# Disciplining deliberation: a sociotechnical perspective on machine learning trade-offs

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This paper focuses on two highly publicized formal trade-offs in the field of responsible artificial intelligence (AI)—between predictive accuracy and fairness and between predictive accuracy and interpretability. These formal trade-offs are often taken by researchers, practitioners, and policy-makers to directly imply corresponding tensions between underlying values. Thus interpreted, the trade-offs have formed a core focus of normative engagement in AI governance, accompanied by a particular division of labor along disciplinary lines. This paper argues against this prevalent interpretation by drawing attention to three sets of considerations that are critical for bridging the gap between these formal trade-offs and their practical impacts on relevant values. I show how neglecting these considerations can distort our normative deliberations, and result in costly and misaligned interventions and justifications. Taken together, these considerations form a sociotechnical framework that could guide those involved in AI governance to assess how, in many cases, we can and should have higher aspirations than the prevalent interpretation of the trade-offs would suggest. I end by drawing out the normative opportunities and challenges that emerge out of these considerations, and highlighting the imperative of interdisciplinary collaboration in fostering responsible AI.

# **1** INTRODUCTION

Our aims and values are diverse and many. So, unsurprisingly, in many cases we can't have them all, as interventions that realize some will sacrifice others. In contending with this reality, we thus regularly face difficult questions about value trade-offs. Formal analyses of decision scenarios can offer valuable assistance in our deliberations about these questions. These analyses can provide decision-makers with a precise perspective for identifying when their values (suitably operationalized) come into conflict, and assessing different ways of navigating those tensions. When used appropriately, incorporating these formal perspectives into practical reasoning promises to bring discipline and rigor to our deliberations. This paper focuses on two highly publicized formal trade-offs in the field of responsible artificial intelligence (AI)—between *predictive accuracy* and *fairness* and between *predictive accuracy* and *interpretability*. Ideally, the adoption of AI tools in social decision-making should enhance decision quality in a way that promotes societal values such as reliability, fairness, transparency, trust, and safety. As the two trade-offs purport to show, however, it may be inherently impossible for AI models to simultaneously promote formal operationalizations of all these relevant values in the general case. Ensuring fairness (in some statistical sense) might necessitate relinquishing the opportunity of deploying more predictively accurate models (Corbett-Davies et al. 2017; Kleinberg 2018). Similarly, the most accurate models might be "blackboxes" that lack interpretability (in some sense), whose deployment can threaten values that interpretability is said to support, such as trust, safety, or procedural fairness (Molnar 2022; Murdoch et al. 2019).

As policymakers seek to better understand value tensions that can emerge in responsible AI governance,<sup>1</sup> these formal trade-offs have become a core locus of normative and policy engagement (Babic et al. 2021; Fazelpour and Danks 2021; Fleisher 2022; Johnson 2021; Kearns and Roth 2019; Loi and Christen 2021; London 2019; Rudin 2019; Tabassi 2023). But, questions remain as to how we should interpret the value implications of these trade-offs. As I explain in Section 2, at a high level of abstraction, both trade-offs can be seen as potential upshots of learning AI models under constraints that encode desiderata other than maximizing predictive accuracy. While relevant to our practical reasoning, there is a gap between these model properties and the impacts of adopting those models on the relevant values. How should we understand the relation between these formal trade-offs, on the one hand, and the interrelation between underlying societal values, on the other?

A prevalent attitude towards this question is to reason as if there is a *direct correspondence* here. In normative literature, this attitude often involves a two-fold process: first, assuming that, given the formal trade-offs, there also exists a tension between corresponding values; second, offering justifications or mechanisms for some way of resolving the value tension, and assuming that it has direct implications for choosing models that

<sup>&</sup>lt;sup>1</sup>See for example the National Institute of Standard and Technology's influential AI risk management framework, and the roadmap for its development, including "Guidance on the tradeoffs and relationships that may exist among trustworthiness characteristics": https://www.nist.gov/itl/ai-risk-management-framework/ roadmap-nist-artificial-intelligence-risk-management-framework-ai.

(supposedly) prioritize the relevant values. Babic et al. (2021), for example, suggest that while in some healthcare scenarios (e.g., diagnosis) accuracy may take precedence, in other cases (e.g., allocating scarce resources) transparency—seen as a means to procedural fairness—should take priority. Taking this to have direct implications for model selection, they note that "in such contexts, even if interpretable AI/ML is less accurate, we may prefer to trade off some accuracy, the price we pay for procedural fairness" (Babic et al. 2021, p. 286). A similar approach pervades other discussions of the trade-offs (Loi and Christen 2021; London 2019; Rahwan 2018). In the reverse direction, many technical works seek to provide a set of suitable models, each exhibiting a different way of striking the trade-off (Kearns and Roth 2019; Molnar 2022), from which stakeholders can choose based on their values and priorities. In this way, this prevalent attitude also involves a convenient division of labor, across disciplinary lines.

In this paper, I argue against this attitude. As emphasized by an emerging body of work, understanding the social impacts of AI requires adopting a *sociotechnical perspective* that encompasses not only the properties of AI models in isolation, but also those of the technological, psychological, and social processes that critically shape the design, development, and deployment of those models (Selbst et al. 2019; Suresh and Guttag 2019). In Section 3, I will show how adopting this sociotechnical perspective complicates the translation of formal model trade-offs into interrelations between values. Specifically, I integrate and thematize different strands of emerging research into three sets of considerations that are critical for interpreting the practical significance of the model-level trade-offs: considerations of *validity and instrumental relevance* (Section 3.1), *compositionality* (Section 3.2), and *dynamics* (Section 3.3).

