The Impact of Features Used by Algorithms on Perceptions of Fairness

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Abstract

We investigate perceptions of fairness in the choice of features that algorithms use about individuals in a simulated gigwork employment experiment. First, a collection of experimental participants (the selectors) were asked to recommend an algorithm for making employment decisions. Second, a different collection of participants (the workers) were told about the setup, and a subset were ostensibly selected by the algorithm to perform an image labeling task. For both selector and worker participants, algorithmic choices differed principally in the inclusion of features that were non-volitional, and either directly relevant to the task, or for which relevance is not evident except for these features resulting in higher accuracy. We find that the selectors had a clear predilection for the more accurate algorithms, which they also judged as more fair. Worker sentiments were considerably more nuanced. Workers who were hired were largely indifferent among the algorithms. In contrast, workers who were not hired exhibited considerably more positive sentiments for algorithms that included non-volitional but relevant features. However, workers with disadvantaged values of non-volitional features exhibited more negative sentiment towards their use than the average, although the extent of this appears to depend considerably on the nature of such features.

1 Introduction

Systems relying algorithms for decision making are increasingly pervasive, and have significantly impacted the information and opportunities that people receive, with examples ranging from housing opportunities through Facebook's advertisements [Ali *et al.*, 2019], job opportunities through LinkedIn's talent search [Geyik *et al.*, 2019], to gig work employment on crowdsourcing markets [Hannák *et al.*, 2017]. This trend has necessitated careful investigations into both the fairness and efficacy of these systems, particularly in the context of vulnerable communities.

The scope of such investigations is two-fold: defining and formalizing what it means for an algorithmic decision-making system to be fair, as well as designing systems with algorithmic procedures or outcomes that adhere to these definitions of fairness. This line of research has lead to numerous conceptual frameworks for understanding algorithmic fairness, such as group fairness [Hardt *et al.*, 2016; Agarwal *et al.*, 2018; Kusner *et al.*, 2017], which aims to ensure that algorithmic decisions do not result in inequitable impacts on certain groups (e.g. historically marginalized communities), and individual fairness [Dwork *et al.*, 2012], which aims to ensure that similar decisions are made for similar individuals. Taking a broader perspective on fairness and justice considerations across a variety of domains, concerns of *procedural justice* aim to ensure that the decision-making procedures and institutions are perceived as *fair* by affected individuals [Thibaut and Walker, 1975; Lemons and Jones, 2001; Lee *et al.*, 2019]. Procedural justice has in turn received some recent attention in the context of algorithmic decision making [Binns *et al.*, 2018; Vaccaro *et al.*, 2019; Lee *et al.*, 2019; Wang *et al.*, 2020; Woodruff *et al.*, 2018]. While there has been considerable theoretical and legal discussion about the fairness of using certain types of features (e.g. race or gender) in decision-making [Fiss, 1970; Sánchez-Monedero *et al.*, 2020; Merritt and Reskin, 1997], a question that has received somewhat less attention in the literature is how the choice of features used by algorithms influences *human perceptions of fairness*. Existing work in this area includes that of Grgić-Hlača *et al.* [2018b], which considered aggregate opinions regarding the fairness of using specific features in specific decision contexts in the design of algorithms, balancing feature fairness and efficiency. We take up this thread by considering perceptions of feature fairness, as well as overall sentiments, from different stakeholders in an employment context.

Specifically, we designed a human subjects experiment in which participants were split into two roles: *selectors*, who are asked to choose which hiring algorithm we should use, and (prospective) *workers*, who are then hired, or not, via the chosen hiring algorithm. The central question in the experiment is how the choice of which features an algorithm uses impacts both the decisions and the sentiments of human participants *in both of these roles*. We systematically study this by viewing features along two dimensions: *volitionality* (a feature is a result of something that the individual can readily con-

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trol, e.g., academic performance) and *relevance* to the task at hand. Relevance, in turn, can take two forms: *direct relevance*, when a feature is relevant to the task as naturally understood by people, e.g., debt in the context of lending decisions, and *implied relevance*, when a feature is not facially relevant, but nevertheless leads to higher accuracy through non-obvious channels. We create three algorithmic options centered around these issues, ordered by increasing accuracy: **Algorithm 1** uses features that are both volitional and directly relevant. **Algorithm 2** adds several non-volitional but directly relevant features to those in Algorithm 1. **Algorithm 3** adds features to Algorithm 2 that are neither volitional nor directly relevant, but which improve accuracy. We explain to participants that the selected hiring algorithm will be used to decide whether a particular individual (worker participant) would be hired to label dog breeds in a series of 10 images.

Selectors are asked to choose between two of these three algorithms, chosen at random, which they recommend to be used in making the above decision. Workers, in turn, first provide information that is used to construct features, and then are chosen (or not) for the image labeling task. Regardless of whether they are chosen, all workers are asked about their sentiments regarding the task, including perceptions of fairness. Finally, workers are asked to split a $1 bonus between themselves and their selector counterpart who chose the algorithm in their treatment; this was essentially a *dictator game* in which the worker played the dictator role [Güth *et al.*, 1982]. Our goal in this design was to elicit both explicit sentiments (via survey questions) as well as any implicit sentiments that do not directly emerge from survey responses (the tendency of workers to share a fraction of their bonus).

The experiment involved the use of deception when conveying the algorithm selection process as well as its possible deployment. Our central interest was in perceptions of fairness, rather than the task itself. Consequently, the choices of which workers to hire were in fact randomized and independent of worker features, despite workers being told that a specific algorithm was used to hire (or not hire) them. In addition, algorithm accuracies, were *design variables* that we created; no actual algorithms were developed or deployed. This experiment was approved by the IRB, subject to a detailed debriefing which was provided to both selectors and workers in the experiment. Throughout the experiment, we have received no complaints about our use of deception.

We found that the overall worker sentiment was quite positive. Workers who were hired expressed a more positive sentiment about the task than those not hired, as also observed in Wang *et al.* [2020]. Surprisingly, however, the fraction of hired workers sharing the final bonus was nearly identical to those not hired. Further, in contrast to Wang *et al.*, we find that the hiring decision is not necessarily the most influential factor in terms of worker sentiment; rather, in some cases having disadvantaged feature has a considerably stronger impact.

Interestingly, perceptions of relative fairness towards the three algorithms were quite different between selectors and workers. Selectors overwhelmingly chose Algorithm 3 over the others, and Algorithm 2 over Algorithm 1, and their fairness judgments generally aligned with this pattern.

Worker perceptions were more nuanced and influenced by contextual factors. Workers who were hired appeared essentially indifferent about which algorithm was used to make this decision. In contrast, those not hired expressed a strong preference towards Algorithm 2 and Algorithm 3 (which use non-volitional features) over Algorithm 1 (which uses only volitional features) when model accuracy was shown. However, there was not a clear preference between Algorithms 2 and 3 in this context. When accuracies were *not* shown, on the other hand, even workers who were not hired exhibited no significant *explicit* preference for any algorithm. However, in this case implicit sentiments were revealing: considerably fewer non-hired workers shared any of their final bonus with selectors when they believed that the algorithm used to make their hiring decision used features which were neither volitional nor directly relevant (Algorithm 3), compared to treatments involving Algorithms 1 and 2. On the other hand, more such workers shared a fraction of the bonus with selectors when the algorithm used non-volitional, but directly relevant features (i.e., Algorithm 2 was favored to Algorithm 1). Thus, in implicit sentiments, non-hired workers generally favored the algorithm using features that were clearly task-relevant, with volitionality being a secondary concern.

Our results thus reveal that neither selectors nor workers appear to view the non-volitionality of features used by the algorithm as inherently unfair. As such, both groups generally favored Algorithm 2 over Algorithm 1, if they favored any at all. On the other hand, the difference between selectors and workers appears to be due to the difference about judgments of feature *relevance*. Selectors seem to view an increase in accuracy as prima facie evidence of relevance. Workers, in contrast, appear to take special account of whether the relevance of features is direct and understandable (Algorithm 2), or solely evidenced by accuracy (Algorithm 3), which can be insufficient on its own to judge their use as fair.

