Overcoming *Failures of Imagination* in AI Infused System Development and Deployment

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Abstract

NeurIPS 2020 requested that research paper submissions include impact statements on “potential nefarious uses and the consequences of failure.” When researching, designing, and implementing systems, a key challenge to anticipating risks, however, is to overcome what [Clarke 1962] called ‘failures of imagination.’ The growing research on bias, fairness, and transparency in computational systems aims to illuminate and mitigate harms, and could thus help inform reflections on possible negative impacts of particular pieces of technical work. The prevalent notion of *computational harms*—narrowly construed as either allocational or representational harms—does not fully capture the open, context dependent, and unobservable nature of harms across the wide range of AI infused systems. The current literature primarily addresses only a small range of examples of harms to motivate algorithmic fixes, overlooking the wider scope of probable harms and the way these harms may affect different *stakeholders*. The *system affordances* and possible usage scenarios may also exacerbate harms in unpredictable ways, as they determine stakeholders’ control (including of non-users) over how they interact with a *system output*. To effectively assist in anticipating and identifying harmful uses, we argue that frameworks of harms must be context-aware and consider a wider range of potential *stakeholders*, *system affordances*, *uses*, and *outputs*, as well as viable proxies for *assessing harms* in the widest sense.

1 Introduction

“To see things as they really are, you must imagine them for what they might be.” [Bell 1993]

There is an increasing number of calls to put processes in place that require researchers, designers, and practitioners to reflect on, anticipate, and communicate possible failures and harmful effects from the technologies and the applications they develop or enable. Some of these calls have been realized through structured documentation and checklists aiming at codifying a range of responsible AI principles [Arnold et al. 2019; Mitchell et al. 2019; Gebru et al. 2018; Sokol and Flach 2020; Stoyanovich and Howel 2019; Madaio et al. 2020; Kiran et al. 2015], and more recently by the NeurIPS conference requirement for research paper submissions to include broader *social impact statements* on “potential nefarious uses and the consequences of failure.”

However, making projections about risks, failures, and harms is by no means trivial. Foreseeing failures and harms that one has not observed before or that occur in new contexts is difficult even when they seem like they should have been predictable in hindsight. The eminent science-fiction author Arthur C. Clarke refers to these lapses as *failures of imagination* [Clarke 1962]. This phenomenon occurs even when the process of identifying risks is guided by extensive, well researched checklists [Madaio et al. 2020; Kiran et al. 2015; Wong et al. 2020]—as they tend to be general and fail to account for differences between technologies, applications, and stakeholders [Kiran et al. 2015], while the norms that shaped their creation often remain hidden [Lucivero et al. 2019]. These may...
even contribute to shaping a ‘limited’ imagination of what sort of harms we consider, when we consider them, how we operationalize and measure them, and what trade-offs we make when attempting to mitigate them. But are there any tools that can help AI practitioners do better? What makes AI systems different from other technologies? What can we learn from the literature on responsible innovation (Stilgoe et al., 2013; Grunwald, 2011), technology assessment (Kiran et al., 2015), critical race theory (Bell, 1995; Benjamin, 2019) or feminist theory (Costanza-Chock, 2018; D'Ignazio and Klein, 2020)?

More often than not existing scholarship on harmful use of technology (Washington and Kuo, 2020; Teddeo and Floridi, 2016; Bijker, 1997) does not capture the complex nature of many AI systems that aim to meet user needs for information, social connection, and entertainment; nor does it address the variety of stakeholders and the way they interact with these systems. Take the example of information retrieval systems that curate, rank, recommend, extract or represent information, among other uses. Retrieval algorithms govern the interaction between systems and humans, determining whose information to show to individual users, and what information to display about individuals (possibly distinct from the user). These interactions might also lead to a wide spectrum of negative overtones or impacts for human stakeholders, ranging from denigration and emotional distress to physical harm and loss of opportunities (Blodgett et al., 2020; Barocas et al., 2017; Kay et al., 2015; Abbasi et al., 2019; Baker and Potts, 2013; Otterbacher et al., 2017).

To understand the effectiveness of the ‘broader impacts’ statement practice introduced by NeurIPS, it is thus useful to examine the critique within the literature on ‘responsible innovation’ where the very possibility of such innovation has been challenged (Blok and Lemmens, 2015; Grinbaum and Groves, 2013). One obstacle is the absence of a consensus on the scope of so-called ‘wicked problems’ and the goal of the innovation process among stakeholders. Another challenge relevant to anticipatory statements on ‘broader impacts’ was captured as a principle by Collingridge (1982): “The social consequences of a technology cannot be predicted early in the life of the technology. [...] This is the dilemma of control. When change is easy, the need for it cannot be foreseen; when the need for change is apparent, change has become expensive, difficult, and time consuming.”

With these difficulties in mind, we underscore the need for a wider discussion, interdisciplinary teams, and tools to assist in anticipating adverse consequences. We conjecture that the failure to anticipate harms is often the result of researchers and practitioners’ own failures of imagination, and ask what can be done to mitigate this. Drawing from a collection of pre-prints of NeurIPS 2020 papers, we discuss how more context-aware frameworks of harms can contribute to a wider imaginative scope. Yet, to serve as an aide for exploration and discovery, we must consider a wide range of 1) stakeholders, system affordances, uses, and outputs, as well as of 2) characteristics and types of harms, and viable proxies for assessing them—going beyond the familiar ‘checklist’ approach.