Taken together, these considerations form a sociotechnical framework that could be adopted by those involved in the evaluation, design, and governance of AI-based decision systems. I draw out these broader epistemic, ethical, and policy implications in Section 4. To be sure, attending to these issues does not obviate the need for navigating various value tensions. In fact, as I also discuss in Section 4, doing so brings into focus new trade-offs and tensions. Nor does it mean that existing normative discussions about these two formal trade-offs are not highly valuable. What these considerations demonstrate is that the relation between formal model-level properties (e.g., model-level predictive loss) and the corresponding values (e.g., decisional accuracy) is not a straightforward one, and involves many assumptions. Importantly, closely examining these assumptions reveals that sometimes sacrificing one formal property for another at the model level can improve *both* values at the practical level. That is, in many cases, we *can* and *should* have higher aspirations than the direct correspondence interpretation would suggest. Importantly, however, taking advantage of these possibilities requires that we broaden the scope of normative engagement with AI technologies and better appreciate the critical importance of interdisciplinary collaboration in fostering responsible AI.

# 2 TRADE-OFFS IN AI-BASED DECISION-MAKING

This section provides the intuition behind the accuracy-fairness and accuracy-interpretability trade-offs and motivates the need for scrutinizing their interpretation in research and policy discussions. It is worth noting that discussions of both trade-offs predate recent AI and ML applications. The accuracy-fairness trade-off, for example, has been discussed in economics (Young 1994) and education (Willingham and Cole 2013). And the accuracy-interpretability trade-off has been discussed by statisticians (Plate 1999).

#### 2.1 Prediction-based decision-making

Let us ground the discussion using a typical binary classification task, where we hope to learn the relation between a set of input features X and a target label Y, with supports X and  $\mathcal{Y} = \{0, 1\}$ , respectively. With this relation in hand, given a feature vector  $x \in X$ , we can then infer the corresponding label  $y \in \{0, 1\}$ , and use this prediction to inform or drive a relevant decision. In the context of informing content moderation decisions, for example, X and Y might correspond to information about social media posts including their metadata and a label indicating whether they contain offensive language, respectively. Supervised learning algorithms help us do this by providing a mapping from datasets of past observations to predictive models (or hypotheses) that can be used to make inferences about new cases. That is, given a dataset of labeled examples, such algorithms output a predictive model  $h : X \to \{0, 1\}$ , from a set of possible predictive models  $\mathcal{H}$ . Typically, these algorithms are designed to find a model  $h^* \in \mathcal{H}$  that optimizes predictive performance according to some evaluation function, such as minimizing a loss function like empirical risk  $\hat{\mathcal{L}}$ :

$$h^* = \operatorname{argmin}_{4}_{h \in \mathcal{H}} \hat{\mathcal{L}}(h)$$

In practice, there is often a multiplicity of models that perform comparably with respect to this optimization objective (Coston et al. 2021; D'Amour 2021; Marx et al. 2020). Let us refer to these as *the set of accurate models*,  $\mathcal{H}_A$ , which, at their worst, only exhibit  $\epsilon$  more loss than our best predictive case  $\hat{\mathcal{L}}(h^*)^2$ :

$$\mathcal{H}_A := \{h \in \mathcal{H} : \hat{\mathcal{L}}(h) \le \hat{\mathcal{L}}(h^*) + \epsilon\}$$

With this notations in hand, we can get an intuition about the trade-offs by considering the act of *enforcing* fairness or interpretability as an intervention that imposes a non-trivial constraint on the set of available predictive models, and in doing so potentially *restricts* our access to only a subset of eligible models in  $\mathcal{H}$  that may not intersect with  $\mathcal{H}_A$  (see Figure 1a).

Of course, there can also be models that do satisfy these additional formal constraints, without thereby suffering in predictive accuracy. This is because, despite exhibiting similar predictive performance, the solutions in the set of accurate models,  $\mathcal{H}_A$ , can have significantly different characteristics when it comes to fairness (Coston et al. 2021; De-Arteaga et al. 2022) and interpretability (D'Amour et al. 2020a; Semenova et al. 2019), formally construed. Accordingly, it would be a mistake to assume *a priori* that there will *in fact* be a cost to enforcing fairness- or interpretability-motivated constraints (See also Rodolfa et al. 2021; Rudin 2019). An exciting avenue of current research is build on existing transparency documentation tools, such as model cards (Mitchell et al. 2019), to better inform regulators and auditors about the potential normative significance of the models within the set of accurate models (See Black et al. 2022; Coston et al. 2021). That said, let us examine in more detail how demands for fairness and interpretability have been formulated as enforcing constraints on learning.

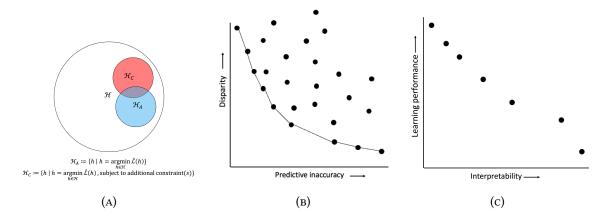


FIG. 1. Figure (a) represents a characterization of the two trade-offs in terms of a possible relation in the hypothesis space  $\mathcal{H}$  between the set of accurate models  $\mathcal{H}_A$  and the set of models that satisfy a fairness constraint  $\mathcal{H}_F$ . The figure is inspired by Figure 1 in Dziugaite et al. (2020). (b) This figure, adapted from Kearns and Roth (2019), offers a toy illustration of the accuracy-fairness Pareto frontier, while Figure (c), adapted from Gunning et al. (2019) (itself adapted from DARPA XAI presentation) offers a widely shared illustration of the accuracy-interpretability trade-off.