Related Work: Common work in algorithmic fairness takes a computational perspective, focusing on defining what it means for an algorithm to be fair [Dwork *et al.*, 2012; Hardt *et al.*, 2016; Verma and Rubin, 2018; Kusner *et al.*, 2017; Buolamwini and Gebru, 2018; Mehrabi *et al.*, 2021; Hort *et al.*, 2022], auditing algorithms for bias [Washington, 2018; Buolamwini and Gebru, 2018; Wilson *et al.*, 2021], and designing algorithms which adhere to these definitions of fairness [Hardt *et al.*, 2016; Kusner *et al.*, 2017; Agarwal *et al.*, 2018]. This line of research does not seek to understand whether particular notions of fairness align with the expectations of individuals interacting with the algorithm. Moreover these definitions are framed over the outcomes of the algorithm, rather than the procedure use by the algorithm. Our work, in contrast, is focused on understanding perceptions of fairness in terms of procedural aspects of algorithmic decisions, in particular, the information (features) used by the algorithms.

Procedural justice, which motivates our work, is concerned with the design of the procedures or institutions with which individuals interact. While typical concepts in algorithmic fairness consider distributions of outcomes of algorithmic decisions, procedural justice is focused on the broader context within which such decisions take place, prioritizing considerations such as ensuring dignity of individuals, giving them a voice, as well as consistency and transparency of

decisions [Tyler, 2006]. Procedural justice has been extensively studied in the context of criminal justice, employment, and promotion decisions [Fodchuk and Sidebotham, 2005; Houlden *et al.*, 1978; Lemons and Jones, 2001; Sunshine and Tyler, 2003; Thibaut and Walker, 1975; Tyler, 2003; Tyler and Huo, 2002; Tyler, 2006]. Such studies commonly demonstrate the significance of procedural justice in increasing social harmony, for example increasing overall satisfaction with decisions [Fodchuk and Sidebotham, 2005], likelihood of compliance with the outcome (e.g., arbitration) [Tyler, 2003; Tyler and Huo, 2002], satisfaction with one's employer, etc. Of particular significance in this line of study is the observation that individuals can maintain positive sentiment towards a system *despite unfavorable outcomes*, an inevitable consequence of scarcity of resources.

Although procedural justice is relatively under-explored in an algorithmic context, this issue has received some recent attention, with scholars investigating the trust, transparency, and accountability, of algorithmic decision-making systems [Binns *et al.*, 2018; Vaccaro *et al.*, 2019; Lee *et al.*, 2019; Wang *et al.*, 2020; Woodruff *et al.*, 2018]. Of particular relevance to our work are recent studies which have investigated the ways in which features chosen impact perceptions of fairness [Grgić-Hlača *et al.*, 2018b; Albach and Wright, 2021; Pierson, 2017; Grgic-Hlaca *et al.*, 2018a]. However, these works consider perceptions by those *outside* the decision-making process. In contrast, we consider the issue of fairness associated with features used by the algorithm in a human subjects experiment of a simulated employment scenario, in which judgments about fairness are made by the individuals who believe themselves to be directly affected by the algorithmic decision. In addition, we elicit fairness perceptions from two other perspectives: those with no stake in the process (pilot survey) and those tasked with selecting the hiring algorithm. Measuring perceptions from three differing perspectives is motivated by work on egocentric notions of fairness [Thompson and Loewenstein, 1992; Gelfand *et al.*, 2002; Greenberg, 1983] which demonstrate that one's role in the process can impact their perspective on fairness.

2 Experimental Design

2.1 Experiment Overview

We investigate judgments about the fairness of features used in an algorithm using a simulated employment experiment. All participants are told that the goal is to select a subset of workers to label a series of images of dogs with their corresponding breeds, and we were deploying an algorithm to make such a selection, from a menu of algorithms with differing sets of features and accuracy. Thus, while all participants were paid, those selected for the task received a pay specific to the task, in addition to all other payments. The stated rationale for this was deceptive by design: in fact, no algorithm was ever designed or used, and workers were selected for the task uniformly at random. Per the IRB-approved protocol, we debriefed all participants after the experiment in full detail.

Our experiment divided participants into two groups: *selectors* ($n = 114$), who were asked to choose between two algorithms in service of our stated (rather than actual) goal described above, and *workers* ($n = 1404$),[†] each paired with an algorithm that—in the way it was described to them—was used to decide whether they were selected for the task after extracting the features from them.

We conceptually categorize features along two dimensions: volitionality (whether it can be readily changed by the individual) and relevance (whether it is relevant to the task, in this case, labeling images). Additionally, we consider relevance from two vantage points: direct relevance, when the relevance of a feature to a task is evident, and implied relevance, when the feature increases accuracy (suggesting relevance), but it is not clear what the mechanism is through which it does so. As the nature of both volitionality and direct relevance is in part subjective, we used a pilot experiment to evaluate human judgments of both of these for a collection of features, as described presently. We used the results of this pilot to choose representative features that were directly relevant but non-volitional, and neither directly relevant nor volitional. At the end of the experiment, each participant was asked to opine on their perceptions of fairness, whether the decision made by the algorithm was justified, and whether they were satisfied overall. Finally, each worker participant was given a bonus, a part of which they are allowed to share with a selector who—according to our description—chose the algorithm that made the hiring decision impacting them (in fact, we did not pair participants directly; so we paid out the total amount of such bonus shares divided evenly among all selector participants).

For our experiment, we recruited a total of 1568 participants from Amazon Mechanical Turk, restricting location to be in the United States. We excluded incomplete responses from our analysis, and paid participants whether or not their data has been excluded. Since all our hypotheses are one-sided pairwise comparisons unless explicitly mentioned otherwise, we test for significance using one-sided t-tests when data is numerical and one-sided proportion z-tests when data is binary. When testing multiple pairwise comparisons, we use Tukey's range test to correct the corresponding p-values. We use TOST (two one-sided tests) with margin ε, to test for approximate equivalence [Lakens, 2017; Wellek, 2010], further details are provided in Section B of the supplement. Next, we provide further details for the main parts of the experiment; the complete set of experiment surveys is provided in Section F of the Supplement.

2.2 Pilot Survey

In order to select features that align well with the common meanings of volitional and relevant pertinent to our task, we first ran a pilot survey from 50 people (residing in the US) on Amazon Mechanical Turk. In this survey, we elicited volitionality and relevance information about the following features: *eyesight, age, race, employment, income, arrest record, history of substance abuse, zipcode, tobacco use, city and state*

[†]During the course of our experiment we made a single change to the worker survey, namely updating the language of the dictator game to more explicitly clarify that workers keep the remainder of the $1 which they did not give to selectors. Of the 1404 workers, 928 were given surveys with the updated language. When analyzing the $1 shares given to selectors we use only those workers who received surveys with updated language.

of birth, parent's occupation,parent's income, and parent's tobacco use. For each feature, we stated a hypothetical situation described as follows: *"Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs"*. We then asked the participant's opinion on (a) whether this information is relevant to the hiring decision (relevance), (b) whether the individual has control over this characteristic (volitionality), and (c) whether it is fair to use particular input features in machine learning algorithms when hiring workers for this task (fairness); each scored on a 5-point Likert scale. Full details of the pilot survey are in Appendix C of the supplement.

We observed that age and race are judged as the least volitional features, while income, substance abuse history, arrest record, zipcode, employment history, and tobacco use are judged as highly volitional. For our task, eyesight and age are perceived as the most relevant features; both are also judged to be among the least volitional. Thus, in the main experiment, eyesight and age represent features that are relevant, but not volitional. We can also note that parent's income and occupation are among the least relevant and volitional features; we chose these to represent features which are not relevant and not volitional in the experiments. These observations align with prior work [Grgić-Hlača *et al.*, 2018b].

Perhaps the most surprising finding in our pilot survey is that judgments of fairness depend strongly on perceived task relevance of a feature, whereas *volitionality appears to play no role*. Specifically, we fit linear regression of fairness against relevance and volitionality. The coefficient corresponding to relevance is $\sim$0.9 ($p < 0.001$), while the coefficient corresponding to volitionality is $\sim$0.0 ($p > 0.3$). As we shall see below, this anticipates our findings in the main experiment.

