Explanations, Fairness, and Appropriate Reliance in Human-AI Decision-Making

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ABSTRACT
In this work, we study the effects of feature-based explanations on distributive fairness of AI-assisted decisions, specifically focusing on the task of predicting occupations from short textual bios. We also investigate how any effects are mediated by humans’ fairness perceptions and their reliance on AI recommendations. Our findings show that explanations influence fairness perceptions, which, in turn, relate to humans’ tendency to adhere to AI recommendations. However, we see that such explanations do not enable humans to discern correct and incorrect AI recommendations. Instead, we show that they may affect reliance irrespective of the correctness of AI recommendations. Depending on which features an explanation highlights, this can foster or hinder distributive fairness: when explanations highlight features that are task-irrelevant and evidently associated with the sensitive attribute, this prompts overridges that counter AI recommendations that align with gender stereotypes. Meanwhile, if explanations appear task-relevant, this induces reliance behavior that reinforces stereotype-aligned errors. These results imply that feature-based explanations are not a reliable mechanism to improve distributive fairness.

CCS CONCEPTS
• Human-centered computing → Empirical studies in HCI.
• Information systems → Decision support systems.
• Computing methodologies → Artificial intelligence.

KEYWORDS
Human-AI interaction, AI-informed decision-making, appropriate reliance, explainable AI, algorithmic fairness, fairness perceptions

1 INTRODUCTION
AI systems are commonly used for assisting decision-making in consequential areas, where they provide human decision-makers with decision recommendations. The human is then tasked to decide whether to adhere to such recommendations or override them. Researchers, policy makers, and activists have expressed concern over the risk of algorithmic bias resulting in unfair decisions. As a response, many have advocated for the need for explanations, under the assumption that they can enable humans to mitigate algorithmic bias. For instance, in a recent Forbes article [61], it is claimed that “companies [in financial services and insurance] are using explainable AI to make sure they are making fair decisions about loan rates and premiums.” Others have claimed that explanations “provide a more effective interface for the human-in-the-loop, enabling people to identify and address fairness and other issues” [35]. However, there is no reliable empirical evidence as to whether existing explainability techniques can live up to these hopes [32, 70].

Previous research on AI-assisted decision-making has studied how explanations affect people’s fairness perceptions and trust (see, e.g., [120, 125]). Prior work has also studied how explanations affect the accuracy of AI-assisted decision-making (e.g., [4, 68, 128]), and people’s overall reliance behavior (e.g., [11, 19, 99]). However, the effect of explanations on distributive fairness of AI-assisted decision-making, and the mechanisms underlying such an effect, have not been studied. Consider the example of financial services referenced above. Grounded on the algorithmic fairness literature, one can argue that whether decisions to allocate loans are “fair” refers to the distributive fairness properties of those decisions [107]. For instance, if there is a demographic group that is systematically denied loans because they are incorrectly predicted to be likely to default on a loan, that could be considered unfair because the decisions incur a high rate of false negatives for that group [53, 76]. Thus, a human-in-the-loop that addresses such fairness issues should have the capacity to identify mistaken recommendations, reducing the false negative errors affecting that group. In this case, the goal of explanations should be to help humans identify such errors, yielding AI-assisted decisions that have better distributive fairness properties than the AI alone. Note that this is different to the perceptions that humans may have of an AI system, and it also differs from the overall accuracy or reliance behavior. In this work, we directly assess how feature-based explanations affect distributive fairness, and the mechanisms underlying this effect. We empirically study this via a randomized online experiment using

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We use reliance as an umbrella term for people’s behavior of adhering to or overriding AI recommendations [66].
a popular task in algorithmic fairness and human-AI interaction studies: predicting a person’s occupation from short textual bios.