### 2.2 Fairness as a constraint

The concern about accuracy-fairness trade-off most naturally arises when we focus on the properties of predictive models (Corbett-Davies et al. 2017; Kearns and Roth 2019). Even given this relatively restrictive lens, there is considerable debate about the appropriate formalization of fairness in terms of model properties (Barocas et al. 2019; Chouldechova 2017; Corbett-Davies et al. 2017). We can largely sidestep these disagreements, however, because in practice many proposed fairness measures can be formulated as non-trivial parity constraints on the joint distribution  $p(X, Y, \hat{Y}, A)$ , where A denotes membership in a protected group and  $\hat{Y} = h(X)$  denotes model predictions (Barocas et al. 2019; Fazelpour and Lipton 2020). For example, according to some, fairness might demand that the chosen predictive model exhibit equal sensitivity across different demographic groups (i.e.,  $p(\hat{Y} = 1 | Y = 1, A = a) = p(\hat{Y} = 1 | Y = 1, A = a')$ ) (Hardt et al. 2016).

<sup>&</sup>lt;sup>2</sup>This formulation is helpful because it leaves it open how many solutions there exists to the optimization problem, which can be more than one even when  $\epsilon = 0$ . As Marx et al. (2020) note, the choice of small  $\epsilon$  can be perfectly justifiable, as small differences in training error, of the sort captured by the empirical risk function  $\hat{\mathcal{L}}(h)$ , does not necessarily correlate with significant performance differences in deployment (See also D'Amour et al. 2020a).

Achieving "fairness", from this perspective, requires enforcing the relevant parity constraint(s) (Corbett-Davies et al. 2017). This might be done, for example, by adding fairness considerations as constraints in optimization (e.g., Zafar et al. 2017), or as penalty terms incorporated in the optimization objective (e.g., Kamishima et al. 2011). Roughly speaking, many of these algorithmic manipulations have the effect of restricting the choice of predictive models to a *subset* of possible predictive models that satisfy the relevant parity constraint(s)  $\mathcal{H}_F \subseteq \mathcal{H}$ . This act of constraining model choice might come with a predictive cost, however, insofar as the best predictive models in this restricted space of "fair" models  $\mathcal{H}_F$ , at best, only equal the predictive performance of the models from the broader hypothesis class  $\mathcal{H}$ . That is,

Since 
$$\mathcal{H}_F \subseteq \mathcal{H}$$
, then  $\min_{h \in \mathcal{H}_F} \hat{\mathcal{L}}(h) \ge \min_{h \in \mathcal{H}} \hat{\mathcal{L}}(h)$ 

Put in terms of the set of accurate models, there might be a predictive "cost" to enforcing fairness-related parity constraints in that  $\mathcal{H}_F$  may not include any of the accurate models:  $\mathcal{H}_A \cap \mathcal{H}_F = \emptyset$ . In such cases, enforcing those constraints will result in drops in accuracy.

#### 2.3 Interpretability as a constraint

While widely discussed in research and policy literature, the trade-off between accuracy and model interpretability (transparency, explainability, or other cognates) is more circuitous with respect to its technical underpinnings as well as the potential value tensions it supposedly signifies. The trade-off is less straightforward in terms of value tensions because "interpretability" is typically not sought as an end in itself. Rather, its value is often tied to a varied set of goals, such as increased understanding, enhancing user trust and decision support quality, improving deployment performance and safety, fostering autonomy and procedural fairness, and ensuring public accountability (Creel 2020; Fleisher 2022; Jobin et al. 2019; Krishnan 2020; Lipton 2018; Murdoch et al. 2019; Vredenburgh 2021).

Even when we assume model interpretability (in some sense) is the requisite means for achieving (some of) those aims, there are substantial disagreements about what precise properties would render a model "interpretable" in the relevant sense (Krishnan 2020; Lipton 2018). Once more, though, we can sidestep these more specific disagreements by

broadly characterizing "interpretability" as a non-trivial constraint, whose enforcement will restrict one's search (or learning) to a *subset* of predictive models  $\mathcal{H}_I \subseteq \mathcal{H}$  judged to satisfy that constraint (Dziugaite et al. 2020). This broad characterization captures various attempts to interpret "interpretability" in terms of some well-defined technical notion (low model complexity, variable decomposability, ...), without committing to one operationalization, which might be contested. It also captures some of the so-called posthoc explainability methods that seek to render blackbox models interpretable, insofar as those methods may depend on restrictions to  $\mathcal{H}$ , whether by being model-specific by design or by depending on certain properties of target models for their proper functioning in practice (Murdoch et al. 2019). Given this characterization, the accuracy-interpretability trade-off can again be seen as an upshot of enforcing a non-trivial constraint on learning namely, "interpretability", whatever it might imply. Thus viewed, enforcing interpretability can result in a loss in predictive accuracy, when  $\mathcal{H}_A \cap \mathcal{H}_I = \emptyset$ . In such cases, one could quantify (in context) the "price" of interpretability in terms of the incurred loss of predictive accuracy (Bertsimas et al. 2019).