2.3 Main Experiment

We now describe the design of our main experiment. Recall that participants were divided into two groups: *selectors*, who chose which hiring algorithm is to be used, and *workers*, who were told that a particular algorithm was used to determine whether they are hired or not. Next, we describe the main elements of the experimental procedure.

At the core of the experiment were three algorithms that differed along two dimensions: 1) the choice of features used and 2) accuracy. The details about the three algorithms (we simply refer to them as Algorithm 1, 2, and 3) are given in Table 1. As this table demonstrates, Algorithm 1 includes only features that are both directly relevant to the task and volitional (in the sense that they measure something prospective workers have significant control over, in our case, knowledge of dog breeds). Algorithm 2 adds two features (eyesight and age) that are deemed non-volitional but relevant (based on the pilot survey), while Algorithm 3 adds two more features (parent's occupation and income) that are generally viewed as neither relevant nor volitional. To avoid complicating the scenario with legal considerations, we deliberately excluded features such as race and gender. This experiment has two treatments on accuracy differences among algorithms: *small* ($\sim$5%) and large ($\sim$10%). For both treatments Algorithm 3 has a fixed accuracy of 94.7%.

	Features	Acc (T1)	Acc (T2)
Alg 1	Performance	88.4%	73.0%
Alg 2	Performance, eyesight, age	91.6%	81.9%
Alg 3	Performance, eyesight, age, parent's occupation/income	94.7%	94.7%

Table 1: Algorithms and accuracy shown to Selector and Workers. Performance is measured on image labeling, while other features are self-reported. T1 and T2 refer to treatments that vary accuracy.

Selector Procedure In our first set of experiments, we recruited 120 participants to the role of selector. Each selector was shown two of the three algorithms above (enabling a direct pairwise comparison), presenting both the features used and associated accuracies (based on two accuracy treatments). At this point, we screened their understanding of the algorithms by having them answer three validation questions, and only moved them forward if all three were answered correctly. We then explained to them that we wish to use one of the two presented algorithms to hire individuals using Amazon Mechanical Turk to label breeds for a collection of dog images. At this point, we asked them to recommend one of the two algorithms for us to use in hiring. After selectors made their recommendation, we asked them which of the two algorithms was more fair. At the end, we asked the selector participants to provide reasons for their recommendation and fairness judgments. Finally, we presented a detailed briefing that explained the deceptive elements of the design, and the actual experiment. In addition to the pair of algorithms presented, we systematically varied two design aspects of the selector survey: 1) small ($\sim$ 5%) vs. large ($\sim$ 10%) difference in accuracy between Algorithms 1 and Algorithm 2, and Algorithm 2 and Algorithm 3; and 2) whether we included an explicit cue in the description of the selector task emphasizing the importance of fairness. Further details are in Appendix E. Each selector was paid \$0.5 (not including the bonus shares described below), and median task completion time was 4.8 minutes.

Worker Procedure Our second experiment involved prospective workers, done independently from the selector experiment. In this setting, each worker was randomly assigned to one of three treatments, each corresponding to an algorithm. We then provided background information about the task (similar to that for selectors), and presented them with all three algorithmic options, highlighting the actual algorithm ostensibly chosen for the task by the selector (who we said was a person we recruited using Amazon Mechanical Turk). We randomly divided workers into three treatment groups: those shown accuracy with 1) *small* differences and 2) *large* differences, and 3) those not shown accuracy information at all. Just as selectors, workers only proceed to the next step of the process if they correctly answer three validation questions ensuring that they have understood the task. Full details are in Appendix A.

Next, we elicit from each worker the full set of features that we tell them will be used by algorithm to make a hiring decision; workers are not told *how* these features will be used. To obtain features about ability to accurately label breeds of dog images, we ask each worker to label breeds for 10 dog images, for which they are paid \$0.5; we do not tell them their efficacy at the end of this task. All other features are

self-reported, and only elicited if the chosen algorithm is said to require them. Next, we introduce a small artificial time delay during which we say that the algorithm is making a hiring recommendation. In reality, the hiring decision itself randomly splits workers into the *hired* and *not hired* treatment groups. Any worker who is hired is asked to label an additional 3 images and receives an additional $0.5 bonus.

Finally, we elicit sentiments about the worker's experience. First, workers are asked to respond to a short survey that elicits their explicit sentiments about the experience in three ways, for which workers are paid $0.2. We ask 1) whether they felt that the procedure used to make the hiring decision was *fair*, 2) whether they felt that the hiring decision in their case was *justified*, and 3) whether they were *satisfied* with their experience. These three aspects capture for us *explicit* sentiments towards the task. Their choices for each sentiment are provided on a 5-point Likert scale, with 1 indicating strong disagreement, 3 indicating neutral sentiment, and 5 indicating strong agreement. Second, we capture implicit sentiments by giving each worker a final $1 bonus, and asking if they would be willing to share a fraction of this bonus with the selector who (they were told) recommended the algorithm used to hire, or not hire, them. This is effectively a well-known *dictator* game in behavioral economics [Camerer, 2011; Eckel and Grossman, 1996]. We measure whether workers *share* a nonzero fraction of the $1 (a decision with direct economic impact on themselves) as a means of capturing their implicit sentiments towards the hiring process.

After the survey we provide a detailed debriefing, describing the experiment and deceptive elements that were used. The median task completion time for workers was 8.4 minutes.

3 Results

Selector Perspective We begin with our analysis of the selector recommendations and fairness judgments. *We hypothesize that selectors will focus on the accuracy of an algorithm in each pairwise comparison; thus we expect that Algorithm 2 would be preferred to Algorithm 1 (H1), and Algorithm 3 to Algorithm 2 (H2).*

Our results support both H1 and H2: *selectors preferred to recommend Algorithm 2 to 1 ($p < 0.001$), and Algorithm 3 to 2 ($p < 0.001$).* Moreover, we find that their recommendations were largely, though not fully, consistent with their judgments of relative fairness of the three algorithms: *by a relatively large margin, Algorithm 3 more fair than 2, and was also judged more fair than 1 ($p < 0.001$ for both comparisons).* While Algorithm 2 was deemed more fair on average than Algorithm 1, this comparison only yielded $p = 0.1$, and is therefore inconclusive. Both of these observations can be gleaned from Figure 1. Across all algorithms selectors' recommendation and perception of most fair have a correlation 0.56 ($p < 0.001$). Thus, both recommendations and fairness judgments of selectors align closely with displayed accuracy of the algorithm. Moreover, when fairness judgments do clash with accuracy, recommendations follow the latter, as we can see in the difference between recommendations and fairness judgments for Algorithm 1 (Figure 1).

This general observation is further supported by qualitative

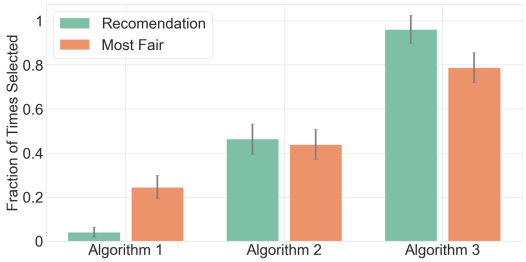

Figure 1: Frequency at which an algorithm was recommended for use, or perceived to be the most fair, scaled by how many times that algorithm was shown to selectors. Algorithm 3 is recommended more frequently, and perceived as more fair, than Algorithms 1 and 2 ($p < 0.001$); Algorithm 2 is recommended more frequently than Algorithm 1 ($p < 0.001$). Error bars represent standard errors.

data provided by the selectors in the form of an open-ended response rationalizing their recommendations and fairness judgments. We group this data into five categories: 1) *performance* (i.e., the algorithm has better performance), 2) *more features* (i.e., the algorithm used more features than other algorithms), 3) *relevance* (i.e., the algorithm used features that are task-relevant), 4) *other* (another reason), and 5) *uninformative* (no meaningful explanation provided; $\sim 35\%$ of responses). Full details are provided in Appendix E.

