A Human-Centric Perspective on Fairness and Transparency in Algorithmic Decision-Making

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ABSTRACT
Automated decision systems (ADS) are increasingly used for consequential decision-making. These systems often rely on sophisticated yet opaque machine learning models, which do not allow for understanding how a given decision was arrived at. This is not only problematic from a legal perspective, but non-transparent systems are also prone to yield unfair outcomes because their sanity is challenging to assess and calibrate in the first place—which is particularly worrisome for human decision-subjects. Based on this observation and building upon existing work, I aim to make the following three main contributions through my doctoral thesis: (a) understand how (potential) decision-subjects perceive algorithmic decisions (with varying degrees of transparency of the underlying ADS), as compared to similar decisions made by humans; (b) evaluate different tools for transparent decision-making with respect to their effectiveness in enabling people to appropriately assess the quality and fairness of ADS; and (c) develop human-understandable technical artifacts for fair automated decision-making. Over the course of the first half of my PhD program, I have already addressed substantial pieces of (a) and (c), whereas (b) will be the major focus of the second half.

CCS CONCEPTS
• Human-centered computing → Human computer interaction (HCI);
• Computing methodologies → Machine learning;
• Information systems → Decision support systems.

KEYWORDS
Algorithmic decision-making, explanations, fairness

1 CONTEXT AND MOTIVATION
Automated decision-making has become ubiquitous in many domains such as hiring [32], bank lending [56], grading [49], and policing [23], among others. As automated decision systems (ADS) are used to inform increasingly high-stakes decisions, understanding their inner workings is of utmost importance—and undesirable behavior can become a problem of societal relevance. The underlying motives of adopting ADS are manifold: they range from cost-cutting to improving performance and enabling more robust and objective decisions [22, 32, 45]. One widespread assumption is that ADS can also avoid human biases in the decision-making process [32]. In fact, if properly designed, ADS can be a valuable tool for breaking out of vicious patterns of stereotyping and contributing to social equity, for instance, in the realms of recruitment [8, 30], health care [20, 57], or financial inclusion [39]. However, ADS are typically based on artificial intelligence (AI)—particularly machine learning (ML)—techniques, which, in turn, generally rely on historical data. If, for instance, this underlying data is biased (e.g., because certain socio-demographic groups were favored in a disproportionate way), an ADS will pick up and perpetuate existing patterns of unfairness [18]. Prominent examples of such behavior from the recent past are race and gender stereotyping in job ad delivery on Facebook and LinkedIn [25], as well as the discrimination of black people in the realm of facial recognition [4] and recidivism prediction [1]. To that end, in recent years, a significant body of research has been devoted to detecting and mitigating unfairness in ADS—particularly from the techno-centric perspective of the AI/ML communities [2]. Yet, most of this work has focused on formalizing the concept of fairness and enforcing certain statistical equity constraints, often without explicitly taking into account the opinions, feelings, and perceptions of the people affected by such automated decisions.

Partly as a response to multiple known instances of adverse behavior by ADS in high-stakes decision-making settings, both researchers and lawmakers have started to demand that decision-subjects be presented with more information about the inner workings of algorithms [55]. In fact, the EU General Data Protection Regulation (GDPR) 1, for instance, requires the disclosure of "the existence of automated decision-making, including [...] meaningful information about the logic involved [...]" to data subjects. Beyond that, however, such regulations generally remain vague and little actionable, which often results in deficient adoption, as noticed in the context of bank lending. 2 Moreover, while the general need for transparency appears obvious, it is also understood that there exists no "one-size-fits-all" explanation technique that addresses all

1https://eur-lex.europa.eu/eli/reg/2016/679/oj (last accessed: October 10, 2021)
2https://algorithmwatch.org/en/poland-credit-loan-transparency/ (last accessed: October 10, 2021)
desiderata of different stakeholders of algorithmic decision-making [3, 14, 35]. This inevitably results in certain stakeholders’—often the system designers’—goals being (implicitly or explicitly) prioritized over more vulnerable groups, such as the decision-subjects, when choosing a means to facilitate “transparency” of ADS [42]. Additionally, it remains an open question (among many others) how to evaluate the effectiveness of explanations with respect to desiderata that are somewhat difficult to measure; such as morality, ethics, responsibility [35], and others.