To capture this framing, in what follows we adopt a general understanding of the accuracy-interpretability trade-off that nonetheless tends to be operative in technical, philosophical and policy discussions: cases where we might need to sacrifice predictive accuracy to make gains in understanding of model behavior (broadly construed), in order to promote one of the aims for which interpretability, explainability, or transparency is taken to be a means (see, e.g., Fleisher 2022; Miller 2019).

### 2.4 Direct correspondence and a convenient division of labor

How should we understand the relation between the formal properties (and trade-offs) of AI models and the (potentially varied) impacts of deploying those models on corresponding values? As mentioned above, a prevalent interpretation of the trade-offs is to proceed as if there is a direct correspondence between these two. Importantly, this prevalent interpretation suggests a straightforward division of labor between technical and normative efforts.

On the technical side, for example, Kearns and Roth (2019) see the role of formal tools as providing guidance for normative deliberation by mapping the accuracy-"fairness"<sup>3</sup> Pareto frontier—consisting of the set of models that cannot be improved in terms of one of these formal measures without incurring a loss on the other (see Figure 1b). Within this framing, normative deliberation has its place in choosing a specific model, depending on the contextually relevant values and priorities. Similarly, other works aim to provide guidance about how decision-makers, once they have decided that some sacrifice in predictive accuracy is justified, might go about choosing an appropriate "interpretable" model (e.g., Molnar 2022) (see also Figure 1c). Conversely, many philosophical and policy discussions simply take it for granted that the formal trade-offs imply the existence of tensions between underlying *values*. And, they see their task as providing means of resolving those tensions, perhaps by offering justifications for when, why, or to what extent some value should be prioritized (Babic et al. 2019; Loi and Christen 2021; London 2019), or by proposing participatory mechanisms for making such determinations (Lee et al. 2019; Rahwan 2018).

We now turn to the different considerations that complicate this picture, discussing the broader implications of this change of perspective for this understanding of the division of labor in Section 4.

# **3 A SOCIOTECHNICAL PERSPECTIVE ON INTERPRETING THE TRADE-OFFS**

Useful as it might be for motivating the discussion of the formal trade-offs, the characterization of AI-based decision-making in the previous section involves significant, and potentially problematic simplifications. Specifically, researchers have argued against framing the value implications of AI models solely in terms of model properties, in isolation from their context of development and use (Fazelpour and Lipton 2020; Herington 2020; Raji et al. 2022; Selbst et al. 2019; Suresh and Guttag 2019). Instead, there have been calls for adopting a sociotechnical perspective that encompasses not only the properties of AI models, but also other technical, psychological, organizational, and social factors that shape the life-cycle of AI-based decision systems, and ultimately their societal impacts. In this section, I approach the trade-offs from this perspective, discussing three sets of

<sup>&</sup>lt;sup>3</sup>Or more accurately, fairness-motivated statistical parity

considerations that are required for bridging the gap between the formal, model-level trade-offs described above and their practical value impacts. As we will see, in each case, attending to these considerations reveals that we *can* have things better than the formal trade-offs might have us expect.

#### 3.1 Validity and relevance

Trade-offs between two formal constructs (e.g., some measure of accuracy and fairness) have the purported normative implications, only if those constructs aptly track our values. But this assumption can fail, when invalid operationalization, measurement, and estimation procedures and practices result in disconnects between formal constructs and the epistemic, ethical, or legal aims and values that those constructs are supposed to capture.

Consider first the notion of "predictive accuracy", which is implicated in both trade-offs. In many prediction-based decision settings, institutions care about inferring outcomes that are ambiguous, latent, and contested, such as being a patient with "severe healthcare needs" (Obermeyer et al. 2019), a child "at risk" (Saxena et al. 2020), or a tweet containing "hate speech" (Waseem 2016). Let us refer to this outcome that we practically care about as  $Y_c$ . Rendering  $Y_c$  suitable for machine learning application often requires selecting a simplified and unambiguously measurable proxy outcome, Y. This is not a trivial task, and often involves various value judgments. In practice, Y might not be a valid proxy for  $Y_c$  for a variety of reasons, ranging from lack of construct validity in operationalization to challenges of bias and validity in measurement, estimation, and aggregation (De-Arteaga et al. 2018; Fazelpour and Danks 2021; Jacobs and Wallach 2021; Kleinberg et al. 2018a).

Importantly, for our purposes, the accuracy-fairness trade-off can arise when the extent of the disconnect between Y and  $Y_c$  is not evenly distributed across the population of interest (De-Arteaga et al. 2022).<sup>4</sup> That is, when Y exhibits differential validity across groups, optimizing for predictive accuracy can undermine some fairness-motivated parity constraints (and vice versa). In a salient example of such differential validity in healthcare, the disconnect between a patient's "healthcare need" and its operationalization in terms

<sup>&</sup>lt;sup>4</sup>Intuitively, this can be thought of as potentially resulting in a statistical dependence between Y and some protected attribute A not because one exists in reality, but as a result of differential validity in our categorization and data collection practices.

of "healthcare expenditure" particularly harmed Black patients, for whom expenditure was particularly an unreliable proxy due to a variety of factors including justice-related ones (Obermeyer et al. 2019). Similar issues arise when our measurement, estimation, and aggregation techniques exhibit differential validity across protected groups (Coston et al. 2023; Jacobs and Wallach 2021).<sup>5</sup>

In such cases, it would be a serious error to take the accuracy-fairness trade-off as an inescapable fact and to focus our deliberative efforts simply on selecting among the set of Pareto optimal solutions. Instead, we need to address the underlying issue of differential validity by adopting better sociotechnical practices in problem formulation, operationalization, and data collection (Hellman 2020; Kleinberg et al. 2018b; Obermeyer et al. 2019). Taking the trade-off at face value not only obscures the underlying epistemicethical problems; doing so also prevents us from recognizing that we *can* have things better than the formal trade-offs lead us to think.