Our work. We conduct a first comprehensive analysis of the effects of feature-based explanations on people’s ability to enhance distributive fairness in AI-assisted decision-making—and how these effects are mediated by fairness perceptions and reliance on AI recommendations. To empirically study this, we conduct a randomized between-subjects online experiment and assess differences in perceptions and reliance behavior when participants see and do not see explanations, and when these explanations indicate the use of sensitive features in predictions vs. when they indicate the use of task-relevant features. We operationalize this by training two AI models with access to different vocabularies. We conduct our study in the context of occupation prediction based on short textual bios, which is an important task in AI-assisted hiring but at the same time susceptible to gender bias and discrimination [17, 30, 106]. We randomly assign participants to one of two groups and ask them to predict whether bios belong to professors or teachers: for one group, recommendations come from an AI model that uses gendered words for predicting occupations, whereas in the other group the AI model uses task-relevant words. Both AI models provide the same recommendations, and their distribution of errors is in line with societal stereotypes and the expected risks of bias characterized in previous research [30]. Participants in both conditions are provided with explanations that visually highlight the most predictive words of their respective AI models. We also include a baseline condition where no explanations are shown. We test for differences in perceptions and reliance behavior across conditions, and measure gender disparities for different types of errors.

Findings and implications. First, we do not observe any significant differences in decision-making accuracy across conditions, i.e., participants did not make more (or less) accurate decisions in the conditions with explanations compared to the baseline without explanations. Since participants were incentivized to make accurate predictions, this implies that explanations did not enable them to make better decisions with respect to accuracy.

Second, no condition improved participants’ likelihood to override mistaken vs. correct AI recommendations, but conditions did affect the likelihood to override AI recommendations conditioned on the predicted occupation: we see that participants in the gendered condition override more AI recommendations to counter existing societal stereotypes (e.g., by predicting more women to be professors), irrespective of whether the prediction was correct. Simultaneously, when explanations highlight only task-relevant words, reliance behavior reinforced stereotype-aligned decisions; e.g., by predicting more men to be professors, even when they are teachers.

This, third, has implications for distributive fairness: by prompting reliance behavior that either counters or reinforces societal stereotypes embedded in AI recommendations, (i) explanations that highlight gendered words led to a decrease in error rate disparities (i.e., fostering distributive fairness), whereas (ii) explanations that highlight task-relevant words led to an increase in error rate disparities (i.e., hindering distributive fairness). These findings emphasize the need to differentiate between improved distributive fairness that is driven by a shift in the types of errors vs. improvements that are driven by humans’ ability to override mistaken AI recommendations.

Fourth, we confirm prior works’ findings by observing that people’s fairness perceptions are significantly lower when explanations highlight gendered words compared to task-relevant words, and empirically show that people override significantly more AI recommendations when their fairness perceptions are low. However, we observe that perceptions solely relate to the quantity of overrides and do not correlate with an ability to discern correct and incorrect AI recommendations. Hence, fairness perceptions are only a meaningful proxy for distributive fairness when it is desirable to override the AI based on its use of sensitive features. However, prior research has shown that the idea of “fairness through unawareness,” which deems an AI system to be fair if it does not make use of information that is evidently indicative of a person’s demographics, is neither a necessary nor sufficient condition for distributive fairness [7, 27, 36, 63, 88, 94].

Recommendations for researchers and practitioners. Overall, our work has direct implications for researchers and designers of socio-technical systems for decision support. First, we suggest to measure the effects of decision support interventions, such as explanations, on human reliance behavior with respect to meaningful endpoints. Importantly, when concerned with fairness, we show that humans may foster or hinder distributive fairness even in the absence of an ability to override mistaken AI recommendations, by merely shifting errors. In that regard, our study design serves as a valuable blueprint for assessing the suitability of other types of interventions as potential pathways towards improved distributive fairness of AI-assisted decisions. We not only emphasize the importance of grounding the design of explanations in specific desiderata, such as distributive fairness, but also of designing explanations in a way that they provide relevant cues which empower humans to achieve these goals. With respect to fostering distributive fairness, our work suggests that explanations must transcend a mere human-in-the-loop operationalization of the idea of “fairness through unawareness” and provide insights to humans that go beyond the fact of whether or not an AI system makes use of sensitive information. To that point, our findings raise doubts about the reliability of popular feature-based explanations as enablers for distributive fairness. Instead, we advocate for a more holistic perspective on algorithmic transparency, one that is grounded in concrete desiderata of relevant human stakeholders and encourages thoughtful design choices to enable truly effective human-AI collaboration.

