Understanding the landscape of potential harms from algorithmic systems enables practitioners to better anticipate consequences of the systems they build. It also supports the prospect of incorporating controls to help minimize harms that emerge from the interplay of technologies and social and cultural dynamics. A growing body of scholarship has identified a wide range of harms across different algorithmic technologies. However, computing research and practitioners lack a high level and synthesized overview of harms from algorithmic systems arising at the micro-, meso-, and macro-levels of society. We present an applied taxonomy of sociotechnical harms to support more systematic surfacing of potential harms in algorithmic systems. Based on a scoping review of computing research ($n=172$), we identified five major themes related to sociotechnical harms — representational, allocative, quality-of-service, interpersonal harms, and social system/societal harms — and sub-themes. We describe these categories and conclude with a discussion of challenges and opportunities for future research.

CCS Concepts: • Social and professional topics → Computing / technology policy; • General and reference → Evaluation.

Additional Key Words and Phrases: harms, algorithms, critical algorithm studies, scoping review

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1 INTRODUCTION

Harms from algorithmic systems — that is, the adverse lived experiences resulting from a system’s deployment and operation in the world — occur through the “co-productive” [98] interplay of technical system components and societal power dynamics [87]. Computing research has traced how marginalized communities — referring to communities that face structural social exclusion [111] — disproportionately experience sociotechnical harms from algorithmic systems (e.g., [80, 85]), including the inequitable distribution of resources [54], hierarchical representations of people and communities [215], disparate performance based on identity [124], and entrenchment of social inequalities (e.g., [26, 74], among others. In this way, algorithmic systems’ enactment of power dynamics [144] can function as a minoritizing practice [55] through which unjust social hierarchies are formed and reinforced.

There is momentum among practitioners to develop practices to better identify and minimize harms from algorithmic systems (e.g., [24, 53, 116, 125]. Alongside broader movements towards regulation and standardization [183], such harm reduction practices often draw on fields of auditing, impact assessment, risk management, and safety engineering where a clear understanding of harm is essential [94]. Researchers have also developed “ethics methods” [131] for practitioners to identify and mitigate harms, including statistical assessment [116, 126], software toolkits [28], and algorithmic impact assessments and audits [157] that offer significant value for practitioners. Existing work on harms, however, is often vast and disparate, focusing on particular notions of harm. As such, it poses navigational challenges for practitioners seeking to comprehensively evaluate a system for potential harms [157, 158, 161]. In addition, the use of different terminologies for describing similar types of harm undermines effective communication across different stakeholder groups working on algorithmic systems [116, 141].

Recognizing these limitations, we conducted a scoping review [109] and reflexive thematic analysis [35] of literature on harms from algorithmic systems, offering this harm taxonomy as a tool for practitioners to consider harms more systematically. A scoping review offers a generative starting place for a harm taxonomy, as it aids synthesis of existing articulations of harm, draws attention to forms of harm that may not be well-captured in regulatory frameworks, and reveals gaps and opportunities for future research. As scholarly articulations of harm emerge from different epistemic standpoints, values, and methodologies, this paper pursues the broader question of: How do computing researchers conceptualize harms in algorithmic systems? Three specific research questions guided our work:

(1) What harms have been described by previous research on algorithmic systems? How are these harms framed in terms of their impacts at the micro-, meso-, and macro-levels of society? What types of social dynamics and hierarchies do we see researchers of algorithmic systems implicate in their descriptions of harms?

(2) Where is there conceptual alignment on types of harms from algorithmic systems? What type of organizational structure of harms is suggested by conceptual alignment?

(3) How do gaps or absences in research on harms from algorithmic systems suggest opportunities for future research?

This research contributes to human-computing scholarship and responsible AI communities, offering:

• A scoping review of harms, creating an organized snapshot of articulations of computational and contextual harms from algorithmic systems;

• A reflexive thematic analysis of harms definitions, their impacts to individuals, communities, and social systems, providing a framework for identifying harms when conducting impact and risk assessments on an algorithmic system;
Support for interdisciplinary communication by providing terms, definitions, and examples of harms and direction for future work.

In the pages that follow, we discuss the sociotechnical character of harms from algorithmic systems and existing harm taxonomies, followed by a description of our methodology. We then detail the harm taxonomy and propose next steps for this work. This analysis offers a starting place for researchers and practitioners to reflect on the myriad possible sociotechnical harms from algorithmic systems with the aim of more proactive surfacing and harm reduction.

2 BACKGROUND

2.1 Sociotechnical harms

Scholars in human-computer interaction (HCI), machine learning, Science and Technology Studies (STS), and related disciplines have identified various harms from digital technologies (e.g., [9, 104, 169, 170, 182]). This literature underscores harm as a relational outcome of entangled relationships between norms, power dynamics, and design decisions [8, 26, 60, 129, 211]. Harms from algorithmic systems emerge through the interplay of technical systems and social factors [31, 80] and can encode systematic inequalities [122]. This duplicity of technology, as Ruha Benjamin [26] describes, is a challenge: algorithms may have beneficial uses, but they often adopt the default norms and power structures of society [137].

Recognizing the sociotechnical character of harms from algorithmic systems draws attention to how the development and experience of digital technologies cannot be separated from cultural and social dynamics [7, 51]. As van Es et al. [198] note, “algorithms and code reduce the complexity of the social world into a set of abstract instructions on how to deal with data and inputs coming from a messier reality” (n.p.). This process involves design decisions predicated on “selection, reduction, and categorization” [33] through which technologies come to reflect the values of certain worldviews [33, 188]. Without intentionally designing for equity, social inequalities are likely to be reinforced and amplified in algorithmic systems [51].

2.1.1 Identifying and anticipating harms in practice. With increased awareness of the need to anticipate harms early in product development [172], designers and researchers are central actors in pursuing harm reduction [34, 49, 87]. Anticipating harms requires considering how technological affordances shape their use and impact [76, 175]. It can be done in relation to the technology holistically or with a focus on certain features of the technology and its use by different groups [37]. This work requires thinking critically about the distribution of benefits and harms of algorithmic systems [29, 150] and existing social hierarchies [31]. It can be strengthened by bringing in different standpoints and epistemologies, such as feminism [63, 136], value-based design [17, 78, 99], design justice perspectives [51], and post-colonial theories [108, 129]. Importantly, the process requires attending to the constitutive role of social power in co-producing sociotechnical harms, which “designers need to identify and struggle with, alongside the ongoing conversations about biases in data and code, to understand why algorithmic systems tend to become inaccurate, absurd, harmful, and oppressive” [7] (p. 2). Thus, in anticipating harms, practitioners need to account for computational harms as well as those arising through contextual use [34, 146, 209].