Similar validity concerns arise for formal notions of "interpretability". Currently, there exists a considerable disconnect between the underlying values for which "interpretability" is sought (e.g., trust, improved decision quality, safety, recourse, …) and the technical operationalizations of the term (e.g., in terms of model complexity, variable decomposability, model type, …) (Krishnan 2020; Lipton 2018). Indeed, in some cases, formal operationalizations appear to undermine the very values they are meant to support, such as when individuals lose their trust in algorithmic predictions upon seeing that they originated from a simple decision tree, whose lack of complexity was meant to invite user trust (Lu et al. 2019). When a measure of "interpretability" lacks validity in this sense, it is unclear why we would want it, especially if attaining it comes at a cost to predictive accuracy. What is more, even if interpretability (in some sense) is *a* means to those underlying values, it may not be the only, or even the most effective, means in context. In healthcare settings, for example, London (2019) proposes a number of alternative, potentially less costly pathways for achieving some of the aims for which interpretability is sought (see also Krishnan 2020).

This is, of course, not to say that interpretability—in the broader sense defined in Section 2.3 and suitably specified—is not critical for supporting key epistemic, social, and

<sup>&</sup>lt;sup>5</sup>For example, if our data collection and aggregation practices make it more likely that tweets from certain marginalized groups are more likely to be labeled as "toxic speech" (Davani et al. 2022).

ethical values in many settings, as will be discussed below (See also Creel 2020; Murdoch et al. 2019; Vredenburgh 2021). But the *practical* implications of a potential accuracyinterpretability trade-off is dubious, if the formalization of interpretability lacks validity or when there exist other sociotechnical interventions that can better promote the values that animate concerns about interpretability without imposing a cost on predictive accuracy. Closely inspecting the validity and instrumental relevance of the formal constructs can uncover normatively significant disconnects and alternatives. In many cases, addressing these underlying issues can enable us to robustly promote both sets of relevant values in ways that remain outside the purview of the narrow formal characterization of the trade-offs.

### 3.2 Compositionality

In many cases of social concern, algorithmic tools are not stand-alone decision-makers, but function as part of broader decision-making systems. Examples include healthcare (Kompa et al. 2021), child welfare services (De-Arteaga et al. 2020), loan approvals (Paravisini and Schoar 2013), and fact-checking (Guo et al. 2022), where algorithms assist (rather than replace) human experts. In such cases, the focus should shift from the AI model's isolated performance to how its integration can improve the overall decision quality, especially compared to the status quo of unaided human experts (See Green and Chen 2019). It thus become crucial to examine how properties of AI models (accuracy, fairness, interpretability, or their respective trade-offs) contribute to the broader decision-making systems those AI models are integrated in.

Works in sociology, organizational science, and philosophy demonstrate that the epistemic norms and properties of groups cannot necessarily be inferred from those of their individual members (Mayo-Wilson et al. 2011; O'Connor and Weatherall 2019). The concept of *complementarity* in teaming and collective intelligence illustrates this divergence (Page 2019; Steel et al. 2018). It suggests that, especially in complex tasks, a group's performance hinges on how its members' cognitive tools (information, background knowledge, decision heuristics, ...) interlink. For instance, one member's unique and different perspective can offer a breakthrough on a problem that hinders another. Conversely, this synergy is lost, if members' strengths and weaknesses are too similar (Bang and Frith 2017). Importantly, selecting individuals with appropriate complementary cognitive capabilities can mean

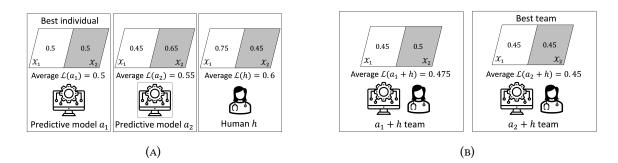


FIG. 2. The importance of complementarity when predictive models function as decision support. (a) represents individual performance of two algorithms  $a_1$  and  $a_2$  and a human expert h on two equally encountered feature regions,  $X_1$  and  $X_2$ , measured by a loss function  $\mathcal{L}(.)$ . Overall,  $a_1$  has the best predictive performance, followed by  $a_2$ . Human h performs worst on the task.Notice, that the mistakes are not similarly distributed across feature regions. (b) represents team performance.  $h + a_2$  is the best team, due to the complementarity in their performance. Notice that the best predictive model  $a_1$  is not the best decision support. It is assumed that a system integrator (possibly h herself) allocates tasks according to each team member's ability on a given feature region.

*not* selecting the "best" performing individuals (according to some measure) (Hong and Page 2004).