2 BACKGROUND

In this section, we provide relevant background on our work and review related literature on explanations, reliance, and fairness. In Section 2.1, we first show how explanations have been touted for their importance towards enhancing different desiderata in AI-assisted decision-making, including fairness. We then briefly review the types of explanations that are relevant to our work, and we summarize some of the existing critique of explanations that our work adds to. In Section 2.2, we revisit prior work on the effects of explanations on human reliance behavior. Here, we see that previous findings have been mostly inconclusive, and that research on
we use LIME in our experiments, due to its popularity in the liter-
whether feature-based explanations can enable humans with discre-

tory power to improve relevant distributive fairness properties

2.1 Explanations of AI

Goals of explanations. AI systems are becoming increasingly complex and opaque, and researchers and policymakers have called for explanations to make AI systems more understandable to hu-
ms [43, 70, 85]. Apart from the central aim of facilitating human understand-
ing, prior research has formulated a wealth of different desiderata that explanations are to provide, most of which cen-
ter one or more different types of stakeholders of AI systems [38, 70, 100]. For instance, system designers might be interested in fa-
cilitating trust in their systems through explanations, whereas a regulator likely wants to assess a system’s compliance with moral and ethical standards [70]. Different goals may sometimes be impossible to accomplish simultaneously [119]. For a comprehensive overview of different aims of explanations, we refer the reader to Langer et al. [70] and Lipton [74]. Relevant to our work are sev-
eral desiderata that concern explanations as an alleged means for better and fairer AI-assisted decision-making [1, 35]. Importantly, many of such claims are lacking nuance [32], which motivates our work. For instance, prior work has claimed that “explainability can be considered as the capacity to reach and guarantee fairness in ML models” [8]. Yet, both explainability and fairness are multi-
dimensional concepts, and it is often unclear what it means to improve fairness through explanations, as well as a lack of evidence studying whether this is possible. In this work, we empirically study whether feature-based explanations can enable humans with discre-
tionary power to improve relevant distributive fairness properties of AI-assisted decisions.

Types of explanations. The scientific literature distinguishes explana-
tions that aim at explaining individual predictions (local expla-
nations) from those that aim at explaining the general functioning of an AI model (global explanations) [52]. However, it has been argued that combining local explanations can also lead to an understanding of global model behavior [78]. So-called local model-agnostic expla-
nations, such as LIME [104] or SHAP [79], have gained popularity in the literature [1]. When applied to text data, these methods can generate a highlighting of important words for text classification. In this work, our focus is on these feature-based explanations, and we use LIME in our experiments, due to its popularity in the liter-

Criticisms of explanations. Most desiderata for explanations are in-
sufficiently studied or met with inconclusive or seemingly contradic-
tory empirical findings [23, 31, 70]. A major line of criticism stems

2.2 Explanations and (Appropriate) Reliance

Effects on accuracy. It has been argued that explanations are an enabler for better AI-assisted decision-making [8, 35, 46, 62, 102]. A recent meta-study [108] on the effectiveness of explanations, however, implies that explanations in most empirical studies did not yield any significant benefits with respect to decision-making accuracy; e.g., in [4, 47, 75, 87, 128]. On the other hand, Lai and Tan [68] find that explanations greatly enhance decision-making accuracy for the case of deception detection. An accuracy increase through explanations may, however, solely be due to (i) an overall increase in adherence to a high-accuracy AI, or (ii) an overall decrease in adherence to a low-accuracy AI [11, 112]. Importantly, even if explanations lead to more (in)accurate decisions, it is unclear from prior work how this relates to distributive fairness properties. In this paper, we show that changes to distributive fairness metrics may occur even in the absence of any effects on accuracy.