2.2 Taxonomies of Sociotechnical Harms, Risk, and Failure

Structured frameworks aid practitioners’ anticipation of harms throughout the product life cycle [116, 212]. They encourage more rigorous analysis of social and ethical considerations [116], especially when operationalizing principles feels opaque [128]. Taxonomizing harms is, however, an exercise in classification, which has potential tradeoffs: taxonomies, as informational infrastructure [171], draw action to certain issues over others, shaping how people navigate and act on...
information [33]. As such, the epistemological choices made in developing harm taxonomies focus practitioner attention on particular areas over others [34].

Many existing harm taxonomies focus on particular domains of use (e.g., [170, 192]) and how they are complex assemblages of actors, social norms, practices, and technical systems that can foster individual and collective harm [154]. Taxonomies have been developed related to online content [19, 170, 201], social media [138, 192, 193], and malicious uses of algorithmic systems [39], including cyber attacks [3] and cyberbullying [12]. Relatedly, they can focus on particular types of harms, such as misinformation [193] or representational harms co-produced through system inputs and outputs, which reinforce social hierarchies [104, 202]. While domain-specific taxonomies draw attention to how context informs the emergent nature of harm, they are not easily applicable to a wide range of algorithmic systems. Many systems deploy across contexts, including, for example, ranking and recommendation systems (e.g., search engines or content sorting algorithms on social media platforms), and object detection models (e.g., video surveillance systems, self-driving cars, and accessibility technology).

Another common approach is to orient harm taxonomies around specific algorithmic or model functions (e.g., [73, 208]). Model-focused taxonomies have been developed for large language models [208], image captioning systems [104, 202], and so-called “foundational models,” such as GPT-3 and BERT, which are applied in a wide range of downstream tasks [32]. Organizing harm by model function is highly useful when practitioners’ focus is on a singular model because it draws attention to relevant computational harms. It does, however, pose limitations to practitioners working downstream on products and features, where multiple model types operate simultaneously, such as in social media, search engines, and content moderation, and where contextual use significantly shapes potential harms.

Scholars have also developed harm taxonomies related to system misbehaviors and failures [18, 173], particularly to aid algorithmic auditing (e.g., [156]). These taxonomies focus on how algorithmic systems are sources of harm (e.g., faulty input/outputs, limited testing, proxy discrimination, and surveillance capitalism) [178]. Bandy [18] summarizes four problematic behaviors of algorithmic systems — discrimination, distortion, exploitation, and misjudgement. These taxonomies focus attention on how specific affordances, training data, and design choices can co-produce harm [22, 34]. Failure-based taxonomies are helpful when practitioners examine potential failure modes of a specific technology, but are often limited in helping anticipate who or what is harmed.

In sum, as harms from algorithmic systems are sociotechnical and co-produced through social and technical elements, they cannot be remedied by technical fixes [83] alone. They also require social and cultural change [152].

### 2.3 Methodology

In alignment with prior calls to anticipate both computational harms and those arising from variable context of use [34], we synthesize different insights on harms from computing research, to aid anticipation of sociotechnical harms. Our findings draw upon a scoping review for data collection and a reflexive thematic analysis of computing research on harms, which we outline below.

### 2.4 Overview of Methodology

Our approach followed prior scoping reviews in HCI literature [65, 197], in alignment with the extension of the PRISMA checklist [114], the PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) [195]. We implemented the six-stage scoping review framework [11, 109]: (1) Identifying research questions; (2) Identifying relevant studies; (3) Study selection; (4) Charting the data; (5) Collating, summarizing, and reporting results; and a (6) Consultation exercise.
2.4.1 Identify Research Questions. To identify the types and range of sociotechnical harms, we developed the three aforementioned research questions (Section 1).

2.4.2 Identify and Select Relevant Studies. We then employed multiple strategies to identify relevant resources through different sources: electronic scholarly databases, a citations-based review, and targeted keyword searches in relevant organizations, and conferences. Using the ACM Guide to Computing Literature as the primary search system – which reflects key computing research databases – we developed the following initial set of key concepts to search full text and metadata: “algorithmic harm”, “sociotechnical harm”, “AI harm”, “ML harm”, “allocative harm”, “representational harm”, “data harm”, and “harm(s) taxonomy.” Next, we reviewed each paper, and conducted a citations-based review to surface additional references (e.g., gray literature by NGOs). The citations-based review revealed highly-cited cross-disciplinary scholarship (e.g., articles from sociology, Science and Technology Studies (STS)). Lastly, we relied on existing knowledge and networks to surface additional sources, including IEEE, NIST, Data and Society, the Aspen Institute, and the AI Incident Database. The identification stage started in February 2022 and was completed in July 2022.

The initial search of the ACM database produced a set of 85 research articles (duplicates removed from 118 papers). The citations-based review and targeted keyword searches in NGO and professional organizations identified an additional 125 resources. We included articles that described or discussed: (1) algorithmic technologies and (2) harms or adverse impacts from algorithmic systems. We excluded 38 articles that: (1) did not meet the inclusion criteria, and (2) did not have full-text available. In total, 172 articles and frameworks were included in our corpus (see Figure 1 and Table 7 in the Appendix).

2.4.3 Data Charting. We employed a descriptive-analytical method for charting data – a process of “synthesizing and interpreting qualitative data by sifting, charting and sorting material according to key issues and themes” [11]. Two researchers independently charted the following data items extracted through reading of the full text of each text and organized these into a spreadsheet: (1) characteristics of sources: publication year and venue; and (2) description of harm: definition or conceptual framing. Discovery of a new concept or type of harm resulted in a new code, and repeat encounters with existing concepts/harm was documented, in order to reach theoretical saturation – a point at which coding additional papers or resources do not yield additional themes [91, 168].