We also consider the impact of different levels of relative Algorithm accuracies, and of the addition of a fairness cue compared to the accuracy-only framing. We found no statistically significant difference between selectors' recommendations and perceptions of fairness across these treatments. Full details are provided in Appendix E.

In summary, the primary consideration for selector's decision is model performance. Given the framing of the selector task, this is not in itself surprising. However, what *is* surprising is that fairness judgments were closely aligned with recommendations, and based primarily on efficacy judgments, with neither volitionality nor direct relevance of features having much impact.

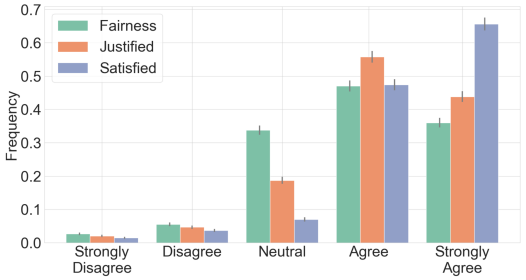

Figure 2: Distribution of worker sentiments.

Worker Perspective We begin by examining workers' general sentiments (perceptions of fairness, whether decision was justified, and overall satisfaction) towards the hiring procedure, aggregated over all treatments. We examine three hypotheses. *First, we expect that sentiments will be higher for workers who are hired than those who are not (H3). Second, we hypothesize that workers who are not hired exhibit less positive sentiments*

when placed in treatments involving the use of non-volitional features (H4). Third, we expect that such workers would also be less positively inclined towards the use of features that are not prima facie relevant to the task (H5).

In general, worker sentiments are broadly positive, as shown in Figure 2. In particular, most participants agreed, or strongly agreed, with the statements that they were satisfied with the process and that the decision was justified. Fairness judgments were slightly more mixed, but again, very few expressed any negative sentiment on this measure either.

As we hypothesized (H3), being hired results in a more positive disposition towards whatever procedure was used in this decision in the case of *explicit sentiments*, as shown Figure 3 (left). The differences for each explicit sentiment

Figure 3: Average explicit sentiments (left) and fraction of workers sharing the $1 bonus during the dictator game (right) for hired vs. not hired workers. Sentiments for hired workers are greater than not hired workers ($p < 0.001$ for all three sentiments). In contrast, the fraction of workers sharing the $1 is approximately equal (margin $\varepsilon = 0.05$) between hired and not hired ($p < 0.001$).

(fairness, justified, and satisfied) between being hired and not hired are statistically significant ($p < 0.001$). Surprisingly, however, the fraction of workers sharing the final $1 bonus with selectors was insensitive to being hired (Figure 3, (right); $p < 0.001$ for approximate equality margin of 0.05). Thus, H3 is not supported in the case of implicit sentiments.

As we show next, judgments of fairness, as well as other sentiments towards procedural issues, such as what information is used in algorithmic decisions, are highly contextual. The first context we consider is the tension between volitionality, direct relevance, and *implied* relevance, i.e., relevance which is not evident but implied by the increased accuracy of the algorithm. We study the impact of this tension on perceptions by considering three treatments: one where workers did not observe accuracy information, and two where they did (differing only in how large the accuracy differences were among the algorithms; 5% for small and 10% for large differences).

Recall that Algorithm 1 includes only features that are volitional and directly relevant, Algorithm 2 additionally includes features that are non-volitional, but still directly relevant, and Algorithm 3 also includes features that are neither, but exhibits a higher accuracy when this information was shown. We find that hired workers are approximately indifferent among the algorithms ($p < 0.05$ for margin $\varepsilon = 0.1$), whether accuracy is shown or not, both for explicit and implicit sentiments. Not so for workers who were not hired. As shown in Figure 4, non-hired workers who were shown model accuracy had a preference for the two algorithms which included non-volitional features, with a stronger preference for larger accuracy differences. This is precisely the opposite direction of the hypothesized impact in H4. However, explicit sentiments were similar for Algorithm 2 and Algorithm 3 when accuracy was shown (H5 is not supported). On the other hand, when information about accuracy was omitted, workers appeared nearly indifferent among the three algorithms (supporting neither H4 nor H5). Thus, our analysis of *explicit sentiments* does not support H4 in its original form, nor does it support H5.

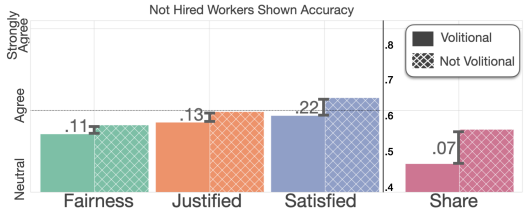

Figure 4: Average sentiment of not-hired workers shown model accuracy, partitioned by whether the hiring algorithm used only volitional features (solid) or used nonvolitional features (hatched). Sentiment differences are statistically significant for justified ($p < 0.05$) and satisfied ($p < 0.005$).

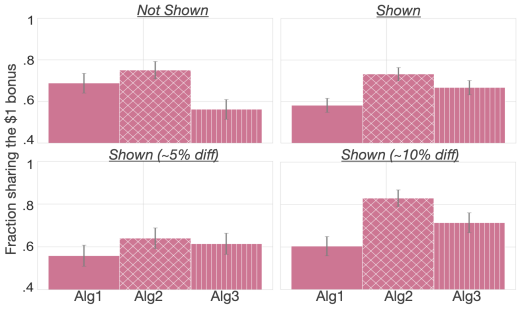

Figure 5: Fraction of not hired workers who share a nonzero amount of the bonus with selectors. These differences are significant for *Not Shown*: Alg2>Alg3 ($p < 0.005$), Alg1>Alg3 ($p < 0.05$), *Shown*: Alg2>Alg1 ($p < 0.005$), Alg3>Alg1 ($p < 0.05$), *Shown with ∼5%*: none, *Shown with ∼10%*: Alg2>Alg1 ($p < 0.001$), Alg2>Alg3 and Alg3>Alg1 ($p < 0.05$).

Considering *implicit* sentiments—the fraction of workers who chose a non-zero share of the final $1 bonus to give the selector—offers rather surprising additional insight, which we can glean from Figure 5. When accuracy information is not shown (Figure 5, left), workers who were not hired had a distinct implicit dislike of Algorithm 3 (which utilizes features that are not facially relevant to the task), compared with either Algorithm 1 ($p < 0.05$) or Algorithm 2 ($p < 0.005$). Thus, without accuracy information to suggest implied relevance, the use of such facially irrelevant features is perceived as undesirable, providing support for H5. On the other hand, Algorithm 2 was slightly preferred to Algorithm 1, albeit not to a statistically significant degree; the use of directly relevant features appears to outweigh their non-volitionality. When accuracy information is shown, implicit sentiments towards Algorithm 3 increase, while those towards Algorithm 1 decrease correspondingly, with implied relevance now playing an important role. Nevertheless, some reservations about implied relevance appear to remain, with Algorithm 2 still preferred over Algo-

rithm 3. In any case, H4 is not supported in its original form for the implicit sentiments.

Overall we observe that while hired workers are relatively indifferent among algorithms, the relative sentiments of those not hired are highly sensitive to context. Throughout, however, volitionality of features is consistently secondary to relevance (direct of implied). Explicit survey results do not yield a clear preference for including features that are not directly relevant, but result in higher accuracy. However, implicit sentiments suggest reservations about including such features.

Perceptions of Workers with Disadvantaged Features Our analysis so far has focused on overall sentiments. However, this does not account for the possibility that sentiments meaningfully differ between people who have different values of the non-volitional features. Recall that our design included three features that are non-volitional, and thereby present significant fairness concerns: eyesight, age, and parent's occupation/income. The former two (eyesight and age) are perceived as being intuitively relevant to the task (see Section 2.2), and the latter is not, but ostensibly increases accuracy in our design. We now consider to what extent the perceptions of individuals with disadvantaged values of these features differ from the population average. In particular, *we hypothesize that these individuals will tend to have less positive sentiments in treatments using such features than the rest, as their use may seem to them particularly unfair (H6).*

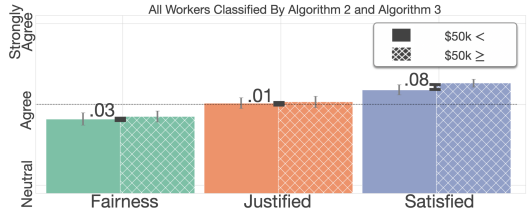

Figure 6: Explicit sentiments of workers divided by reported annual income. Only works classified with Algorithm 2 or Algorithm 3 reported their age. No sentiment difference is statistically significant.

