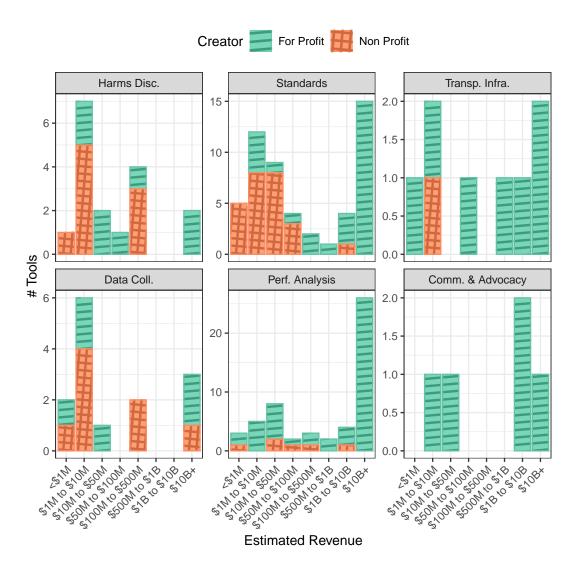


Figure C.9: Number of tools by taxonomy category. Workforce size of creating organization sourced from Crunchbase [25]. Tools from organizations without Crunchbase revenue estimates excluded.

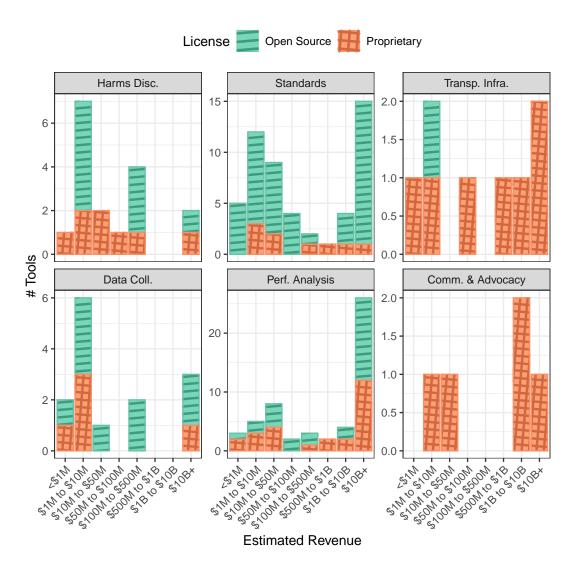


Figure C.10: Number of tools by taxonomy category. Workforce size of creating organization sourced from Crunchbase [25]. Tools from organizations without Crunchbase revenue estimates excluded.

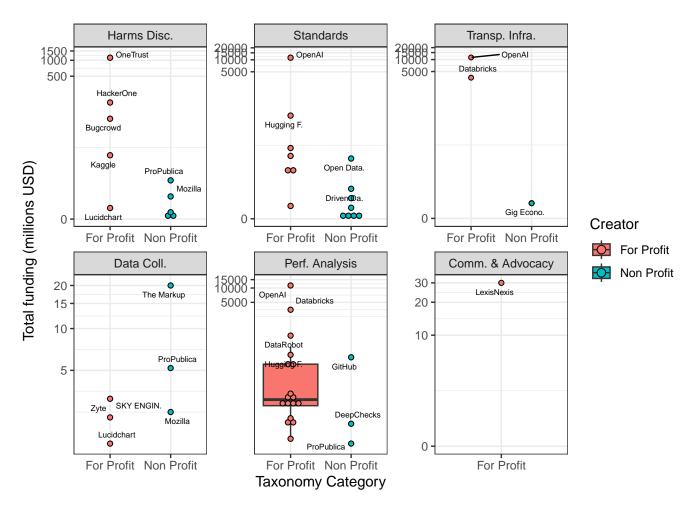


Figure C.11: Private (pre-IPO) organizations with Crunchbase entries (114/311 organizations). Total funding sourced from Crunchbase [25].