In this doctoral thesis, I aim to address selected open questions around fairness and transparency in algorithmic decision-making from the perspective of the most vulnerable stakeholders: decision-subjects. In Section 2, I summarize key related work and highlight specific research gaps. Next, in Section 3, I derive open research questions and outline how I plan to fill the previously identified gaps. After that, in Section 4, I summarize my previous results and contributions to date; and I lay out specific next steps in my dissertation in Section 5. To conclude, I briefly address my long-term goals.

2 KEY RELATED WORK AND RESEARCH GAPS

In this section, I summarize key related work along the dimensions of algorithmic fairness, explainable AI, and perceptions of fairness and trustworthiness, and I highlight certain research gaps that I address in my doctoral thesis.

Algorithmic fairness. Fairness is a contested concept [44]. Mehrabi et al. [43], similarly to existing laws and regulations, define fairness in the context of decision-making as the “absence of any prejudice or favoritism towards an individual or a group based on their intrinsic or acquired traits.” Generally, the (mostly AI/ML-driven) algorithmic fairness literature distinguishes individual from group fairness definitions [43]. A widely-used notion of individual fairness is fairness through awareness (FTA) [15]. FTA says that an algorithm is fair if it gives similar predictions to similar individuals. As stated by Dwork et al. [15], the main challenge with this notion is defining an appropriate distance metric—for instance, to measure differences in qualification between individuals. Regarding group fairness metrics, popular notions include demographic parity [6] (“predictions should be independent of sensitive information”) and equalized odds/equal opportunity [21] (“predictive error rates should be equal for all demographic groups”). Most often, these statistical notions are then enforced as constraints during the training phase of the associated ML model (in-processing techniques [43]); meaning that predictive performance (e.g., accuracy) still remains the primary objective. There are, however, several limitations to this: first, most existing approaches to fairness-aware ADS are specifically designed for (often binary) classification tasks, whereas fairness-aware regression is still relatively under-researched. Furthermore, error rate-based fairness notions—as well as the whole idea of optimizing for predictive performance in ADS—rely on the availability of ground-truth labels; for instance, whether or not an applicant actually paid back a loan. This is a strong assumption that is often not met in real-world decision-making scenarios [33, 51]. Specifically, if ground-truth labels are not (or selectively) available [33], then maximizing for accuracy subject to fairness constraints seems counterintuitive and is, in fact, sub-optimal [26]. Lastly, and perhaps most importantly, it has been shown that many notions of fairness are mutually incompatible [9, 29]. For instance, demographic parity will generally be at odds with individual fairness. This implies that there cannot be a technical fairness definition that universally works for everyone and every use case. Hence, it is important to consider alternative fairness criteria, such as human perceptions of fairness, as well.

Explainable AI. Despite being a popular topic of current research, explainable AI (XAI) is a natural consequence of designing ADS and, as such, has been around at least since the 1980s [40]. Its importance, however, keeps rising as increasingly sophisticated (and opaque) AI techniques are used to inform ever more consequential decisions. Common approaches to XAI are (a) employing “white-box” ML models that are interpretable by design (e.g., logistic regression), or (b) providing post-hoc explanations (e.g., LIME [48] or SHAP [41]). Explainability is not only required by law (e.g., GDPR, ECOA); Eslami et al. [17], for instance, have shown that users’ attitudes towards algorithms change when transparency is altered. In fact, both quantity and quality of explanations matter: Kulesza et al. [31] explored the effects of soundness and completeness of explanations on end users’ mental models and suggest, among others, that oversimplification is problematic. Recent findings from Langer et al. [34], on the other hand, suggest that in certain cases it might make sense to withhold pieces of information in order to not evoke negative reactions. Either way, even in the presence of explanations, people sometimes rely too heavily on system suggestions [5], a phenomenon sometimes referred to as automation bias [13, 19]. Eventually, latest research cautions that explanations can also have negative consequences—either through intentional deception of certain stakeholders [10] or even unsuspecting downstream effects [16]. In fact, a major share of prior work in this area has been looking at issues of opaque ADS through the lens of powerful stakeholders, such as decision-makers, and how to benefit them through explanations. There are still significant contributions to be made with respect to designing (possibly combinations of) explanations that meet the needs of more vulnerable groups (e.g., decision-subjects). Generally, as pointed out by Langer et al. [35], many prior studies have gathered mixed or inconclusive empirical evidence regarding the general effectiveness of explanations—which again demands follow-up work, for instance within specific communities or subgroups of a population. Finally, as recent XAI literature seems to have been favoring post-hoc techniques over “white-box” ML, it should be noted that explaining highly-nonlinear ML models in a post-hoc fashion can lead to somewhat ambiguous insights or recommendations that violate common social norms such as “do not penalize good attributes” [58].