Surprisingly, we find that H6 is not well supported in the case of parent's income and age. Specifically, participants with low-income parents exhibit only small difference in their sentiment compared to average (0.01-0.08, depending on the sentiment measure), and the difference is not statistically significant; see Figure 6. We find similar results in the case of age (Figure 12 in the Supplement).

A striking exception is eyesight. In this case, we find that workers reporting poor eyesight exhibit sentiments that are considerably lower than those reporting neutral or good eyesight, providing strong support for H6. In particular, the average sentiment difference between those with neutral or good eyesight, and those with poor eyesight was ~ 1.0 for each of the three sentiment types (this corresponds to a difference between "Agree" and "Strongly Agree", for example); see Figure 7. For example, these sentiment differences are larger than the differences between those of hired and not-hired workers, and that the sentiment difference between good-eyesight and poor-eyesight is even greater when only considering workers who are not hired. Each difference was statistically significant ($p < 0.005$) with the exception of the *fairness* sentiment if we only consider no hired workers ($p > .1$).

Figure 7: Sentiment of all workers (top), and not-hired workers (bottom), divided by reported eyesight; "Good Eyesight" indicates reports of neutral or better, while "Poor Eyesight" indicates reports of worse than neutral. Each sentiment difference is statistically significant at $p < 0.005$ level except fairness for not hired workers.

4 Discussion

The central takeaways from our analysis are two-fold. First, those in the managerial role of selecting workers were primarily focused on improving the accuracy of the selection algorithm, and considered that entirely fair along all dimensions. Second, negative sentiment about particular algorithms compared to others was limited to workers who were not hired; yet, preference was consistently for including features that are relevant even if they are not volitional.

Nevertheless, we now highlight important limitations of our study. First, as most human subjects experiments, it was low stakes. This has two motivations. First, it would be impractical to run an experiment of comparable complexity and size with significantly higher payments. Second, high payments can have an effect of implicit coercion, and would thereby pose a serious ethical concern. The consequence of small payments is that we do not know to what extent higher stakes would impact perceptions of fairness, and this is an important open question. More broadly, generalizability beyond our simple setting is an open issue. The key evidence that our results are likely to generalize is that they are broadly consistent with what we observe in the pilot survey as well, when we inquired about perceptions of volitionality and relevance of features abstractly: here we found near-perfect correlation between judgments of fairness and relevance, but volitionality is essentially uncorrelated with fairness. Indeed, our experiment suggests that the situation is more nuanced once real stakes are involved. Finally, while it may be tempting to draw simplistic conclusions that people do not care about volitionality, our results are in fact considerably more subtle, and this interpretation is unwarranted. Moreover, observations about general perceptions need not imply that our practice of algorithmic use must necessarily cater to these; ethical considerations may well transcend general perceptions—what is popular need not be the same as what is right.

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Supplement

A Further Details on Surveys

Validation Questions Participants from both the set of workers and selectors are required to complete a series of validation questions. In to our analysis, we only include participants who correctly answer all validation questions. For both surveys participants where shown the potential hiring algorithm (workers see all three while selectors see only two), and are then asked which features each algorithm makes use, and which algorithm had the highest accuracy (in the case where workers are not shown accuracy this was validation question was omitted). An example of these validation questions can be seen in Figure 8.

Treatment Variation Several components of worker and selector surveys have multiple treatment options e.g., whether to show accuracy, which two algorithms the selector sees, whether to hire or not hire a worker, etc.. Pilot surveys do not differ in treatment. For each participant, the choice of treatment is made uniformly at random, e.g., in expectation each algorithm is responsible for $1/3$ of the hiring decisions, of which $1/2$ are positive in expectation.

Copies of each type of survey are provided in full at the end of the supplement. All information which is presented to each participant is shown in these surveys, however we redact a few survey components which contain identifying information such as emails (black boxes).

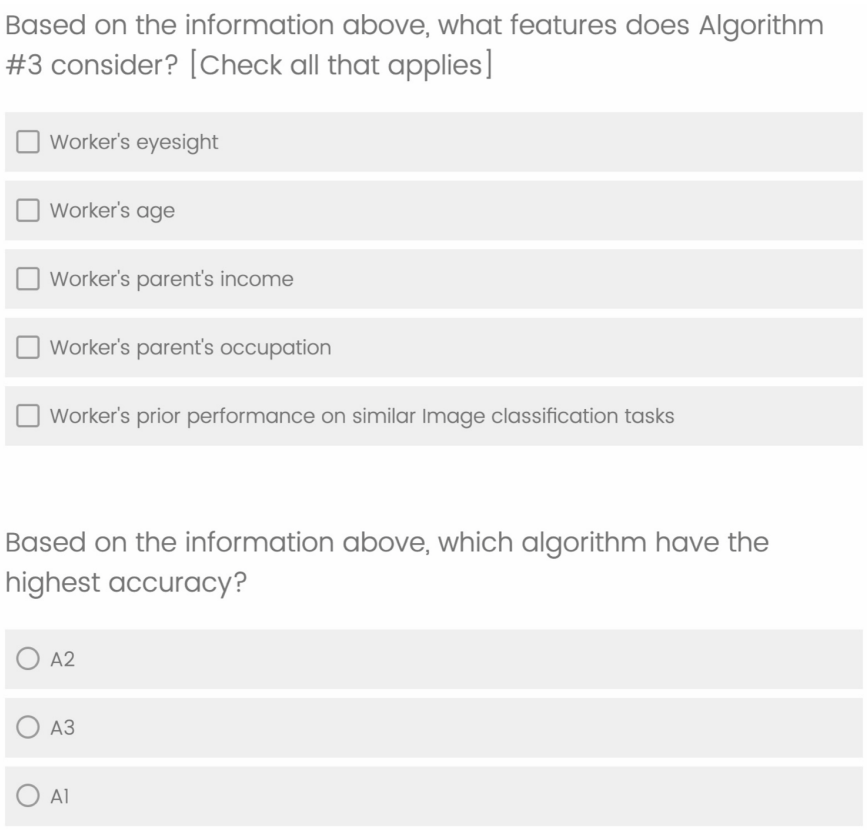


Figure 8: Example of validation questions on worker surveys.

B Statistical Testing

When performing statistical tests we use use t-tests for the case of numerical data (e.g., explicit worker sentiments), and z-tests for cases of binary data (e.g., whether an algorithm was recommended by a selector). When testing multiple samples we use one-sided F-tests. For hypothesis of the form "the mean of sample A is greater than the mean of sample B", we use one sided tests (e.g., worker sentiment is more positive among hired workers than not hired workers). For hypothesis of the form "the means of sample A and sample B are approximately equal" we use two one-sided tests (TOST) with t-test for numerical data and z-tests for binary data. TOSTs make use of a margin parameter ε and the resulting p-value of the TOST corresponds to the means of both samples being within ε of one another, i.e.,

$$-\varepsilon \leq \text{avg}(A) - \text{avg}(B) \leq \varepsilon.$$

C Pilot Surveys

Pilot surveys were used to guide the design of main experiment. Participants in pilot surveys are asked to rate volitionality and relevance of the following features: eyesight, age, race, employment, income, arrest record, history of substance abuse, zipcode, tobacco use, city and state of birth, parent's occupation,parent's income, and parent's tobacco use. For each feature, we stated a hypothetical situation described as follows:

```
"Suppose we wish to develop a machine learning algorithm for hiring
 Amazon Mechanical Turk workers to provide labels for photographs..."
```

We then asked the participant's opinion on (a) whether this information is relevant to the hiring decision (relevance), (b) whether the individual has control over this characteristic (volitionality), and (c) whether it is fair to use particular input features in machine learning algorithms when hiring workers for this task (fairness). In addition to rating the statements above on 5-point Likert scales, participants were asked to provide an explanation for their fairness ratings.