Effects on reliance. In the context of AI-assisted decision-making, appropriate reliance is typically understood as the behavior of hu-
mans of overriding incorrect AI recommendations and adhering to correct ones [109, 112]. Humans’ ability to override mistaken recommendations has also been referred to as corrective overriding [45]. When considering the role of explanations in fostering appropriate reliance, it has been claimed that “transparency mecha-
nisms also function to help users learn about how the system works, so they can evaluate the correctness of the outputs they experience and identify outputs that are incorrect” [102]. Empirical evidence, however, is less clear: several studies have found that explanations can be detrimental to appropriate reliance [11, 19, 66, 99, 110, 123], when they increase or decrease humans’ adherence to AI recommen-
dations regardless of their correctness. These phenomena are
commonly referred to as over-or under-reliance [112]. Our work also studies people’s reliance behavior, but with a focus on how it relates to distributive fairness—which has not been studied before. In that regard, we show that explanations may foster reliance behavior that either reinforces or counters stereotypical AI recommendations, independent of the correctness of said recommendations.

**Conflation of reliance and trust.** Our work is also motivated by the fact that prior work has often conflated human attitudes and behavior. For instance, many studies have treated reliance and trust interchangeably [66], sometimes calling reliance a “behavioral trust measure” [91]. However, definitions of trust are often inconsistent [58, 72, 91], which makes empirical findings challenging to compare. More importantly, trust and reliance are different constructs [66]: reliance is the behavior of adhering to or overriding AI recommendations, whereas trust is a subjective attitude regarding the whole system, which builds up and develops over time [92, 103, 126]. It has been argued that trust may impact reliance [37, 72, 115], but trust is not a sufficient requirement for reliance when other factors, such as time constraints, perceived risk, or self-confidence, impact decision-making [45, 72, 105]. In our work, we directly measure participants’ reliance behavior and do not assume an equivalence between reliance and trust.

### 2.3 Explanations and Fairness

**Goal of promoting algorithmic fairness.** It is known that AI systems can issue predictions that may result in disparate outcomes or other forms of injustices for certain socio-demographic groups—especially those that have been historically marginalized [13, 20, 29, 57]. When AI systems are used to inform consequential decisions, it is important that a human can override problematic recommendations. To that end, the literature has often framed explanations as an important pathway towards improving algorithmic fairness [8, 28, 35, 70]. Grounded on the organizational justice literature [26, 48], researchers distinguish different notions of algorithmic fairness, among which are (i) distributive fairness, which refers to the fairness of decision outcomes [127], and (ii) procedural fairness, which refers to the fairness of decision-making procedures [73]. Distributive fairness is typically measured in terms of statistical metrics such as parity in error rates across groups [12, 24], which is closely related to notions like equalized odds or equal opportunity [53]. In this work, we apply this notion and measure distributive fairness as disparities in error rates across genders (see Section 3.3). Importantly, there is no conclusive evidence from prior work showing that explanations lead to fairer decisions, and it remains unclear how explanations may enable this [70]. To understand these mechanisms better, we therefore conduct a comprehensive analysis of explanations’ effects on the human ability to improve distributive fairness, and we also study in depth the mediating roles of fairness perceptions and reliance behavior.

**Fairness perceptions.** Prior work at the intersection of fairness and explanations has primarily focused on assessing how people perceive the fairness of AI systems [66, 120]. Empirical findings are mostly inconclusive, stressing that fairness perceptions depend on many factors, such as the explanation style [16, 35], the amount of information provided [113], the use case [6], user profiles [35], the decision outcome [116], or whether the final decision is made by a human or an algorithm [86]. Surprisingly, few works have examined downstream effects of fairness perceptions on AI-assisted decisions, which has also been noted by Starke et al. [120]. Our work complements prior studies by centering distributive fairness and how it relates to fairness perceptions. Importantly, in this work we stress the importance of not conflating fairness perceptions with the ability to improve distributive fairness.