The logic of complementarity also applies to cases where AI models function as decision aids. Consider our classification task from 2.1, where the feature space is divided into two equally probable regions  $X_1$  and  $X_2$  (e.g., corresponding to different types of patients in a healthcare setting) (see Figure 2).<sup>6</sup> Evaluating predictive performance as before, we might have:

- i Algorithm  $a_1$  with equal performance in both regions  $\hat{\mathcal{L}}(a_1 \mid X_1) = \hat{\mathcal{L}}(a_1 \mid X_2) = 0.5$ , and so  $\hat{\mathcal{L}}(a_1) = 0.5$  overall;
- ii A less accurate algorithm  $a_2$  with  $\hat{\mathcal{L}}(a_2 \mid X_1) = 0.45$  and  $\hat{\mathcal{L}}(a_2 \mid X_2) = 0.65$ , and so  $\hat{\mathcal{L}}(a_2) = 0.55$  overall;
- iii A human *h*, who is the least accurate overall, with  $\hat{\mathcal{L}}(h \mid X_1) = 0.75$  and  $\hat{\mathcal{L}}(h \mid X_2) = 0.45$ , and so  $\hat{\mathcal{L}}(h) = 0.6$ .

Suppose knowing these, a decision-maker (possibly *h* herself) can allocate tasks to individuals accordingly. Which of  $a_1$  or  $a_2$  should partner *h*? If we simply focused on overall

<sup>&</sup>lt;sup>6</sup>The example is based on Donahue et al. (2022)

performance, it might be tempting to select  $a_1$  due to its superior accuracy.<sup>7</sup> But, the concept of complementarity suggests a different approach. Precisely on account of suitable differences in their predictive capabilities, the human-AI team  $h + a_2$  turns out to be the best overall team with  $\hat{\mathcal{L}}(h + a_2) = 0.45$ , outperforming the  $h + a_1$  team as well as  $a_1$  (Figure 2b). Crucially, then, the most accurate model is not necessarily part of the most accurate human-AI team.

As this example shows, for groups to benefit from complementarity, there needs to be relevant variability in individual performance, stemming from underlying differences in background knowledge, representation, available information, or heuristics. Crucial too are appropriate task allocation (who should do what cases) and effective information integration (whose prediction should weigh how much). Recent works on human-AI collaboration have explored these factors: by characterizing the extent of variability required for complementarity (Donahue et al. 2022) and mechanisms that could give rise to such differences between humans and AI models (Rastogi et al. 2022); by designing optimization objectives to suitably complement human experts (Mozannar and Sontag 2020); by developing optimal task allocation schemes (Madras et al. 2018); and by facilitating effective information integration (Bansal et al. 2019a).<sup>8</sup>

These works underscore that properly evaluating AI model properties and trade-offs depends on understanding their contribution to the qualities of the broader decision-making system. Many of the above techniques can result in reduced model accuracy, but improve accuracy at the system-level. Notably, in some cases, model accuracy is traded for improved understanding. This might be done to help experts construct suitable mental models of the AI behavior (Bansal et al. 2019a) or be better placed to combine AI outputs with their own knowledge (Caruana et al. 2015). More generally, interpretability, as defined in Sec 2.3, can also alleviate experts' distrust of AI models, promoting better

<sup>&</sup>lt;sup>7</sup>In fact, this is currently standard practice where predictive models are primarily optimized for individuallevel properties.

<sup>&</sup>lt;sup>8</sup>Some of this work can also be seen as ways of incorporating other group-level norms. For example, works on tools that ask for second opinions (e.g., Kompa et al. 2021; Raghu et al. 2019) can be seen as computational implementations of *contestability* considerations—proposed by many philosophers as a group-level epistemic norm (e.g., Anderson 2006; Landemore 2020).

informational uptake and integration (Zerilli et al. 2022).<sup>9</sup> Thus, a perceived compromise at the model-level can in fact translate into an advantage at the broader system-level.

The study of "fairness under composition" reveals a similar insight (Dwork and Ilvento 2018; Wang et al. 2021). As Chouldechova and Roth (2020) note "often the composition of multiple fair components will not satisfy any fairness constraint ... [while] the individual components of a fair system may appear to be unfair in isolation" (p. 86). Here too, moving beyond a model-centric view is essential to recognize potential (individual vs. system) divergences and understand how principled model-level losses in a given dimension can result in system-level gains along that same dimension.

Of course, as will be discussed in Section 4, this system-level perspective doesn't mean that "we can have all the good things at once" without facing trade-offs. Rather, the suggestion is that we *can* have higher aspirations compared to what a simple interpretation of the two trade-offs would suggest. When predictive models compose just one *part* of broader decision-making systems, it is a *category mistake* to focus on their properties apart from those of the other parts (e.g., user characteristics and capabilities, organizational norms). In such cases, the simple interpretation of the two trade-offs is not only misguided, it can also distract us from other promising (and challenging) epistemic and ethical considerations.

### 3.3 Deployment dynamics

To responsibly integrate AI models into social decision pipelines, it's essential to understand more than just model properties within a static testing environment. It also requires a grasp of the mechanisms governing the dynamic interactions of AI outputs with their organizational and social embeddings. Understanding these dynamics is key for properly contextualizing model-level trade-offs. What appears as a sacrifice of one desideratum for

<sup>&</sup>lt;sup>9</sup>Some techniques for providing explanations (e.g., local saliency explanations) have been shown to have *detrimental* impact on the quality of AI-informed decisions by increasing experts reliance on (and reducing their vigilance about) AI output, even in cases of incorrect AI predictions (Bansal et al. 2021). But, caution is needed when interpreting such findings. We must distinguish between the values of interpretability and the effectiveness of particular interpretability-seeking techniques in achieving those values; the fact that some techniques can result in misleading explanations does not undermine the value of explanations (Lombrozo 2011) or improved understanding (Grimm 2012) in general. Moreover, even when sometimes unjustified, increased reliance overall on AI can still be a net epistemic good, depending on the status quo of unaided human decision making.

another from a static perspective could be necessary for ensuring sustained gains in the former in the longer term.