2.4.4 Collating and Summarizing Results. As collation of themes requires synthesis and qualitative analysis of articles, we used Braun and Clarke’s reflexive thematic analysis [35, 36]. As coding is an evolving, self-reflective process in reflexive thematic analysis, the authors engaged in deep data immersion, interpretation, and discussion, including sharing of disagreements. First, we sorted definitions of code thematically and looked at the frequency at which harm definitions appeared to begin to identify dominant terms and definitions. Then, we conducted a first line-by-line pass reviewing each phrasing and terminology of each specific kind of harm. In this initial phase, we identified codes that could be easily condensed. For instance, ‘physical harm’ and ‘physical injury’ were condensed into one code: physical harm. We then began to cluster harms based on the context or domain in which they were mentioned. For example, specific harms describing forms of harassment (e.g., non-consensual sharing of explicit images, or online stalking) were clustered under an initial theme of “hate, harassment, and violence.” There were many conceptual overlaps among harm types; definitions were not always consistent. If there was a dominant term or definition in the cluster that could encompass different sub-types of harm (based on frequency of citation), that term was chosen as the primary category. As RQ2 sought to uncover where there was conceptual alignment, three of these harm types — allocative, representational, and quality
of service — reflect where there was strong definitional consensus in the literature. Social system harms and interpersonal harms emerged through the collating and summarizing process. From this clustering, we developed a first version of the harm taxonomy.

In scoping reviews, collating and summarizing findings requires researchers to make choices about what they want to prioritize. As the guiding purpose of this research was to develop an applied taxonomy, we prioritized keeping the number of major categories comprehensive yet manageable, envisioning a practitioner with minimal knowledge of harms as the primary user of this taxonomy. With the goal of making the taxonomy accessible to practitioners with different disciplinary backgrounds, we repeated this process of clustering and synthesizing three times, refining language and examples of harms to ensure clarity and conceptual cohesion.

**2.4.5 Consultation Exercise.** Scoping reviews and their results are more useful if practitioners are contributors [140]. We therefore involved four groups of stakeholders: Product and Program Managers; Software Engineers; UX Researchers, and AI Ethicists and Social Scientists. Contributors provided additional references and valuable insights about terminology and language within the proposed taxonomy. For example, communicating more clearly where harm may directly arise from the AI system; from already-existing social dynamics; and technology-facilitated violence (e.g., malicious use). We also invited stakeholders to use the taxonomy as a tool to reflect on potential harms in existing or imagined projects and identify potential gaps or limitations. This process helped clarify that the taxonomy is applicable across ML functions (e.g., generation, classification, ranking and retrieval, localization and tracking, clustering, regression), and spotlight limitations in the research literature, where additional scholarly research may be beneficial.

### 2.5 Limitations

In seeking to map how computing researchers conceptualize harms in algorithmic systems, our scoping review focused on academic outlets. The findings are reflective of existing scholarly knowledge. Like all knowledge systems, computing research scholarship is not neutral; it is shaped by various influences, including researcher and institutional priorities, access to resources, thematic conferences, and targeted calls that advance research in particular areas.

Articulations of harm described in computing scholarship may derive from work with individuals and communities who describe harms in ways that differ from scholarly discourse. Indeed, there may be many types of harm that are not recognized or articulated in scholarship. As research literatures are always partial and in progress, the harms described in our taxonomy reflect the partial and in progress nature of the field. These dynamics are especially relevant to the study of emergent technologies, where individual, collective, and societal impacts of these technologies may be anticipated but not fully known. We also acknowledge the literature reviewed here aligns primarily with Eurocentric worldviews, which undoubtedly shape the articulation and description of harms. We are attentive to how these absences likely persist in our taxonomy, having engaged in much discussion around how perceived and real gaps in the taxonomy should motivate future research.

### 3 TAXONOMY OF SOCIOTECHNICAL HARMs

Our analysis identified five major types of sociotechnical harms reflective of the micro-, meso-, and macro-level impacts of algorithmic systems (see Table 1). These categories emphasize (1) how socially constructed beliefs and unjust hierarchies about social groups are reflected in model inputs and outputs (*representational harms*); (2) how these representations shape model decisions and their distribution of resources (*allocative harms*); (3) how choices made to optimize models for particular imagined users result in performance disparities (*quality-of-service harms*); (4) how
technological affordances adversely shape relationships between people and communities (interpersonal harms); and (5) how algorithmic systems adversely impact the emergent properties of social systems, leading to increased inequity and destabilization (social system/societal harms).

In developing a framework that supports more systematic analysis of potential harms in algorithmic systems, we recognize the complex and often concurrent ways harms are experienced. Conceptualizations of harm do not always fit neatly within a compartmentalized structure. Accordingly, there may be gray areas within and across harm categories, and multiple harms may occur in a single use case or system. This taxonomy is not prescriptive in its ordering of harms. Instead, we encourage readers to consider the multiple dimensions in which harms may play out. In what follows, we discuss each major harm classification, including sub-types and how they emerge through the interplay of technical components and social dynamics.

3.1 Representational Harms: Unjust Hierarchies in Technology Inputs and Outputs

Representational harms concern beliefs about different social groups that reproduce unjust societal hierarchies [22, 104]. These harms occur when algorithmic systems reinforce the subordination of social groups along the lines of identity, such as disability, gender, race and ethnicity, religion, and sexuality [22]. Representational harms include instances where certain social groups experience both over- and under-exposure [26], leading to unequal visibility [215]. Prior work identifies representational harms in many algorithmic systems, including through classifiers [40], natural language processing [31], computer vision [104], and image tagging and captioning [27]. Representational harms reflect assumptions that algorithmic systems make about people, culture, and experiences, which perpetuate normative narratives that adversely shape people’s sense of identity and belonging [101]. Andalibi and Garcia [8] characterize the lived experience of representational harms as algorithmic symbolic annihilation through which the normative narratives built into technologies become power structures that shape people’s experiences with algorithms. The people and communities likely to experience these harms are those who already experience social marginalization. Representational harms thus entrench and exacerbate social stereotypes and patterns of erasure [25]. Specific dimensions of representational harms include stereotyping, demeaning, erasing, and alienating social groups, denying people the opportunity to self-identify, and reifying essentialist social categories (see Table 2).

3.1.1 Stereotyping. Stereotyping arises when a system conveys overly simplistic understandings of groups that reinforce undesirable social hierarchies [22]. People marginalized in society face numerous explicit and implicit stereotypes conveyed in various forms of data [147], coding schema [137], and design choices [30] that drive algorithmic systems. Stereotyping often reflects repeated patterns of over- and under-representation — for instance, how gendered beliefs about women’s submissiveness are reflected in digital assistants [43, 185, 205]. In fact, research identifies narrow stereotypes about masculinity and femininity represented and expressed in natural language processing and computer vision systems, particularly in relation to professions [105], cooking and shopping [217], and sport [42]. While computing literature often describes stereotyping along single-axis dimensions of identity, an intersectional approach draws attention to how harms play out for people whose lives are shaped by interlocking forms of oppression [203] — for example, when a search for the term “unprofessional hairstyles” disproportionately returns images of Black women [6].