### 2 Overcoming Failures of Imagination

“Radical assessment can encompass illustration, anecdote, allegory, and imagination, as well as analysis of applicable doctrine and authorities.” – Bell (1995)

The discussions about the safety of technology outcomes, including for existing or potential research applications, are often dominated by how to forecast failures. Clark (1962) describes two ways by which forecasting can fail: failure of nerve and failure of imagination. Failure of nerve prevents us from imagining entirely new possibilities (discoveries, technologies). The current popularity of AI has rendered this first warning of Clark less poignant: a series of notable advances, the excited discourse, and the widespread adoption of AI have accustom both researchers and users of technology to thinking about virtually every problem as amenable to some sort of AI solution.

The second ‘hazard of forecasting’—the failure of imagination—refers to insufficient, impoverished visions of the future that do not adequately capture the complexity of the upcoming reality. While ‘failures of nerve’ might arguably be of less concern, fast and short research-to-application pipelines and extensive scope of AI impact have made the failures of imagination more material. At the same time, there is a movement to bring harm minimization closer to the stage of technology design.

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1 *Wicked problems* are characterized by having no definitive formulation, while their solutions are not true-or-false, but *better or worse* to some. Mitigating biases or unfairness in AI systems is an example of a ‘wicked problem,’ in contrast to more tangible challenges like gaming algorithms for personal gain.
### Table 1: Example themes present in broader impact statements from NeurIPS’20 papers.

- **Themes**
  - Neglecting stakeholders (typically minority groups), by assuming
    - ‘benefits’ to mean benefits to companies, governments, etc.
    - ‘harm’ to mean impediments to technology deployment and adoption
    - ‘bad intentions’ to be of users and not of technology developers
    - ‘harm’ only in relation to war, government, or ‘mass disaster’
    - or using terms like ‘reliable’, ‘secure’ without specifying for who
  - Outsourcing the ethical responsibility to others or other stages of technology deployment by ignoring theoretical or technical affordances for misuse and instead referencing biased inputs, engineering mistakes or malicious uses
  - Confusing technical advances with positive impact, by
    - assuming adoption of technical solutions to constitute a benefit
    - failing to question assumptions behind performance metrics
    - treating impact statement as a ‘sales pitch’
  - Suggesting the research topic bounds the scope of inquiry (e.g., fairness papers failing to acknowledge limitations or possible unintended negative effects, theory papers suggesting they are exempt from reflections on impact)
  - Emphasizing the net impact of the paper, (e.g. defending, de-emphasizing, or ‘balancing’ harms with unrelated benefits)
  - Overconfidence and not acknowledging epistemic uncertainty (e.g. ascertaining no harm).
  - Examples of encouraging leitmotifs
    - Considering a variety of stakeholders, including by situating harms on micro and macro levels (environmental, economic, individual)
    - Admitting uncertainty by stating epistemic limitations to envisioning possible impacts
    - Promoting involvement of and collaboration with domain experts
  - Deliberating even about the risks of mitigation strategies by
    - examining known fairness or accountability issues (e.g., whether better interpretability can lead to harm by advancing stereotypes)
    - examining weaknesses of technological improvements
  - Giving examples (tasks, failure scenarios, situations of harm)

- **Example quotes**
  - “our work can bring both beneficial and harmful impacts and it really depends on the motivation of the users” and “[the work is] academic in nature, and does not pose foreseeable risks regarding defense, security, and other sensitive fields.” (Aksan et al., 2020)
  - “there exist risks that some engineers can deliberately use the algorithm [to] harm the performance of the designed system.” (Hu et al., 2020)
  - “[this work] is theoretical and conceptual in nature and so is its likely current broader impact.” ([Valard et al., 2020], “[the] study is crucial as it indicates the vulnerability of [DNN] classifiers to adversarial attacks.” (Delatava and et al., 2020)
  - “the positive impact of foundational research on public datasets, such as is presented in this paper, far outweighs [risks] lying further downstream.” (Asano et al., 2020)
  - “If the method fails in some extreme circumstances, it will confuse researchers or engineers [but] it will not bring about any negative ethical or societal consequences.” (Wang et al., 2020)

- **Examples of concerning trends**
  - Examine pre-prints of NeurIPS’20 accepted papers
    - With the duty of imagining the consequences of technology being placed on the researchers and developers themselves.
    - Understood current practices. To understand how the ‘broader impacts’ call was construed, we examined pre-prints of NeurIPS’20 accepted papers with Table 1 overviewing emerging themes.

  - Broadly, we observe that even acknowledging uncertainty in imagining adverse consequences of technology can itself be a pitfall. Authors commonly assess impact only through the narrow lens of specific technical contributions. For example, authors might position work on preventing adversarial attacks as innately positive and fail to deliberate about limitations and unintended harms. Another concerning theme is overlooking the harms and interests of certain (often disadvantaged) stakeholders. This is often the result of only considering ‘benefits’ to those developing and deploying the technology and ‘harm’ as synonymous with harm to a company, or some type of mass disaster. The severity and importance of harms to individuals is also often ignored.