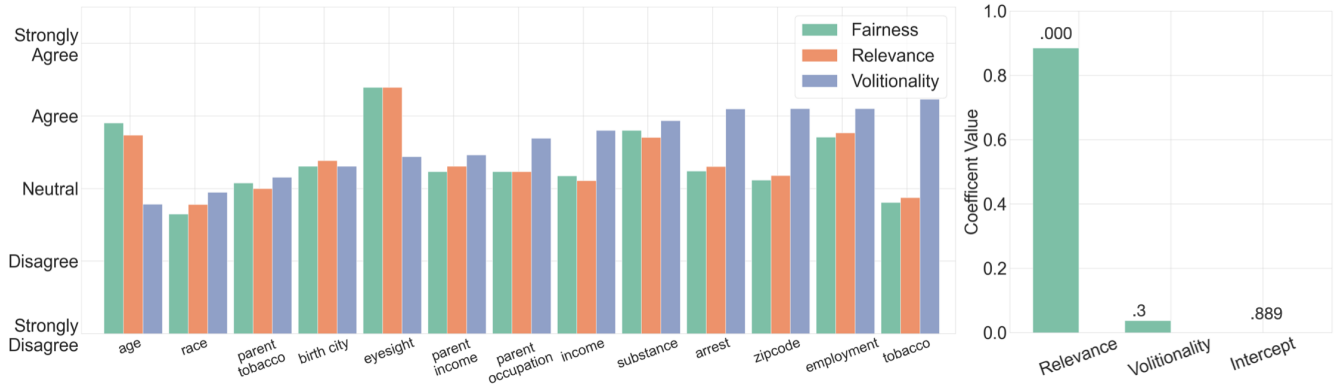


Figure 9: Average perception of participants (left), and regression coefficients(right), regarding the fairness, relevance, and volitionality of each feature (provided on a 5-point Likert scale). Features are sorted by volitionality. Regression coefficients are given for linear regression model predicting fairness, when given relevance and volitionality (R2 $= 0.805$). Above each bar is the p-value corresponding to significance of the corresponding coefficient being nonzero.

In Fig. 9 we provide the average perception for each type of perception and each feature above. What we observe is largely consistent with intuition (as well as the results observed by [Grgić-Hlača *et al.*, 2018b]). Age and race are judged as the least volitional features, while income, substance abuse history, arrest record, zipcode, employment history, and tobacco use are judged as highly volitional.

As stated in the main body, Fig. 9, outlines a clear relationship between perceptions of fairness and relevance. Moreover, the linear regression coefficient corresponding to relevance is approximately 0.9 ($p < 0.001$). In contrast, the coefficient corresponding to volitionality is nearly zero ($p > 0.3$).

D Worker Surveys

Figure 10 provides an outline of the procedure that each worker goes through when completing a survey. Note that all workers, even those not hired, go on to the procedural fairness survey (where we elicit explicit sentiments) and the dictator game (where we elicit implicit sentiments). When workers are shown the selector's choice, they see all three algorithms (along with accuracy if they receive the *shown* treatment) and are told which algorithm the selector chose. An example of the information provided to workers about the selectors choice is shown in Figure 11.

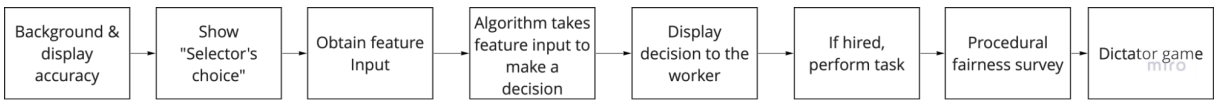


Figure 10: Worker survey workflow.

Tukey's Range Test When analyzing worker surveys our hypothesis constitute one-sided tests, .e.g., "Hired workers posses a more positive sentiment towards the hiring process". However, we also provide an analysis of their two-sided counterparts, which also accounts for the multitude of pairwise comparisons. Here we remake on which hypothesis are no longer significant when converting to their two-sided counter part and performing Tukey's range test. In particular we

	Features	Accuracy
Algorithm #1	• Worker's prior performance on similar Image classification tasks	88.4%
Algorithm #2	• Worker's prior performance on similar Image classification tasks • Worker's eyesight and age	91.6%
Algorithm #3	• Worker's prior performance on similar Image classification tasks • Worker's eyesight and age • Worker's parent's occupation and parent's income	94.7%

Figure 11: Example of how each algorithm is presented to works. Yellow indicates the algorithm chosen by the selector. In this example. the worker is shown model accuracy with a ∼5% difference between models, and is told that the selector choose algorithm 3.

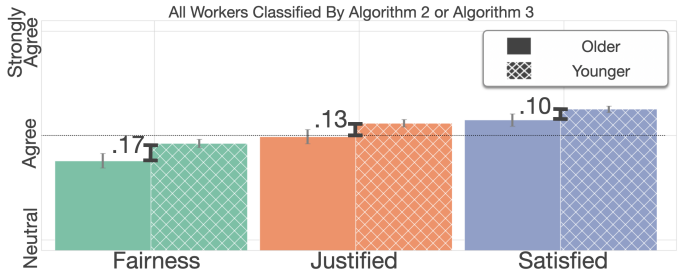


Figure 12: Explicit sentiments of workers divided by reported age; "Older" corresponds to workers reporting ages of 40 or greater, while "Younger" corresponds to workers reporting ages of less than 40. Only works classified with Algorithm 2 or Algorithm 3 reported their age. Each sentiment difference is statistically significant at the $p < 0.05$ level.

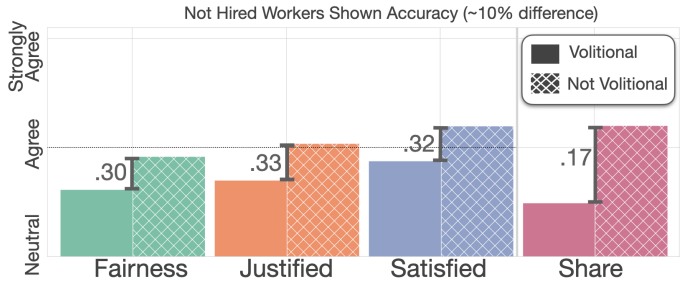


Figure 13: Sentiment of not-hired workers shown ∼10% accuracy difference, these differences are statistically significant for fairness ($p < 0.01$), justified ($p < 0.005$), satisfied ($p < 0.005$), and share ($p < 0.01$).

After Tukey's range test $p > 0.05$ for sentiment differences among not-hired workers who are shown accuracy for fairness and justified, as well as among not-hired workers shown ∼10% difference for fairness. When examining sentiments for those repoting disadvantaged features, after Tukey's range test we find $p > 0.05$ for differences between fairness and justified for not-hired workers reporting poor-eyesight compared to those reporting good-eyesight. Similarly, for all workers, the sentiment differences for fairness between those reporting poor-eyesight and good-eyesight also has $p > 0.05$.

E Selector Surveys

Treatment Variations In addition to varying the choice of algorithm (recall that selectors are presented only two of the three algorithms, chosen randomly) we also vary the difference in algorithm accuracy as well as the language used in the description of the selector's task. The impact of algorithmic options presented to the selectors is discussed in the main body, here we comment on the other two treatment types, beginning with the *fairness cue*. When presented with the task description on the selector surveys, we present half of the selectors with language indicating the importance of making fair decisions. The standard language

and fairness cue language are respectively,

```
"Our goal is to hire workers who can accurately label
 the dog breeds in the images..."
```

```
"Our goal is to hire workers who can accurately label
 the dog breeds in the images and to make fair hiring decisions..."
```

All selectors are shown model accuracy, with roughly 50% being shown $\sim$5% differences in model accuracy and the other 50% being shown $\sim$10% differences in model accuracy. Ultimately we find that differences in model accuracy and choice of language had little effect on the choice of selectors.

Results shown in Figure 14 for different cues (left) and different relative accuracy levels (right) suggest that neither had much impact on the results (none of the comparisons were statistically significant). As noted in the main body, the dominant consideration for selector's decisions and fairness judgments had to do with performance.