3.1.2 Demeaning social groups. Demeaning social groups occurs when systems reinforce a representation of a particular group as of a lower social status [31]. This type of representational harm speaks to what sociologist Patricia Hill Collins [48] calls controlling images, which refers to the discourses, images, or language used to marginalize or oppress a social group. Controlling
Table 1. Sociotechnical harm framework with specific harm types

| Harm Theme                  | Sub-Types               | Specific Harms                                                                 |
|-----------------------------|-------------------------|-------------------------------------------------------------------------------|
| Representational harms      | Stereotyping            | Oversimplified and undesirable representations                               |
|                             | Demeaning social groups | Narratives used to socially control or oppress social groups                  |
|                             | Qualitative differential representations of social groups |                                                                         |
|                             | Erasing social groups   | Hegemonic ideas or social relations normalized in algorithmic systems          |
|                             |                         | Systemic illegibility or absence of social groups in algorithmic system inputs/outputs |
|                             |                         | Unequal visibility of certain social groups                                   |
|                             | Alienating social groups| Failure to acknowledge one’s membership in a culturally significant social group |
|                             |                         | Classifying or describing socially significant events in ways that ignore social injustices |
|                             |                         | Reifying essentialist social categories                                        |
| Allocative harms            | Opportunity loss        | Discrimination in critical resource domains (e.g., education, government, healthcare, or housing) |
|                             |                         | Inequitable access to resources needed to equitably participate in society     |
| Economic loss               |                         | Employment or hiring discrimination                                           |
|                             |                         | Discrimination in insurance, banking, or other financial sectors              |
|                             |                         | Financial losses or injuries, including price discrimination                   |
| Quality-of-service harms    | Alienate               | Adverse effects (e.g., frustration, bother, disappointment, or anger) experienced when interacting with technologies that fail based on one’s identity characteristics |
|                             |                         | Algorithmic invisibility, or feelings of exclusion from using non-inclusive technologies |
|                             | Increased labor         | Additional effort required to make technologies operate as intended           |
|                             |                         | Identity-based accommodation to technologies (e.g., linguistic)               |
|                             | Service or benefit loss | Degraded performance based on identity characteristics                        |
|                             |                         | Disproportionate loss of technological benefits                               |
| Interpersonal harms         | Loss of agency, Social control | Algorithmically-informed identity change                                      |
|                             |                         | Algorithmic profiling                                                         |
|                             |                         | Loss of autonomy                                                              |
|                             |                         | Required use of specific technologies to access domains that affect material well-being |
|                             | Technology-facilitated violence | Coercive control, or intimate partner violence                               |
|                             |                         | Device lockout and control                                                     |
|                             |                         | Inciting or enabling offline violence                                          |
|                             |                         | Online abuse (e.g., cyberbullying, deadnaming, doxxing, trolling, hateful or toxic language, gender-based sexual harassment) |
|                             | Diminished health and well-being | Emotional harms (e.g., dignity loss, invalidation, misgendering, psychological harms) |
|                             |                         | Physical harms                                                                |
|                             |                         | Reputation harms                                                              |
| Privacy violations           | Exploitative or undesired inferences                                      |
|                             |                         | Feelings of surveillance, or loss of desired anonymity                        |
|                             |                         | Loss of right to be forgotten                                                  |
|                             |                         | Non-consensual data collection                                                 |
|                             |                         | Privacy attacks (e.g., identity theft, doxxing)                               |
| Social systems/ societal harms| Information harms       | Distortion of reality (e.g., creation of information “bubbles”)              |
|                             |                         | Malinformation                                                                |
|                             |                         | Misinformation                                                                |
|                             |                         | Subjugating knowledges or foreclosing alternative ways of knowing             |
| Cultural harms              |                         | Cultural hegemony                                                             |
|                             |                         | Deteriorating social bonds                                                     |
|                             |                         | Proliferating false perceptions about cultural groups                          |
|                             |                         | Systemic erasure of culturally significant objects and practices              |
| Political and civic harms   |                         | Erosion of democracy (e.g., election interference, censorship, harm to civil liberties) |
|                             |                         | Human rights violations                                                        |
|                             |                         | Legal system harms (e.g., wrongful arrest, court transcription errors, unreasonable searches) |
|                             |                         | Nation destabilization (e.g., social polarization, loss of legitimacy)         |
| Macro socio-economic harms  |                         | Digital divides                                                               |
|                             |                         | Labor exploitation                                                             |
|                             |                         | Systemic failures of financial systems                                         |
|                             |                         | Technological unemployment (e.g., deskilling, devaluation of human labor, or job displacement) |
| Environmental harms         |                         | Damage to natural environment                                                  |
|                             |                         | Damage to built environment or property                                         |
|                             |                         | Depletion or contamination of natural resources                               |
|                             |                         | Injury to animals                                                              |

Images include forms of human-animal confusion in image tagging systems [199], which reflect dehumanizing gendered and racialized discourses used to socially exclude and control Black, Indigenous, and other people of color [84]. Such controlling images have appeared in ranking and retrieval systems, including reinforcing false perceptions of criminality by displaying ads for bail bond businesses when searching for Black-sounding names versus white-sounding names [189]. Similarly, patterns of demeaning imagery have been found in hateful natural language predictions.
| Harm Theme                  | Definition                                                                 | Sub-Type of Harm                               | Example                                                                 |
|----------------------------|----------------------------------------------------------------------------|-----------------------------------------------|-------------------------------------------------------------------------|
| Representational harms     | When algorithmic systems reinforce subordination of social groups along the lines of identity | Stereotyping social groups                    | “Exclusionary norms [in language models] can manifest in ‘subtle patterns’ like referring to women doctors as if doctor itself entails not-woman.” [208] |
|                            |                                                                            | Demeaning social groups                       | “A greater percentage of [online] ads having “arrest” in ad text appeared for Black identifying first names than for white identifying first names in searches...” [189] |
|                            |                                                                            | Erasing social groups                        | “I’m in a lesbian partnership right now and wanting to get married and envisioning a wedding [...] and I’m so sick of [searching for ‘lesbian wedding’ and seeing] these straight weddings.” [61] |
|                            |                                                                            | Alienating social groups                      | “[lack of representation] further promotes the idea that you don’t belong and perpetuates the sense of alienation.” [61] |
|                            |                                                                            | Denying opportunity to self-identify          | “It’s definitely frustrating having [classifiers] get integral parts of my identity wrong. And I find it frustrating that these sorts of apps only tend to recognize two binary genders.” [27] |
|                            |                                                                            | Reifying essentialist social categories       | “[automatic gender recognition] aim(s) to capture the morphological sexual differences between male and female faces by comparing their shape differences to a defined face template. We assume that such differences change with the face gender.” (quoted in [106]) |

about Muslim people [1], and toxicity and sentiment classifiers that are more likely to classify descriptions or mentions of disabilities [95, 189] and LGBTQ identities [191, 210] as toxic or negative. As these identities are often weaponized, models struggle with the social nuance and context required to distinguish between hateful and non-hateful speech [210].