**Perceptions and sensitive features.** A series of prior studies have found that knowledge about the features that an AI model uses influences people’s fairness perceptions [49–51, 88, 98, 122]. This type of information is, e.g., conveyed by feature-based explanations like LIME. Specifically, people tend to be averse to the use of what is typically considered sensitive information, e.g., gender or race [27, 49–51, 88, 98, 113]. Interestingly, people’s perceptions towards these features may change after they learn that “blinding” the AI model to these features can lead to worse outcomes for marginalized groups [88]. Similarly, it has been shown that people’s perceptions towards the inclusion of sensitive features switch when they are told that this inclusion makes an AI model more accurate [50] or equalizes error rates across demographic groups [54]. In fact, it is known that prohibiting an AI model from using sensitive information is neither a necessary nor sufficient requirement for fair decision-making [7, 27, 36, 63, 88, 94], and that there exist several real-world examples where the inclusion of sensitive features can make historically disadvantaged groups like Black people or women better off [27, 84, 97, 117]. In this work, we build upon these findings on the interplay of fairness perceptions and sensitive features. Concretely, we assess differences in reliance behavior when participants see explanations that highlight task-relevant vs. sensitive features, and derive implications for distributive fairness.

### 3 STUDY DESIGN

In this section, we outline our study design. First, we introduce the task and dataset for our study, then we explain the experimental setup and our dependent variables, and, finally, the data collection process.

#### 3.1 Task and Dataset

**Task.** Automating parts of the hiring funnel has become common practice of many companies; especially the sourcing of candidates online [17, 106]. An important task herein is to determine someone’s occupation, which is a prerequisite for advertising job openings or recruiting people for adequate positions. This information may not be readily available in structured format and would, instead, have to be inferred from unstructured information found online. While this process lends itself to the use AI systems, it is susceptible to gender bias and discrimination [17, 30, 106]. De-Arteaga et al. [30] show that these biases can manifest themselves in error rate disparities between genders, and that error rate disparities are correlated with gender imbalances in occupations. For instance, women surgeons are significantly more often misclassified than men surgeons because the occupation surgeon is heavily men-dominated. Similar disparities occur, among others, for professors and teachers. Interestingly, the disparate impact on people persists when the AI model does not consider explicit gender indicators (e.g., pronouns) [30].
Such misclassifications in hiring have tremendous repercussions for affected people because they may be systematically excluded from exposure to relevant opportunities. In our study, we instantiate an AI-assisted decision-making setup where participants see short textual bios and are asked—with the help of an AI recommendation—to predict whether a given bio belongs to a professor or a teacher. Professors are historically a men-dominated occupation, whereas teachers have been mostly associated with women [85].

Dataset. We use the publicly available BIOS dataset, which contains approximately 400,000 online bios for 28 different occupations from the Common Crawl corpus, initially created by De-Arteaga et al. [30]. This data set has been used in other human-AI decision-making studies as well, such as the ones by Liu et al. [75] or Peng et al. [95]. For each bio in the dataset we know the gender of the corresponding person and their true occupation. Gender is based on the pronouns used in the bio, and a limitation of this dataset is that it only contains bios that use “she” or “he” as pronouns, excluding bios of non-binary people. We only consider bios that belong to professors and teachers, which leaves us with 134,436 bios, out of which 118,215 belong to professors and 16,221 to teachers. In line with current demographics and societal stereotypes [85, 129, 130], we have more men (55%) than women (45%) bios of professors and more women (60%) than men (40%) bios of teachers.

3.2 Experimental Setup

General procedure. We conduct a between-subjects study where participants see 14 bios one by one, each including the AI recommendation as well as an explanation highlighting the most predictive words. We also include a baseline condition without explanations. The crux of our experimental design is that we assign participants to conditions where they see recommendations and explanations either from (i) an AI model that uses task-relevant features, or (ii) an AI model that uses gendered (i.e., sensitive) features. An exemplary bio including explanations is depicted in Figure 1. Note that the AI predictions and explanations stem from actual AI models that agree in their predictions for the 14 bios shown to participants; we outline the construction of these models later in this section as well as, more extensively, in Appendix A.