Consider first how our thinking about fairness and accuracy can be informed by better understanding social dynamics.<sup>10</sup> Findings from workforce diversity research offer a salient example. These works show that the benefits of increased team diversity-often understood in this literature to be maximal at demographic parity-is not linear, and depends, among other things, on how diverse a team *initially* is (Bear and Woolley 2011; Phillips 2017; Post and Byron 2015). That is, while moving towards demographic parity can have negative effects on team performance in highly homogeneous teams, it can improve performance in groups that are already (to some extent) diverse (Steel et al. 2018). Accordingly, making short-term utility losses for the sake of parity on fairnessrelated grounds can result in robust, long-term utility gains (understood as improved team performance on a variety of tasks). In other cases, making short-term gains in fairness at the cost of accuracy can result in compounding injustices in the longer term (Fazelpour et al. 2021). Take, for example, fairness-related disparities in lending that arise because of conditions affecting the repayment ability of members of certain disadvantaged groups. In such cases, achieving fairness-related parities requires reducing predictive accuracy, resulting in granting loans to individuals who may not be able to repay them. Yet, the resulting disproportionate defaults can widen existing discrepancies (e.g., due to its impacts on other opportunities via damaging credit scores) (D'Amour et al. 2020b; Liu et al. 2018).

Examining these dynamics is also crucial for improved reasoning about longer term predictive accuracy and its relationship with interpretability. Issues around updating AI models offer an apt example here. Updating can improve predictive accuracy by leveraging increased data, especially from post-deployment observations; it is also crucial for addressing dynamic distribution shifts (e.g., due to environmental changes or strategic behavior of decision subjects) that can undermine predictive capabilities (Babic et al. 2019; Zrnic et al. 2021). <sup>11</sup>

But the accuracy of the updated AI model with respect to a static dataset is not the only consideration. We also need to consider the dynamic interactions between the updated

<sup>&</sup>lt;sup>10</sup>For a similar discussion on accuracy-fairness see De-Arteaga et al. (2022) and Fazelpour et al. (2021)

<sup>&</sup>lt;sup>11</sup>Babic et al. (2019) provide a thoughtful discussion of policy and regulatory challenges around these updates.

model and the rest of the decision-making system (Bansal et al. 2019a,b; Srivastava et al. 2020). For example, while enhancing a model's overall accuracy, updates can degrade accuracy in cases where users had come to justifiably rely on the model (Bansal et al. 2019b). These unexpected shifts can hurt the overall human-AI performance, and undermine trust, in ways that negatively affect experts' long-term adoption of AI tools (Dietvorst et al. 2015). Updating that ensures sustained improvements can thus require potential sacrifices of model accuracy for the sake of backward compatibility (Bansal et al. 2019a,b; Srivastava et al. 2020).<sup>12</sup> These sacrifices can be due to interventions that make the models more interpretable (in the sense discussed in Section 2.1), and can result in performance gains at the system level over time.

More generally, AI models are often embedded in complex epistemic practices (Creel 2020; Fleisher 2022). Appreciating the dynamic and evolving nature of these practices should inform our understanding of the relation between accuracy and interpretability. As noted by Rudin (2019), for example, interpretable models that exhibit lower accuracy on a static dataset (compared to a "blackbox" model) may afford better opportunities for understanding and iteratively refining the knowledge discovery process, thus improving accuracy in the longer run (See also Murdoch et al. 2019).

Overall, then, static properties of predictive models do not tell the full story about what we stand to gain or lose by adopting the models in complex, changing environments. What might appear to be an inescapable trade-off from a static perspective may not be one, once we adopt a broader and longer term perspective. Similarly, justifications developed in the abstract about how such trade-offs should be navigated may provide hardly any epistemic or ethical reassurance in complex social systems.

#### 4 **DISCUSSION**

Having discussed each of the considerations separately, let us bring out some of the shared lessons.

<sup>&</sup>lt;sup>12</sup>For example, because some interventions to make updated models backward compatible restrict the space of learning according to some consistency criteria (with past prediction).

#### 4.1 Expanding normative engagement, new opportunities, new challenges

The previous section showed how the direct correspondence interpretation of the formal trade-offs can result in misplaced justifications, and interventions that miss out on better epistemic and ethical possibilities. Importantly, achieving these better possibilities requires that we expand the scope of epistemic and ethical normative engagements to include issues that arise throughout the operationalizations, measurement, and modeling practices that influence the validity of model properties (Section 3.1) as well as the cognitive, organizational, and social factors that shape the situated impacts of AI models in setting (Sections 3.2 and 3.3). And we must do so in an integrated and coherent manner.

For example, in his insightful discussion of the accuracy-interpretability trade-off, London (2019) highlights how, in medical practice, *decisional accuracy* and reliability take precedence over interpretability and mechanistic understanding. Should we thus dismiss the search for interpretable models, when they come at a cost to *model accuracy*? Not insofar as London's discussion does not attend to considerations of compositionality and dynamics that (as discussed in Sections 3.2 and 3.3) are critical in many medical settings where AI models are used as decision supports. Importantly, what these considerations show is that even when, as London argues, decisional accuracy matters more than mechanistic understanding, the best way to improve AI-enabled decision-making in dynamic medical environments may not be choosing the most accurate *model*. Indeed, as argued above, this may require selecting an interpretable, even if less predictively accurate model.