**3.1.3 Erasing social groups.** Erasing social groups occurs when people, attributes, or artifacts associated with social groups are systematically absent [104, 202]. Whereas stereotyping reflects systematic patterns of over- and under-representation, erasure reflects its extremes. In instances of erasure, certain social groups are not legible to algorithmic systems. Erasure, as Dosono and Semaan [68, 210] describe, reflects algorithmic hegemony through which the dominant “system of ideas, practices, and social relations that permeate the institutional and private domains of
society” [86] are further normalized in sociotechnical systems. Design choices [124] and training data [188] influence which people are legible to an algorithmic system. Prior work examined erasure in the context of misgendering [58, 106], the systematic erasure of transgender and non-binary people [58, 106], disability and ableism in image descriptions [27], and marginalization of non-Western and underrepresented religious identities in systems [104].

3.1.4 Alienating social groups. Alienating social groups occurs when system outputs, such as automated image descriptions, do not acknowledge someone’s membership in a specific social group, resulting in feelings of disconnection or isolation [21, 104]. This dimension of representational harm diminishes human dignity [120] and is especially likely when “a system fails to recognize the injustices suffered by specific social groups” [104]. A study of user-elicited identification of harms in image search describes the impacts of such failures as “further promot[ing] the idea that you don’t belong and perpetuat[ing] a sense of alienation” [61] (p. 8).

3.1.5 Denying people the opportunity to self-identify. Denying people the opportunity to self-identify occurs when algorithmic systems classify people’s membership without their knowledge or consent [104]. This dimension of representational harm reduces autonomy [89] through non-consensual representations [147] that undermine people’s ability to disclose aspects of their identity on their own terms [50]. One clear example is when classifiers categorize someone who identifies as non-binary into a gendered category they do not belong [203]. This loss of autonomy reduces people’s control over data collection, through which data about people, their bodies, and presumptions about their behavior can be extracted into big data flows [63]. As classification systems are used across many consequential domains, denying opportunities to self-identify can materially impact marginalized communities, ranging from nonconsensual use of images in datasets to surveillance and wrongful arrest [27].

3.1.6 Reifying essentialist social categories. Reifying essentialist social categories occurs when algorithmic systems classify a person’s membership in a social group in ways that reinforce socially constructed inclusion and exclusion criteria as seemingly natural [21, 59, 104]. Reifying essentialist categories can contribute to “existential harm” in which people are “portrayed in overly reductive terms” [164] (p. 162), often from a Western or eurocentric perspective [59]. When such classification relies on phenotypes, this dimension of representational harm essentializes historically contingent identities [75] through which classification systems entrench and produce meaning about what they represent [89, 93]. The harms of reifying social categories are especially likely when ML models or human raters classify a person’s attributes – for instance, their gender, race, or sexual orientation – by making assumptions based on their physical appearance.

3.2 Allocative Harms: Inequitable Distribution of Resources
Allocative harms encompass problems arising from how algorithmic decisions are distributed unevenly to different groups of people [22, 162]. These harms occur when a system withholds information, opportunities, or resources [22] from historically marginalized groups in domains that affect material well-being [127], such as housing [41], employment [176], social services [15, 176], finance [100], education [102], and healthcare [139]. Allocative harms “arc towards existing patterns of power” [56] (p. 2) as they entrench material divisions between social groups [216]. When occurring in consequential domains, these harms reflect what Mimi Onuhoha [143] describes as algorithmic violence, in which algorithmic systems “prevent people from meeting their basic needs” (n.p.). Scholarly literature describes two specific dimensions of allocative harm — opportunity loss and economic loss — reflecting and reinforcing existing social hierarchies along axes of disability gender, race, or sexuality among others (see Table 3).
### Allocative harms: definition, sub-types, and examples

| Harm Theme          | Definition                                                                 | Sub-Type of Harm   | Example                                                                                                           |
|---------------------|-----------------------------------------------------------------------------|--------------------|------------------------------------------------------------------------------------------------------------------|
| Allocative harms    | When algorithmic systems withhold opportunities, resources, or information to historically marginalized groups in domains that affect material well-being | Opportunity loss   | "Systems...wrongfully deny welfare benefits, kidney transplants, and mortgages to individuals of color as compared to white counterparts." [52] |
|                     |                                                                            | Economic loss      | "Language models may generate content that is not strictly in violation of copyright but harms artists by capitalizing on their ideas...this may undermine the profitability of creative or innovative work." [208] |

#### 3.2.1 Opportunity loss

Opportunity loss occurs when algorithmic systems enable disparate access to information and resources needed to equitably participate in society, including withholding of housing [10] and services [74]. Researchers contextualize how opportunity loss arises through algorithmic systems and existing patterns of inequality. In relation to housing, for instance, when advertisers target ads based on race and ethnicity, minoritized people are provided fewer options and opportunities to purchase or rent homes [10]. In the employment domain, recommender or ranking systems that match employers and potential candidates may prioritize the resumes of men over other genders [176, 198]. Relatedly, these systems may “codify algorithmic segregation” (p. 704) whereby Black candidates are systematically matched to Black-owned businesses and white candidates are systematically matched to white-owned businesses [214]. In the government or social services domain, screening tools to identify children at-risk for maltreatment can amplify already-existing biases against poor parents [74, 214].

#### 3.2.2 Economic loss

Economic loss is often entwined with opportunity loss, though it relates directly to financial harms [45, 142] co-produced through algorithmic systems, especially as they relate to lived experiences of poverty and economic inequality. This harm reinforces “feedback loops” between existing socioeconomic inequalities and algorithmic systems [66] (p. 14). Researchers recognize economic loss as a form of harm that intersects with racialized, gendered, and globalized inequalities [13]. It may arise through different technologies, including demonetization algorithms that parse content titles, metadata, and text, and it may penalize words with multiple meanings [44, 71], disproportionately impacting queer, trans, and creators of color [71]. Differential pricing algorithms, where people are systematically shown different prices for the same products, also leads to economic loss [46]. These algorithms may be especially sensitive to feedback loops from existing inequities related to education level, income, and race, as these inequalities are likely reflected in the criteria algorithms use to make decisions [22, 145].