Participants in each condition first complete the task of predicting occupations for 14 bios, and—if assigned to a condition with explanations—answer several questions regarding their fairness perceptions. Since the baseline condition does not provide any cues regarding the AI’s decision-making procedures, we do not ask about perceptions there. Finally, participants provide some demographic information. A summary of our general setup in illustrated in Figure 2. Note that we ask about fairness perceptions after the task is completed, so as to prevent these questions from moderating reliance behavior [22]. Given that distinguishing professors and teachers based on their bios can be at times ambiguous and not everyone may be familiar with the differences, we also ask at the beginning of our questionnaires what participants consider the difference between professor and teacher to be. Additionally, after completing the task, we ask participants an open-ended question on what information they relied on when differentiating professor and teacher. This way, we were able to confirm—both quantitatively and qualitatively—that participants thought consistently about this distinction between conditions.

Task completion. Figure 1 shows the interface that participants in the task-relevant as well as the gendered condition see during the completion of the task. In line with traditional LIME applications for text data [83], explanations involve a dynamic highlighting of important words for either AI model (task-relevant and gendered).
Figure 2: Study participants are randomly assigned to one of three conditions. In each condition, they first complete the task of predicting occupations from 14 short bios, and complete a demographic survey. In the conditions with explanations (Task-relevant and Gendered), participants are also asked about their fairness perceptions after completing the task.

For a given prediction, the colors indicate which outcome prediction (professor or teacher) a word contributes towards (see [104]). The binary prediction is then obtained using a threshold applied to the predicted probability. For instance, in Figure 1 (task-relevant condition), the word students is indicative of teacher (orange), and the word research is indicative of professor (blue). The binary prediction is professor because the predicted probability that the bio belongs to a professor is greater than 50%. Lastly, the color intensity shows the importance of a given word in the AI’s prediction. This interface is similar to related studies on AI-assisted text classification [67, 75, 109]. Participants in the task-relevant and the gendered condition are confronted with 14 bios similar to the one in Figure 1, whereas participants in the baseline condition are shown the same set of bios without highlighting of words, and the AI prediction without color coding. Recall that the AI recommendations are identical across conditions. For each instance, participants are asked to make a binary prediction about whether they believe that a given bio belongs to a professor or a teacher. We incentivize accurate predictions through bonus payments (see Section 3.4).

Task-relevant and gendered classifiers. We provide intuition for how we constructed the AI models that generate recommendations and explanations in the task-relevant and gendered conditions. We defer a detailed explanation to Appendix A. The general idea is to train two classifiers with access to mutually disjoint vocabularies as predictors. The task-relevant vocabulary consists of words that appear on average—for both men and women—more often in professor or teacher bios than in any of the 26 remaining occupations in the BIOS dataset. The resulting vocabulary consists of words such as faculty, kindergarten, or phd. The gendered vocabulary, on the other hand, consists of words that are most predictive of gender, which includes, apart from gender pronouns and words such as husband and wife, words like dance, art, or engineering, which are not evidently gendered but highly correlated with the sensitive attribute. Finally, we train two logistic regression models4 on a balanced set of professor and teacher bios, and we employ the TextExplainer from LIME [104] to generate dynamic explanations with highlighting of predictive words.

3.3 Measuring Reliance and Fairness

Selection of bios. In order to be able to assess differences in reliance behavior across conditions, participants see a mix of cases where the AI is correct and where it is incorrect. More specifically, we distinguish six types of scenarios that make up the 14 bios that participants see—they are summarized in Table 1. We distinguish these scenarios based on three dimensions: (i) gender of the person associated with a bio; (ii) true occupation of that person; (iii) AI recommended occupation. We show 3 cases each of correctly recommended women teachers (WTT) and men professors (MPP), as well as 3 cases of incorrectly recommended women professors (WPT) and men teachers (MTP). Note that our focus is on scenarios where the AI recommendations are in line with gender stereotypes. To preempt the misconception that the AI always recommends teacher for women and professor for men, we also include one case each of correctly recommended woman professor (WPP) and correctly recommended man teacher (MTT). We include the WPP and MTT scenarios early on in our questionnaires. Precisely, we randomize the order in which participants see the 14 bios, with the restriction that the WPP and MTT scenarios are shown among the first five—that way, we aim to avoid situations where participants see too many incorrect AI recommendations (in line with stereotypes) early on, which has been shown to negatively affect human reliance on AI systems [60] and might, therefore, bias our results. We do not consider scenarios where women teachers are classified as professors, or where men professors are classified as teachers, because our focus is on the errors that are more likely to occur in practice [30].