  - Context-aware frameworks of harm. Avoiding a broader range of harms is difficult as they might require different optimization and design goals, with some types of harm also being harder to operationalize than others. A framework for systematically reasoning about harms could, however, assist practitioners in probing them across applications and usage scenarios. Drawing from the literature on risk perception, computational fairness, and psychology of decision making, we briefly highlight contextual idiosyncrasies with respect to stakeholders, usage affordances, and system response that may affect the (perceived) salience, severity, and attribution of harms.

  - The stakeholders. Those at risk of being affected are central to understanding potential harms. Their traits and circumstances can help delineate various types of harms. Affected stakeholders might be neither users of a system under examination (e.g., recruiters on LinkedIn) nor those developing it, but also subjects being rated or ranked by a system (e.g., an academic ranked on Rate My Professors) or content producers (e.g., musicians on Spotify). Stakeholders vulnerability (propensity to be affected)

We surveyed 35 papers that were available on arXiv.org before the NBI AIR workshop submission deadline.
and agency (degree of control over a system behavior and their interaction with it) may mediate the salience and severity of harm. In addition, demographic cues can also activate stereotypical beliefs and affect the imagination of what harms are possible.

System affordances. The idiosyncrasies of a system (e.g., search engine versus specialized prediction software) and of particular usage scenarios can also provide cues about the range of possible harms. The mechanisms through which stakeholders interact with a system may determine what harms are more likely and who might be affected. For instance, while restricted access to some critical service for some stakeholders (Abbasi et al., 2019) affects them directly, the exposure or representation of stakeholders (Biega et al., 2018; Singh and Joachims, 2018) may also affect those creating or consuming the content.

System use and response. It is critical to consider under what circumstances harm might occur or could be actualized, such as what may be affected (e.g., well-being, opportunities, dignity), how it may happen (e.g., immediately, frequently, by altering beliefs or by taking an action), and why it may happen (e.g., due to a process or an outcome). Problematic system behavior and outputs may lead to harms if there is any threat of unjust resource allocation or of opportunity loss; of unfair representation of someone in the system output, such as reinforcing stereotypes about a group (Abbasi et al., 2019; Crawford, 2017); or to stakeholders’ agency or autonomy (e.g., nudged towards certain actions or beliefs); and their physical or emotional well-being (e.g., trauma, anxiety).

3 Towards Responsible AI Innovation

While the introduction of impact statements to NeurIPS is an important step towards establishing the evaluation of harm as a research practice, some emerging patterns necessitate further analysis. By broadly outlining challenges to deliberating about harms as part of impact statements and describing who is affected and how they are affected, we ask what can be done to address possible failures of imagination. Rather than suggesting a definitive approach, we hope to draw attention to the need for context-aware frameworks that can help anticipate harmful outcomes of AI systems.

Stilgoe et al. (2013) highlight four dimensions of responsible innovation: anticipation, reflexivity, inclusion, and responsiveness. We suggest probing the limits of harm anticipation by thinking systematically about sociotechnical affordances, use context, and the conflicting interests of various stakeholders. Reflexivity means questioning one’s own assumptions about e.g., the neutrality or the benefits of technology adoption (a persistent assumption among NeurIPS authors). Beyond hypothesizing about stakeholders, true inclusion cannot be achieved if the intended beneficiaries are not part of the conversation. Soliciting input from those that may be affected by the applications of research work is thus critical. A natural follow-up to admitting the limits of one’s knowledge is to also engage with domain experts (e.g., social scientists, social workers) over time, including both during the envisioning (model design) and the response (mitigation) stages. These dimensions particularly challenge two concerning trends present in the broader impact statements (Table II):

Challenging the technological benevolence frame. Construing ethics as strictly the responsibility of practitioners and users (and not that of researchers) is a notable theme in NeurIPS’20 submissions. Changing research norms can however impact practice in the industry and beyond. The ‘broader impact’ statements we examined suggest that the research community presumes the neutrality of general-purpose algorithms. However, base models and architectures may be originally developed with particular applications and stakeholders in mind, which may result in performance disparities. There are also implications of whether the process by which designers are considering potential harms is prescriptive (i.e., ‘allow lists’) or restrictive (i.e., ‘block lists’). Reflecting on the implicit assumptions of each approach is a necessary step towards probing the limits of one’s concept of harm.

Reflecting on who is vulnerable. Some NeurIPS’20 authors also appear to overlook the most vulnerable stakeholders in their deliberations of broader impacts. The notions of vulnerability and harm are defined in relation to specific stakeholders and are inseparable from the sociotechnical context (Bijker, 1997). This is why a better understanding of human perceptions of harm and what impacts these perceptions is necessary to identify and categorize problematic practices, as well as to obtain insights into users’ choices around how and when to use certain systems (Skirpan et al., 2018). It can also assist in determining whether and when such harms are foreseeable and by whom.
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