Response Categorization As mentioned in the main body, we elicit from selectors a written response for *why* they recommended an algorithm or believed believed it to be the most fair. We group this data into five categories:

1. *performance:* responses which mentioned the algorithm performance.
2. *more features* responses which noted that one algorithm made use of more features than the other algorithm.
3. *relevance:* responses which mentioned that the features being used by one algorithm played a role in either a person's ability to perform the task, or in an algorithm's ability to properly select people to perform the task.
4. *other:* responses which were well formulated, but did not fall into the three aforementioned categories
5. *uninformative:* responses which did not provide a meaningful justification for the selector's decision.

The creation of these categories, as well as which grouping selectors into these categories, was done manually. Responses can fall under multiple categories. When deciding if a response is uninformative, we follow two rules

- any response which contains only non-English words (e.g., "aklsdfjasdklf") is *uninformative*.
- any response which is a *copy-paste* from our survey (e.g., "Our goal is to hire workers who can accurately label") is *uninformative*.

For the other categories it is difficult to rigorously outline precise rules which where followed, but we have tried to adhere to what we believe is the most conventional interpretation of each category. For example, if a selector stated, "I don't see how tobacco use matters", we interpret this as speaking to the relevance of tobacco use with respect to the given task. If instead the selector had stated, "Although I don't think age is an important factor, overall #2 has a higher accuracy score", then we would interpret this response as speaking to both relevance and performance.

F Copies of Pilot, Selector, and Worker Survey

In this section we provide copies of the surveys given to each type of participant. Each copy is an example survey given to a participant, as such, only one treatment option is displayed. The only information portions of the survey which are not shown are those containing identifying information such as email addresses (these have been redacted and are covered by black boxes).

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

There are several characteristics of workers that we could ask the algorithm to consider when making this hiring decision. For each type of information described below, we would like your opinion on

(a) whether it is fair to use this information in hiring workers for this task,
(b) whether this information is relevant to the hiring decision, and
(c) whether the individual has control over this characteristic.

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **employment status** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **employment status** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **employment status**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **eyesight** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **eyesight** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **eyesight**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **age** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **age** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **age**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **parent's occupation** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **parent's occupation** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **parent's occupation**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **arrest record** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **arrest record** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **arrest record**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **City and State of brith** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **City and State of brith** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **City and State of brith**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **parent's income** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **parent's income** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **parent's income**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is **tobacco use** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is **tobacco use** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **tobacco use**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **ZIP Code** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **ZIP Code** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **ZIP Code**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **income** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **income** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **income**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **parent's tobacco use** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **parent's tobacco use** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **parent's tobacco use**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **past history of substance abuse** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **past history of substance abuse** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **past history of substance abuse**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

Next

Suppose we wish to develop a machine learning algorithm for hiring Amazon Mechanical Turk workers to provide labels for photographs.

Is a prospective worker's **race** a fair feature to use in our hiring algorithm?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

Please explain your reasoning to the answer above

Is a prospective worker's **race** relevant to our hiring task?

- ◯ Definitely not
- ◯ Probably not
- ◯ Might or might not
- ◯ Probably yes
- ◯ Definitely yes

To what extent can individual control their **race**?

1 (no control)	2	3	4	5 (full control)
◯	◯	◯	◯	◯

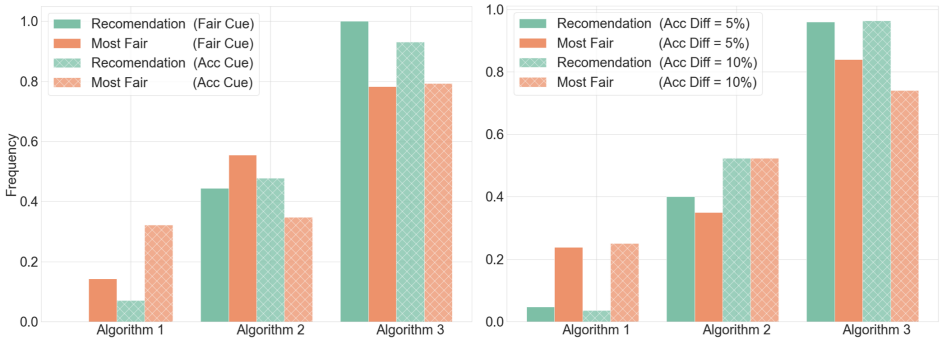
Next

Thank you for completing our survey. Here is your survey code:

Please copy this number. Once you have copied your code, please click Submit to finish the survey.

Submit

We thank you for your time spent taking this survey.
Your response has been recorded.



re 14: Distribution of algorithm recommendation and fairness perception for different cues (left) and levels of model accuracy (right). We rve no statistical significance with respect to how either different cues, or different accuracy levels, change the frequency of algorithm mmendation or perceived fairness.

Selector Surveys

Please read the prompt carefully:

We are developing a machine learning algorithm to use to hire workers. The workers' task will be to identify the breed of dog in a collection of dog images. Depending upon the algorithm selected, the selected algorithm will use certain information provided by prospective workers to determine who will be hired. **Our goal is to hire workers who can accurately label the dog breeds in the images.**

On the next page, we will describe two hiring algorithms and ask which one you recommend.

We will pay you $0.5 for this recommendation.

I have read the prompt carefully: See Algorithms

Below are the two machine learning hiring algorithms that you will chose from. These two hiring algorithms are identical in all ways but which features (attributes) of the individuals they use. Each of the algorithms also list its associated accuracy.

The accuracy of our hiring algorithm is the fraction of instances which the algorithm predicts correctly. In our case, the algorithm predicts whether or not an Amazon Mechanical Turk worker correctly labels a dog's breed.

	Features	Accuracy
Algorithm #1	• Worker's prior performance on similar Image classification tasks	73.0%

	Features	Accuracy
Algorithm #2	• Worker's prior performance on similar Image classification tasks • Worker's eyesight and age	81.9%

Based on the information above, which algorithm have the highest accuracy?

- ○ A1
- ○ A2

Based on the information above, what features does Algorithm #2 consider? [Check all that applies]

- ☐ Worker's parent's occupation
- ☐ Worker's prior performance on similar Image classification tasks
- ☐ Worker's age
- ☐ Worker's eyesight
- ☐ Worker's parent's income

Based on the information above, what features does Algorithm #1 consider? [Check all that applies]

- ☐ Worker's age
- ☐ Worker's parent's occupation
- ☐ Worker's eyesight
- ☐ Worker's parent's income
- ☐ Worker's prior performance on similar Image classification tasks

Move on to make a recommendation

	Features	Accuracy
Algorithm #1	• Worker's prior performance on similar Image classification tasks	73.0%

	Features	Accuracy
Algorithm #2	• Worker's prior performance on similar Image classification tasks • Worker's eyesight and age	81.9%

After carefully considering the two algorithms above, which algorithm would you recommend?

- ◯ Algorithm 1
- ◯ Algorithm 2

Please explain the reason for your recommendation:

Next

	Features	Accuracy
Algorithm #2	• Worker's prior performance on similar Image classification tasks • Worker's eyesight and age	81.9%

	Features	Accuracy
Algorithm #1	• Worker's prior performance on similar Image classification tasks	73.0%

Which of the two algorithms do you feel is most fair:

- ◯ Algorithm 1
- ◯ Algorithm 2

Please explain your reasoning to the previous question

Next

Debrief

Thank you for your participation. You just participated in an experiment. The central goal of this experiment is to understand human perceptions of what constitutes algorithmic fairness in an employment context. We simulated this scenario by asking a selector to act as an employer and choose an algorithm. We are interested in what algorithms the selectors chose, why they chose them, and which algorithms are perceived as fair by the prospective workers.

We asked each selector to choose between two algorithms. To set this up, we defined a total of three algorithms with two sets of corresponding accuracies as listed below. Two of the algorithms were randomly presented to each selector. Additionally, each selector was assigned to one of two "accuracy" treatments. In the first (Treatment 1 below), accuracy differences between the algorithms are relatively small, whereas these are considerably larger in Treatment 2.