All bios shown to participants are taken from a random holdout set of BIOS that our two classifiers make predictions on. Specifically, we choose bios that are reasonably similar in length and where both classifiers yield the same predicted occupation as well as similar prediction probabilities. We also require that these prediction probabilities for a bio must not be too high, which aims at eliminating bios that are “too easy” to classify. The authors then

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4We use logistic regression to ensure that explanations are faithful to the underlying model.
manually screened the remaining contenders to settle on the final 14 bios. The whole selection process is described in more detail in Appendix B.

**Measuring reliance behavior.** In our assessment of reliance behavior, we distinguish four cases, as depicted in Table 2. We refer to cases where humans adhere to correct AI recommendations as **correct adherence**, to cases where humans adhere to incorrect recommendations as **detrimental adherence**, to cases where humans override correct recommendations as **detrimental overriding**, and to cases where humans override incorrect recommendations as **corrective overriding**. Note that the sum of shares of correct adherence and corrective overriding make up the final decision-making accuracy [112]. This taxonomy is similar to the one proposed by Liu et al. [75] for trust; however, we want to stress the difference between trust and reliance (see Section 2.2). When comparing participants’ reliance behavior across conditions, we compute and report the relative shares of any of these four types of reliance behavior on the 14 bios that participants see.

Table 2: We distinguish four types of reliance in AI-assisted decision-making: humans can adhere to or override correct AI recommendations, or they can adhere to or override incorrect AI recommendations.

| Gender of bio | True occupation | AI recommendation | AI correct? | Acronym | #Bios |
|---------------|-----------------|-------------------|-------------|---------|-------|
| Woman         | Teacher         | Teacher           | ✓           | WTT     | 3     |
| Woman         | Professor       | Teacher           | ✗           | WPT     | 3     |
| Man           | Teacher         | Teacher           | ✓           | MTT     | 1     |
| Man           | Teacher         | Professor         | ✗           | MTP     | 3     |
| Man           | Professor       | Professor         | ✓           | MPP     | 3     |

**Measuring distributive fairness.** To evaluate distributive fairness of decisions, we measure disparities in error rates across gender [12, 24], which is closely linked to the ideas of *equalized odds* and *equal opportunity* [53]. From a fairness perspective, the goal is to minimize such disparities, so as to equalize the burden of being misclassified and, as a result, being excluded from exposure to relevant opportunities between men and women. We formalize these disparities as follows: let $F_P$ be the share of incorrectly predicted woman professors, i.e., women professors that are predicted to be teachers, and $F_T$ the share of incorrectly predicted woman teachers. Similarly define $F_P$ and $F_T$ for men. We can then quantify disparities in error rates as follows:

\[
\text{Error rate disparity (Teacher → Professor)} = |F_T - F_P| \\
\text{Error rate disparity (Professor → Teacher)} = |F_P - F_T|,
\]

where we use the notation of "Teacher → Professor" to indicate teachers that are incorrectly predicted as professors, and vice versa for "Professor → Teacher." If we assume that the occupation of professor is associated with a higher societal status than teacher, we may also refer to cases of "Teacher → Professor" as *promotions*, and to "Professor → Teacher" as *demotions*. This will be important in the discussion of our findings.

**Measuring fairness perceptions.** To measure fairness perceptions, we provide a brief introduction and then ask participants’ agreement with three statements, measured on 5-point Likert scales from 1 ("Fully disagree") to 5 ("Fully agree"). We operationalize this in our questionnaires similar to Colquitt and Rodell [26] as follows:

The questions below refer to the procedures the AI uses to predict a person’s occupation. Please rate your agreement with the following statements.