#### 3.3 Quality-of-Service Harms: Performance Disparities Based on Identity

Quality-of-service harms encompass disparities in the performance of algorithmic systems that do not provide the same service quality to different groups of people [28]. These harms occur when algorithmic systems disproportionately fail for certain groups of people along social categories of difference such as disability, ethnicity, gender identity, and race. They are a reflection of how system training data are optimized for dominant groups [62]. Prior work has described how quality-of-service harms are especially likely when system inputs rely on biometric data (e.g.,
facial features, skin tone, or voice), such as computer vision [40, 155], natural language processing [95, 112, 153], and speech recognition systems [107, 124]. Quality-of-service harms are often conceptualized as experiences of directly interacting with an algorithmic system that fails based on identity characteristics, resulting in feelings of alienation, increased labor, and service or benefit loss.

### Table 4. Quality-of-Service harms: definition, sub-types, and examples

| Harm Theme                      | Definition                                                                 | Sub-Type of Harm | Example                                                                                           |
|---------------------------------|---------------------------------------------------------------------------|------------------|--------------------------------------------------------------------------------------------------|
| Quality-of-Service harms        | When algorithmic systems disproportionately fail for certain groups of people along the lines of identity | Alienation       | “It [voice technology] needs to change because it doesn’t feel inclusive when I have to change how I speak and who I am, just to talk to technology.” [124] |
| Increased labor                 |                                                                           |                  | “I modify the way I talk to get a clear and concise response. I feel at times, voice recognition isn’t programmed to understand people when they’re not speaking in a certain way.” [124] |
| Service or benefit loss         |                                                                           |                  | “It conveyed the opposite message than what I had originally intended, and cost somebody else a lot (of time).” [124] |

#### 3.3.1 Alienation

Alienation encompasses feelings of frustration, annoyance, disappointment, or anger when interacting with technologies that do not recognize one’s identity characteristics [124]. Research on trans and queer people’s experiences with voice-activated assistants, for instance, describes an awareness of limited representation, noting these technologies “were not designed for trans/or queer people” [163], (p. 8). Similarly, content creators from marginalized communities describe feelings of alienation as they navigate what Duffy and Meisner [71] term algorithmic invisibility, whereby topics important to marginalized communities are rendered invisible by content moderation algorithms.

#### 3.3.2 Increased labor

Increased labor refers to the additional effort required by certain social groups to make systems or products work as well for them as others. Research on automatic speech recognition, for instance, has found substantial disparities in word error rates between Black and white speakers (0.35 and 0.19 respectively) [107]. Similar disparities have been found relative to sociolect [5], gender [5, 190], age [113], and region [5], among others. To correct for these limitations, speakers have to modify their speech to meet system expectations through linguistic accommodation [124].

#### 3.3.3 Service or benefit loss

Service or benefit loss is the degraded or total loss of benefits of using algorithmic systems with inequitable system performance based on identity [124]. Accommodating technology shortcomings limits the potential benefits of technologies. However, when technologies with performance disparities are used in consequential domains — such as in job application videos — degraded service can not only stigmatize users but also lead to other types of harm, such as allocative harms [121].

#### 3.4 Interpersonal Harms: Technological Affordances Adversely Shape Relations

Interpersonal harms capture instances when algorithmic systems adversely shape relations between people and communities. As algorithmic systems mediate interactions between people and
institutions, interpersonal harms do not necessarily emerge from direct interactions between people, as is the more classic understanding of interpersonal relations, but can emerge through power dynamics of technology affordances. Usability can become a vector for harm [92]. Like other sociotechnical harms, existing power asymmetries and patterns of structural inequality constitutionally shape them. They can have an intrapersonal element, through which people feel a diminished sense of self and agency. Prior work describes different types of interpersonal harm, including loss of agency, technology-facilitated violence, diminished health and well-being, and privacy violations (see Table 4).

3.4.1 Loss of Agency/Social Control. Loss of agency or social control occurs when the use [106, 118] or abuse [123] of algorithmic systems reduces autonomy. These harms occur when there is required use of algorithmic technologies to access basic services, such as housing [10, 180], through which participation in algorithmic systems that users have little control over say in its design become required. Another dimension of agency loss is algorithmic profiling [119], through which people are subject to social sorting and discriminatory outcomes [167]. Algorithmic profiling is amplified when there is insufficient ability to contest or remedy the decisions of algorithmic systems [57]. As algorithms increasingly curate the flows of information in digital spaces, Karizat, Delmonaco, Eslami, and Andalibi [101] describe how the presentation of content may lead to “algorithmically informed identity change... including [promotion of] harmful person identities (e.g., interests in white supremacy, disordered eating, etc.)” (p. 20). Similarly, for content creators, desire to maintain visibility or prevent shadow banning, may lead to increased conformity of content [191].

3.4.2 Technology-facilitated violence. Technology-facilitated violence occurs when technological features enable actors to use a system for harassment and violence [2, 16, 38, 70, 92]. Gender violence scholars have uncovered how digital technologies can become conduits for stalking [77, 92], online sexual harassment and assault (e.g., sharing images of sexual coercion and violence, sextortion) [38], and coercive control backed by the threat of violence (e.g., accessing accounts, impersonating a partner, doxxing, sharing sexualized content) [70]. For example, abusers may misuse Wi-Fi enabled devices, including locking out and controlling devices to terrorize and harass users [38, 149], or use technology to generate or share non-consensual sexually explicit images [15, 123]. Beyond gender violence, other facets of technology-facilitated violence, include doxxing [69], trolling [14], cyberstalking [14], cyberbullying [14, 88, 179], monitoring and control [38], and online harassment and intimidation [88, 169, 174, 200], under the broader banner of online toxicity [88, 117]. Technology-facilitated violence leads to co-occurring harms, including feeling of distress, fear, and humiliation [38], while often infringing personal and bodily integrity, dignity, and privacy and inhibiting autonomy and expression [123].