Perceptions of fairness and trustworthiness. Due to the contested nature of the fairness concept [44] as well as shortcomings of the typical AI/ML approaches to algorithmic fairness listed previously, researchers (primarily from HCI) have turned to more empirical and human-centric ways of assessing fairness and transparency of ADS. For instance, Binns et al. [3] and Dodge et al. [14] compare...
human fairness perceptions of ADS for four distinct post-hoc explanation styles. Their works suggest differences in effectiveness of individual explanation styles—however, they also note that there does not seem to be a single best approach to explaining automated decisions. Lee [36] compares perceptions of fairness and trustworthiness depending on whether the decision-maker is a person or an algorithm in the context of managerial decisions. Their findings suggest that, among others, people perceive automated decisions less fair and trustworthy for tasks that require typical human skills. An interesting finding by Lee et al. [37] suggests that fairness perceptions decline for some people when gaining an understanding of an algorithm if their personal fairness concepts differ from those of the algorithm. Regarding trustworthiness, Kızılce [28], for instance, concludes that it is important to provide the right amount of transparency for optimal trust effects, as both too much and too little transparency can have undesirable effects. One major weakness of related work is addressed by Lee and Rich [38], who point out that prior studies have mostly recruited respondents from Amazon Mechanical Turk [47], which has predominantly white participants [24]. Moreover, it is often argued that one goal of explanations should be to facilitate positive perceptions (e.g., fairness and trustworthiness) towards ADS—which implicitly assumes that the respective ADS is fair and trustworthy, to begin with. Examining which explanations allow for calibrated perceptions is a significant research gap. It will also be important to empirically measure novel “flavors” of fairness; for instance, based on established constructs from other disciplines like psychology.

3 RESEARCH OBJECTIVES

Based on research gaps identified in the previous section, I aim to contribute towards answering the following three main research questions through my doctoral thesis:

RQ1 How do (potential) decision-subjects perceive consequential algorithmic decisions, primarily with respect to fairness; and how do explanations impact these perceptions?

RQ2 How and when can explanations enable (potential) decision-subjects to appropriately assess the quality (e.g., fairness) of ADS?

RQ3 Considering that in many real-world decision-making scenarios we do not have access to ground-truth labels, how can we design fair and transparent ADS that—unlike traditional ML approaches—do not rest on this assumption?

I aim to investigate RQ1 through an experimental study conducted with online study participants. Contrary to existing work, I provide combinations of different explanation styles to (potential) decision-subjects, thereby simulating different levels of transparency. I study perceptions of fairness and trustworthiness for the specific use case of bank lending, and I also analyze the moderating effects of people’s AI literacy on their perceptions. Based on findings from RQ1, I aim to analyze for RQ2 whether people’s perceptions are calibrated—meaning that they should be high if and only if the underlying ADS is fair and trustworthy. To that end, I aim to conduct a randomized online experiment as well. Finally, regarding RQ3, I propose a paradigm shift from making accurate predictions to making good decisions. Specifically, I aim to (a) make an algorithmic contribution to the fairness- and transparency-aware ADS toolbox; and (b) evaluate empirically how (potential) decision-subjects perceive this “white-box” artifact compared to traditional ML approaches with post-hoc explanations.

4 RESULTS AND CONTRIBUTIONS TO DATE

In this section, I briefly summarize main results and contributions of my dissertation-related academic work to date. An overview of peer-reviewed accepted and in-submission work is given in Table 1.