	Features	Accuracy (Treatment 1)	Accuracy (Treatment 2)
Algorithm #1	• Worker's prior performance on similar image classification tasks	88.4%	73.0%
Algorithm #2	• Worker's prior performance on similar image classification tasks • Worker's eyesight and age	91.6%	81.9%
Algorithm #3	• Worker's prior performance on similar image classification tasks • Worker's eyesight and age • Worker's parent's occupation and parent's income	94.7%	94.7%

In order not to taint the results, we used several elements of deception in this experiment:

1) We masked the nature of the task and our goals. We described our actual experiment above.

2) We did not actually implement the algorithms as stated. Instead, we made the hiring decisions randomly. Each prospective worker had a 50% chance of being hired for the dog image labeling task. The only exceptions to this were: a) if the worker labeled all 3 test images incorrectly, they were never chosen, and b) if the worker labeled all 3 test images correctly, they were always chosen.

3) The information we elicited from prospective workers was not informed by choices made by the selectors. Instead, it was instead a randomized decision between the three Algorithms described above.

All prospective workers were shown the table describing the three algorithms above, with the algorithm ostensibly chosen for them highlighted (as mentioned above, in fact the choice of the algorithm for the prospective workers was randomized). We also divided the workers into three treatments: 1) no accuracy information about algorithms was provided, 2) accuracy information from Treatment 1 above was provided, and 3) accuracy information from Treatment 2 above was provided.

We ask you to please not discuss this experiment with anyone. If you have any questions about the experiment, please feel free to contact the lead investigator for this study at [redacted]

Obtain your code

Here is your survey code:

Please copy this number. Once you have copied your code, please click Submit to finish the survey.

Submit

We thank you for your time spent taking this survey.
Your response has been recorded.

Worker Surveys

screening, even if you are not hired. If you are hired to perform the task, you will receive an additional $0.5 for identifying the breed of several dog images. Finally, whether you are hired or not, you will receive a bonus of up to $1 at the end of the experiment that you can share at your discretion with individuals who recommended the hiring algorithm that we use. This entire task should take 2-5 minutes. You will only receive your payment if you complete all of the requested steps; however, you are welcome to stop and withdraw at any time.

We developed three machine learning algorithms, and asked other Amazon Mechanical Turk workers to recommend one of these for us to use to make hiring decisions:

	Features	Accuracy
Algorithm #1	• Worker's prior performance on similar Image classification tasks	88.4%
Algorithm #2	• Worker's prior performance on similar Image classification tasks • Worker's eyesight and age	91.6%
Algorithm #3	• Worker's prior performance on similar Image classification tasks • Worker's eyesight and age • Worker's parent's occupation and parent's income	94.7%

Based on the information above, what features does Algorithm #1 consider? [Check all that applies]

- ☐ Worker's eyesight
- ☐ Worker's prior performance on similar Image classification tasks
- ☐ Worker's age
- ☐ Worker's parent's occupation
- ☐ Worker's parent's income

Based on the information above, what features does Algorithm #3 consider? [Check all that applies]

- ☐ Worker's eyesight
- ☐ Worker's age
- ☐ Worker's parent's income
- ☐ Worker's parent's occupation
- ☐ Worker's prior performance on similar Image classification tasks

Based on the information above, which algorithm have the highest accuracy?

- ○ A2
- ○ A3
- ○ A1

Based on the information above, what features does Algorithm #2 consider? [Check all that applies]

- ☐ Worker's eyesight

	Features	Accuracy
Algorithm #1	• Worker's prior performance on similar Image classification tasks	88.4%
Algorithm #2	• Worker's prior performance on similar Image classification tasks • Worker's eyesight and age	91.6%
Algorithm #3	• Worker's prior performance on similar Image classification tasks • Worker's eyesight and age • Worker's parent's occupation and parent's income	94.7%

A selector recommended that we use **Algorithm 3**. We will use the information you provide as input into this algorithm, which will then determine whether you will be hired to do the task, for which you will be paid **$0.5 bonus**.

To begin, we will pay you a **$0.5 base** to provide us with the information we need for the hiring algorithm. First, we ask you to perform a test tasks, and we will use the information about how well you have done on these, along with additional information we will subsequently request, as input into the algorithm which then decides whether you are hired.

Perform Test Task

4) Identify the breed of this dog in the picture

- ◯ Chihuahua
- ◯ Papillon

5) Identify the breed of this dog in the picture

- ◯ Shih Tzu
- ◯ Japanese Spaniel

6) Identify the breed of this dog in the picture

- ◯ Labradoodle
- ◯ Gordon Setter

7) Identify the breed of this dog in the picture

- ◯ Irish Wolfhound
- ◯ Golden Retriever

Thank you for completing the test tasks. Next, we would like you to provide us with the following information for the algorithm to make a decision:

How good is your eyesight

- ◯ Extremely bad
- ◯ Somewhat bad
- ◯ Neither good nor bad
- ◯ Somewhat good
- ◯ Extremely good

What is your age?

- ◯ 18 or younger
- ◯ 18-30
- ◯ 31-40
- ◯ 41-50
- ◯ 51 or older
- ◯ Prefer not to say

Next

Finally, algorithm #3 uses worker's parent occupation and income to make a prediction.

What is your parent's occupation?

- ○ Prefer not to say
- ○ Professional
- ○ Technicians and associate professionals
- ○ Clerical support workers
- ○ Service and sales workers
- ○ Agricultural, forestry and fishery workers
- ○ Craft and related trades workers
- ○ Plant and machine operators, and assemblers
- ○ Others

What is your parent's income?

- ○ Less than $20,000
- ○ Between $20,000-$50,000
- ○ Between $50,000-$80,000
- ○ More than $80,000
- ○ Prefer not to say

View Decision

The Algorithm has made a recommendation. Proceed to view your hiring decision on the next page.

View Hiring Decision

Thank you for providing the information.

Based on the algorithm chosen by the selector you have been hired.

Perform Task

Thank you for your help! Finally, we ask you to complete a very brief question about your experience. It should take no more than 1 minute, and you will receive a bonus for completing this question.

Next

Please read the survey carefully, you will receive $0.2 bonus for completing this 5 question survey. We want to know your opinion about our hiring algorithm and hiring process.

For the following statements, please choose a number on the scale from 1 (strongly disagree) to 5 (strongly agree), where 3 means neither agree nor disagree:

Overall, I had a positive experience with this HIT

1 (strongly disagree)	2	3	4	5 (strongly agree)
○	○	○	○	○

I feel that the process by which I was either hired or not hired for the labeling task was fair.

1 (strongly disagree)	2	3	4	5 (strongly agree)
○	○	○	○	○

I feel that the hiring decision for the labeling task was justified.

1 (strongly disagree)	2	3	4	5 (strongly agree)
○	○	○	○	○

I am satisfied with my experience working on this HIT.

1 (strongly disagree)	2	3	4	5 (strongly agree)
○	○	○	○	○

Do you have any other comments or concerns about this HIT?

Next

In addition to the other payments, we want to **split a final $1 bonus** between you and the selector who recommended the algorithm. The selector is a Mturk worker who chose the algorithm that we used to make the hiring decision earlier. It is up to you to decide how to split this between yourself and the selector. Please decide **how to split the $1 between you and your selector counterpart**:

- ◯ You get $0, Selector gets $1
- ◯ You get $0.25, Selector gets get $0.75
- ◯ You get $0.5, Selector gets get $0.5
- ◯ You get $0.75, Selector gets get $0.25
- ◯ You get $1, Selector gets get $0

Finish Survey

Debrief

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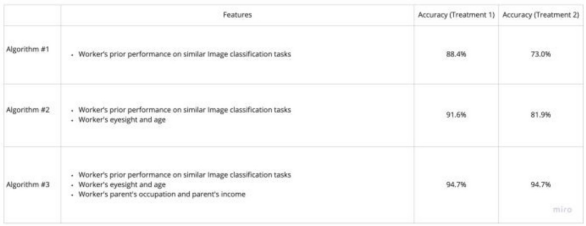

	Features	Accuracy (Treatment 1)	Accuracy (Treatment 2)
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