3.4.3 Diminished health and well-being. Diminished health and well-being can arise through purposeful behavioral exploitation [18, 184] or emotional manipulation [177], whereby algorithmic designs exploit user behavior, through safety failures (e.g., collisions) [57], or when algorithmic systems make incorrect health inferences [139]. They can lead to both physical harms [61, 69, 120, 160], emotional harms, such as distress [208], dignity loss [38, 120], and misgendering [106], and reputational harms [132, 160]. Diminished health and well-being may accompany other identified sociotechnical harms – for example, experiences of representational harms, including algorithmic annihilation [8] or the internalization of stereotypes, may spark other emotional or psychological effects, such as “epistemic doubt” [205], which affects overall health. As constructs of well-being are culturally relative [134], health promotion efforts through technological design may “not be relevant, or potentially even harmful, to users living differently to the ways assumed by situated
| Harm Theme              | Definition                                                                                                                                                                                                 | Sub-Type of Harm                  | Example                                                                                                                                                                                                 |
|------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Interpersonal harms    | When technological affordances adversely shape relations between people and communities. May have an intrapersonal element, through which people’s sense of self, and agency are diminished | Loss of agency / Social control   | “[a photo recommender shared a] picture of my deceased mother [and it] just kind of caught me, and I sat there and thought about different things for a little bit. Then I had to get back to work. But I was distracted the whole time.” [115] |
| Technology-facilitated violence |                                                                                                                                                                                                 |                                   | “[she] broke up with [him] due to his controlling behavior. After the break-up, he began to appear where she was...One day, while driving her [car], the air conditioner turned off...After a few failed attempts, she figured the unit was broken...After a call with the [car’s] customer support, she discovered a second person using the [car] app to connect.” [149] |
| Diminished health and well-being |                                                                                                                                                                                                 |                                   | “A group of people decided to start invading the servers and they made a huge campaign on the “aspec” (asexual spectrum) [server]. They were known to have abused and stalked one user and they were trying to shit on the staff everywhere they could on Tumblr, on Discord. One was harassing me via Discord and ... so if they had more personal info about me they would probably use it in really bad ways.” [169] |
| Privacy violations     |                                                                                                                                                                                                 |                                   | “[the loan app] contacted my friends and family through WhatsApp….saying I had taken a loan and hadn’t repaid...Because of this I lost a lot of friends. I even had troubles with relatives. I ended up losing my job. At one point I even tried to commit suicide.” [159] |

Thus, designers must be attentive to forms of distress that fall outside Eurocentric and Western care models [148].
3.4.4 Privacy violation. Privacy violation occurs when technology design leads to diminished privacy, such as enabling the undesirable flow of private information [159], instilling the feeling of being watched or surveilled [160], and the collection of data without explicit and informed consent [100]. These violations have also been framed as “data harms” [130], which encompass the adverse effects of data that “impair, injure, or set back a person, entity, or society’s interests” (n.p.) [160]. Here, privacy violations may reflect more traditional conceptualizations of privacy attacks or security violations [69, 90] and privacy elements beyond what may be protected by regulations or under the traditional purview of a privacy officer [119, 159]. For instance, privacy violence may arise from algorithmic systems making predictive inference beyond what users openly disclose [196] or when data collected and algorithmic inferences made about people in one context is applied to another without the person’s knowledge or consent through big data flows [119], even after those datasets or systems have been deprecated [50, 72]. Even if those inferences are false (e.g., the incorrect assessment of one’s sexuality), people or systems can act on that information in ways that lead to discrimination and harm [208]. Privacy violations may also occur through ubiquitous surveillance, surveillance based on emotional/affective targeting [184], or coercive and exploitative data practices [100].

3.5 Social System / Societal Harms: System Destabilization and Exacerbating Inequalities

Social system or societal harms reflect the adverse macro-level effects of new and reconfigurable algorithmic systems, such as systematizing bias and inequality [74] and accelerating the scale of harm [118]. Social systems are instantiated through recurrent social practices, shaped by existing and intersecting power dynamics. As Dosono and Semaan [68] summarize, “people with marginalized identities—those who are pushed to the boundaries of society based on various intersections of their identity such as race and gender—continue to experience oppression, exclusion, and harassment within sociotechnical systems” (p. 2). Compared to other harm types, social system harms are often indirectly felt and occur downstream; they do not necessarily arise from a single incident or problematic system behavior. Societal harms reflect the “widespread, repetitive or accumulative character” of algorithmic systems in the world [182] (p. 10), which contribute to institutional exclusions [205]. Harm to social systems is thus about how algorithmic systems adversely shape the emergent properties [110] of social systems [144]. Prior research outlines such harms in relation to knowledge systems, culture, political and civic harms, socioeconomic systems, and environmental systems (see Table 6).

3.5.1 Information harms. Knowledge systems can be conceived as localized processes through which social knowledge is produced, circulates, and is destabilized. Janzen, Orr, and Terp [97] use the term information-based harms to capture concerns of misinformation, disinformation, and malinformation. Misinformation refers to the spread of misleading information whether or not there is intention to deceive and disinformation is deliberately false information [133, 186, 194, 206]. Malinformation describes “genuine information that is shared with the intent to harm” [97] (p. 2). Information harms are often accompanied by co-occurring impacts, including physical, psychological or emotional, financial, and reputational harms [3, 193, 207, 213], which scale into broader societal harm. Beyond misinformation, disinformation, and malinformation, knowledge systems may be harmed through “subjugation,” whereby dominant discourses proliferate through algorithmic systems and foreclose alternative ways of knowing [82, 164, 165].

3.5.2 Cultural harms. Cultures are collectively and dynamically produced [96]. Cultural harm has been described as the development or use of algorithmic systems that affects cultural stability and safety, such as “loss of communication means, loss of cultural property, and harm to social values”
Table 6. Social system / societal harms: definition, sub-types, and examples

| Harm Theme                  | Definition                                                                 | Sub-Type of Harm                        | Example                                                                                                                                 |
|-----------------------------|---------------------------------------------------------------------------|-----------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|
| Social system / Societal harms | When the development or use of algorithmic systems leads to adverse societal effects | Information harms                      | “users are increasingly exposed to information assembled and presented algorithmically, and many users lack the literacy to comprehend how algorithms influence what they can and cannot see.” [68] |
| Cultural harms              | “[an image search for ‘thug’ showing predominantly Black men]...It damages all the Black community because if you’re damaging Black men, then you’re hurting Black families.” [61]  |
| Political and civic harms   | “Bots, automated programs, are used to spread computational propaganda. While bots can be used for legitimate functions ... [they] can be used to spam, harass, silence opponents, ‘give the illusion of large-scale consensus’, sway votes, defame critics, and spread disinformation campaigns.” [160] |
| Macro socio-economic harms  | “Harms associated with the labour and material supply chains of AI technologies, beta testing, and commercial exploitation.” [151] |
| Environmental harms         | “The energy cost of training machine learning models...[and] harms from intensive water and fuel usage and server farms, consequent chemical and e-waste.” [151] |

As algorithmic technologies can “foreclose alternative ways of understanding the world and restricting imaginations about possible futures” (p. 162) [164], the nature of their harm can encompass adverse cultural such as systemic erasure [61], eurocentric ideas being exported to Global South [67, 129], harmful cultural beliefs [66], such as normalizing a culture of non-consensual sexual activity [123], or proliferating false ideas about cultural groups [68, 167].