Regarding RQ1. For understanding people’s perceptions towards ADS better, I have already conducted two studies. The first one [53, 54] examines the effects of ADS transparency on people’s perceptions of informational fairness and trustworthiness. To that end, I have designed and conducted a randomized online experiment around automated loan decisions with 400 participants recruited through Prolific [46]. Participants were assigned one of four transparency treatments (between-subject) and asked multiple questions based on established constructs from the information systems [7] and organizational justice [11] literature. Please refer to [53] for samples of the employed questionnaires as well as the precise study setup including explanations. Through analyzing group differences and estimating a full structural equation model (SEM), I found that an increase in transparency leads to an increase in both informational fairness and trustworthiness perceptions. It is interesting to note, however, that informational fairness appears to act as a mediator between transparency and trustworthiness perceptions. Additionally, I found evidence that people with higher AI literacy tend to perceive ADS more informationally fair and trustworthy than people with little or no knowledge in this field. In the second study [52], I have similarly conducted an online experiment (200 participants, recruited through Prolific) to compare perceptions between human-made and automated decisions in the context of lending. Study participants were randomly assigned one of two
Unfair ADS with the highest possible qualification towards a given outcome. I aim to spend a major share of ADS as well as their data-driven approach. Again, please refer to proposed decision criterion can be seen as a “white-box” approach relationships between legitimate features and the outcome, the Star North distances between individual data points and a so-called Specifically, I introduce a decision criterion based on weighted correlation between sensitive (e.g., gender) and legitimate features. Information from historical decisions, and (b) accounts for unwanted pose a novel ranking-based decision system that does not result of (potentially biased) human-made decisions. In [51], I propose statistical fairness constraints while maximizing for predictive performance. This approach, however, is sub-optimal when ground-truth labels are unavailable [27]. In fact, in many real-world settings, we only have access to data with imperfect labels, as the artifact [51] with respect to people’s perceptions and understanding. I have also shown theoretically that my method is consistent with the prominent individual fairness notion of FTA (see Section 2).

5 NEXT STEPS AND OUTLOOK

Based on my results and contributions to date, most work remains to be done around RQ2. In fact, after presenting and gathering feedback on the proposed idea and study setup of [50] at CSCW 2021, I intend to design and carefully evaluate a suitable experiment. A blueprint of the preliminary study setup is depicted in Figure 1. Specifically, I aim to conduct a between-subject experiment where treatments (human vs. automated), where both groups were shown identical explanations about the decision-making logic—either employed by a human being or an ADS. Interestingly, and contrary to some prior works’ findings, I found that automated decisions are perceived as fairer than human-made decisions in the given context. Based on an analysis of qualitative responses, it appears that people particularly appreciate the absence of subjectivity in ADS as well as their data-driven approach. Again, please refer to the full publication [52] for further details.

Regarding RQ3. As outlined in Section 2, the general approach of in-processing fairness-aware ML techniques is to enforce certain statistical fairness constraints while maximizing for predictive performance. This approach, however, is sub-optimal when ground-truth labels are unavailable [27]. In fact, in many real-world settings, we only have access to data with imperfect labels, as the result of (potentially biased) human-made decisions. In [51], I propose a novel ranking-based decision system that does not learn to mimic biased decisions but (a) incorporates only useful information from historical decisions, and (b) accounts for unwanted correlation between sensitive (e.g., gender) and legitimate features. Specifically, I introduce a decision criterion based on weighted distances between individual data points and a so-called North Star, which represents the (potentially hypothetical) observation with the highest possible qualification towards a given outcome. By taking into account known (or easily identifiable) monotonic relationships between legitimate features and the outcome, the proposed decision criterion can be seen as a “white-box” approach that is readily interpretable by decision-subjects and allows for meaningful recourse (as opposed to many nonlinear ML models).

Through extensive experiments on synthetic and real-world data, I have shown that the proposed method is fair in the sense that it (a) assigns the desirable outcome to the most qualified individuals, and (b) removes the effect of stereotypes in decision-making, thereby outperforming traditional classification algorithms. Finally, in [51], I have also shown theoretically that my method is consistent with the prominent individual fairness notion of FTA (see Section 2).
examine techniques for making my approach from [51] applicable to regression settings as well.

With this dissertation at the intersection of HCI, computer science, and information systems, I aim to contribute towards solving issues of unfairness and non-transparency in algorithmic decision-making, from the perspective of the most vulnerable stakeholders: decision-subjects. After finishing my PhD program, it is my utmost desire to continue conducting research on this important topic—either in a postdoctoral researcher role or as a researcher in industry. My long-term career goal is to become a full professor.

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