As discussed above, the sociotechnical perspective can bring into view new design and governance opportunities for improving the overall quality of AI-based decisionmaking (e.g., focusing on *team* complementarity, instead of individual performance). This does not mean that we never face those value trade-offs. Indeed, this perspective also reveals difficult questions about *other* value tensions. For example, enhanced participation and contestation can improve group decision-making in a way that can be pertinent to considerations ranging from operationalization and measurement (Lee et al. 2019; Martin Jr et al. 2020) to human-AI teaming (Kompa et al. 2021; Raghu et al. 2019) in the AI lifecycle. But, they can also result in delays and even undermine group cohesion and decision quality (Dobbe et al. 2020; Fazelpour and De-Arteaga 2021). Similarly, when thinking about issues of compositionality, we are likely to face the so-called diversity-stability trade-off familiar from other complex systems, where too much variability—a requirement for complementarity—can destabilize the system and degrade performance (Eliassi-Rad et al. 2020; Page 2019). The crucial point is that these practically relevant debates can remain outside the purview of normative deliberation about AI governance, if attention is instead focused on a formal trade-off that might not have the purported value significance.

# 4.2 The meaning of "AI talent" and the need for interdisciplinarity

As mentioned in Section 2.1, the direct correspondence interpretation is often accompanied by an implicit division of labor between technical and normative efforts. In particular, it suggests that once researchers, stakeholders, or policy-makers decide which of their values should be prioritized in a given context, the rest is technical work. Notably, these judgments about the relevance and priority of values are often made without close engagement with the various choices involved throughout the design, development, and deployment processes of AI. For example, arguments about the priority of accuracy over interpretability are offered by considering the demands of different medical applications, as opposed to how AI models are designed for and embedded into those applications.

This conception of the disciplinary division of labor may also underpin recent governmental orders and directives that aim to promote responsible AI. For example, in its recent efforts to promote responsible AI, the United States government has launched an *AI Talent Surge*.<sup>13</sup> Importantly, however, the notion of the "AI talent" that is meant to help "federal agencies to responsibly leverage AI" is understood exclusively in technical terms in terms of data science and tech talent.<sup>14</sup> But, if the considerations above are on the right track, this is serious misconception.

As discussed above, the prevalent interpretation of the formal trade-offs can mislead our normative deliberation and result in costly disconnects between implementations and justifications that are meant to ground them. A sociotechnical perspective not only offers a safeguard against misinterpreting the trade-offs (and model properties more generally); it can also offer improved epistemic and ethical opportunities. But taking advantage

<sup>&</sup>lt;sup>13</sup>See for example, the recent directives by the Biden-Harris Administration:

https://www.whitehouse.gov/briefing-room/statements-releases/2024/01/29/fact-sheet-biden-harrisadministration-announces-key-ai-actions-following-president-bidens-landmark-executive-order/ <sup>14</sup>See https://ai.gov/apply/

of these opportunities requires serious interdisciplinary collaborations. Advancing our understanding of any of the considerations above (e.g., operationalizing social phenomena, human-AI complementarity and collaboration) requires drawing on significant domain expertise as well as the knowledge and methodologies from a variety of disciplines, including those in the humanities and social sciences (For related points see Fazelpour and De-Arteaga 2021; Rudin 2019; Stinson and Vlaad 2024).

Of course, in taking an interdisciplinary approach to responsible AI seriously, we need to address many challenging questions. For example, at an interpersonal level, diverse and interdisciplinary teams often face communicative problems (O'Rourke et al. 2013; Page 2019). What type of upskilling is needed to address these challenges in the context of responsible AI design and governance? At an organizational level, successful interdisciplinary collaboration appears to require factors such as sustained leadership support, egalitarian power relations between groups, and more (Phillips 2017). What interventions and incentives can effectively realize these factors in the responsible AI ecosystem? At a structural level, what are the appropriate organizational structures for effective interdisciplinarity (e.g., should we have teams of mostly interdisciplinary individuals or disciplinary clusters with interdisciplinary bridges; what type of publication and conferences venues are most suitable)? (Leydesdorff et al. 2008) The first step towards making advances on these questions is to appreciate that responsible AI governance cannot simply be achieved by the vision of disciplinary division of labor underpinning the prevalent interpretation. If "AI talent" is key to responsible innovation and design, then that talent needs to be understood in an interdisciplinary way.

## 5 CONCLUSION

With the increasing social use of AI, we need to carefully examine the epistemic and ethical questions posed by these technologies. Taken together, the three sets of considerations discussed above can provide a lens that can assist those involved in evaluating, designing, and investigating these systems. While the focus here is on the two formal trade-offs in AI-based decision-making, the considerations may be applicable to formal trade-offs in other normatively significant and policy-relevant scenarios. This is because turning a policy scenario into one amenable to formal treatment often requires abstractions and assumptions about the broader sociotechnical context that often tend to be neglected in

interpreting. The discussion can thus potentially offer something to researchers interested in those other scenarios. Hopefully, the considerations above allow us to leverage these formal trade-offs in our practical deliberations, without allowing a misleading interpretation of them punish our normative aspirations in a negative sense.

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