3.5.3 Political and civic harms. Political harms emerge when “people are disenfranchised and deprived of appropriate political power and influence” (p. 162) [164]. These harms focus on the domain of government, and focus on how algorithmic systems govern through individualized nudges or micro-directives [165], that may destabilize governance systems, erode human rights, be used as weapons of war [166], and enact surveillant regimes that disproportionately target and harm people of color [103]. More generally, these harms may erode democracy [87], through election interference or censorship [182]. Moreover, algorithmic systems may exacerbate social inequalities and reduction of civil liberties within legal systems [120, 160], such as unreasonable searches [132], wrongful arrest [52, 52, 107], or court transcription errors [107]. These harms adversely impact how a nation’s institutions or services function [3] and increase societal polarization [182].

3.5.4 Macro socio-economic harms. Algorithmic systems can increase “power imbalances in socio-economic relations” at the societal level [4, 118] (p. 182), including through exacerbating digital divides and entrenching systemic inequalities [96, 204]. The development of algorithmic systems may tap into and foster forms of labor exploitation [67, 129], such as unethical data collection,
worsening worker conditions [25], or lead to technological unemployment [45], such as deskillling or devaluing human labor [151]. For instance, text to image models may undermine creative economies [208]. While big data flows reshape power within socio-economic systems [129, 167], when algorithmic financial systems fail at scale, these can lead to “flash crashes” and other adverse incidents with widespread impacts [118].

3.5.5 Environmental harms. Environmental harms entail ecological harms, such as the depletion or contamination of natural resources [23, 81, 120, 129, 181, 182, 208], and damage to built environments [120]. Ecological harms concern adverse changes to the “ready availability and viability of environmental resources” (p. 738) [126] that may occur throughout the lifecycle of digital technologies [151, 210] from “cradle (mining) to usage (consumption) to grave (waste)” (p. 169) [23]. Similar to other sociotechnical harms, the “benefits and burdens of extractivism are unevenly distributed around the planet” whereby consumption in the economic core are contingent on extraction from the economic periphery [23] (p. 170).

4 DISCUSSION
A taxonomy of harms that incorporates both computational and context-aware harms aids in anticipating harms. Synthesizing findings from computing research on harms can support this kind of “anticipation work.” Through a scoping review and reflexive thematic analysis, we identify five harm categories: representational, allocative harms, quality-of-service, interpersonal harms, and social system harms. Harm is a broad concept. Thus, any taxonomy is limited. Our scoping review process, where the corpus of majority academic and gray literature published in English, presents inherent biases and does not resonate globally. It would be a mistake to consider this taxonomy as a comprehensive list of harms, or to use it as a means to quantify the overall degree of harms a system can pose in our society. It is, however, a tool that can be built upon and extended. Assessing the overall ethics of an algorithmic system using only harm as a framing also likely misses other negative implications of technology (e.g., inconveniences in exercising the right to data portability, the right to be forgotten). Shared language can, however, accelerate the capacity building of practitioners across organizations - which is our objective in presenting these findings. In addition to the taxonomy, we suggest three calls-to-action for practitioner communities to advance more systematic surfacing of potential harms, discussed below.

4.1 Expand practitioners’ focus beyond “user” harms
This taxonomy emphasizes harms occurring at the individual, community, and societal level. It is our hope that the breadth of harms covered in the taxonomy will inspire practitioners to more systematically reflect on adverse impacts of algorithmic systems, as they extend beyond users. This taxonomy is intended to be useful to practitioners working on various types and aspects of algorithmic systems (e.g., computer scientists working on models, product teams developing products and features, ethics and social scientists assessing systems for harms, program managers developing ethical review programs). We therefore do not offer normative guidance on identifying, evaluating, or controlling for harms from these various practitioner standpoints. Rather, this taxonomy can supplement and strengthen existing harms assessment processes and provide a starting point for establishing a shared vocabulary on sociotechnical harms.

4.2 Proactive and reflexive harm anticipation
Encouraging practitioners to reflect on potential harms throughout the product life cycle can help anticipate harms and minimize reactionary harm reduction efforts. Not considering harms until the deployment phases of a system’s life cycle leads to compromises. Prior HCI scholarship emphasizes
the critical role epistemic [51] and contextual [64, 135] values play in shaping the production and
design choices of algorithmic systems. Attention to values unveil the social and cultural relations
of power that underlie algorithmic systems’ deployment and active reshaping of the world [60] —
a critical component of anticipating various harms from algorithmic systems. With more practi-
tioners equipped to identify and reflect on sociotechnical harms, more stakeholders can become
stewards of harm reduction monitoring by managing ethical deployment of algorithmic systems
in proactive manners. In surfacing harms, critical HCI methodologies can be leveraged to illumi-
nate how technologies shape and are shaped by social power dynamics, including feminist [20],
postcolonial [96], and queer [187] design approaches.

4.3 Advancing sociotechnical research on harms
The taxonomy offered here is a starting point for surfacing harms. We expect and hope it will
evolve as research progresses, particularly in terms of user and community-driven research method-
ologies (e.g., [58, 61, 79]). The CHI community is well positioned to strengthen understandings of
harm. As the taxonomy reveals, while there is greater consensus and depth of work in investigat-
ing particular harms, such as representational and allocative harms, there are also gaps where the
full range of possible harms is likely under articulated (e.g., cultural harms and quality-of-service
harms). Moreover, the existing literature reveals a privileging of Western perspectives [129, 151].
To ensure that harm reduction practices and design strategies are culturally relevant, future re-
search should investigate mental models of harm and social benefit with communities traditionally
marginalized from technology development (e.g., [47]).

5 CONCLUSION
Through a scoping review and reflexive thematic analysis of computing research on harms, we
offer a taxonomy of computational and contextual harms as a guide to support practitioners in
addressing a range of adverse impacts informed by algorithmic systems. It is our stance that devel-
oping a richer understanding of sociotechnical harms can create more generative paths towards
harm reduction for all.

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