1. The AI’s procedures are free of bias.
2. The AI’s procedures uphold ethical and moral standards.
3. It is fair that the AI considers the highlighted words for predicting a person’s occupation.

Note that items (1) and (2) are taken from the *procedural justice* construct of Colquitt and Rodell [26] and slightly rephrased to fit our case of AI-assisted decision-making. These items have been frequently used in other human-AI studies, e.g., [16, 82, 111, 114]. Note that prior work has often measured fairness perceptions through single items only [120]. Colquitt and Rodell [26] propose up to eight measurement items for procedural justice in the organizational psychology context; however, several of these items are not applicable here. Instead, we amend our questionnaires by a third item (3) that is more tailored to our experimental setup. Since item (3) is more explicit and we want to avoid priming, we ask (3) last and without possibility to modify responses for (1) and (2) retroactively. To obtain a single measure of fairness perceptions per participant, we eventually average ratings across the three items per participant; and we also confirm scale reliability in Section 4.3.
We first present results on the effects of explanations on accuracy with explanations (whenever applicable, and two-tailed Mann-Whitney U tests [81] for was conducted) per hour, excluding individual bonus payments

we were 18–24 years old, 32.6% were 25–34 years old, 21.3% between (7.0%) and Asian (6.1%). For their participation, participants were

corresponding figures. We report p-values for omnibus tests and

terparts. Specifically, we conduct Kruskal-Wallis omnibus tests [64]

nonparametric tests because we cannot confirm the prerequisites

of fairness perceptions. For all statistical comparisons, we conduct

hypothesis testing to determine if there are significant differences between the three means (p = 0.260). Recall that participants were incentivized through bonus payments to accurately predict occupations. This suggests that explanations did not aid AI-assisted decision-making when measured in terms of accuracy.

Effects on overriding behavior. In Figures 4 and 5, we see that participants in the gendered condition overrode more AI recommendations than in the task-relevant condition (p = 0.005). From Figure 5 we further conclude that both corrective and detrimental overrides are highest in the gendered condition, with detrimental overrides being significantly higher than the baseline (p = 0.012). We interpret this increase in overrides further in Section 4.2. In the task-relevant condition, we see that overall overrides are lowest across conditions (Figure 4), with corrective overrides being marginally higher (p = 0.097) and detrimental overrides not significantly different (p = 0.374) compared to the baseline (Figure 5). Overall, we conclude that people’s reliance behavior is affected by how the AI explains its recommendations; notably, people override AI recommendations more often when explanations highlight features that are evidently associated with gender. Across conditions, we also infer from Figure 5 that participants generally performed more corrective than detrimental overrides, and that the ability to perform corrective vs. detrimental overrides (i.e., the ratio of

3.4 Data Collection

Our study received clearance from an institutional ethics committee. Participants were recruited via Prolific—a crowdworking platform for online research [90]. We required participants to be at least 18 years of age, and to be fluent in English. We also sampled approximately equal amounts of men and women; no other prescreeners were applied. After consenting to the terms of our study, participants were then randomly and in equal proportions assigned to one of our three conditions and asked to complete the respective questionnaire. Overall, we recruited 600 lay people through Prolific. At the time of taking the survey, 13.5% of participants were 18–24 years old, 32.6% were 25–34 years old, 21.3% between 35–44, 13.8% between 45–54, 11.3% between 55–64, and 7.6% were older than 65. Regarding gender, 49.2% identified as women, 48.0% as men, and 1.8% identified as non-binary / third gender, or preferred not to say. 8.0% of participants are of Spanish, Hispanic, or Latinx ethnicity; and the majority (78.4%) considered their race to be White or Caucasian, followed by Black or African American (7.0%) and Asian (6.1%). For their participation, participants were paid on average £10.58 (approximately $12.70 at the time the study was conducted) per hour, excluding individual bonus payments of £0.05 per correctly predicted occupation. Participants took on average 10:12min (baseline), 12:51min (task-relevant), and 12:27min (gendered) to complete the survey.

4 ANALYSIS AND RESULTS

We first present results on the effects of explanations on accuracy as well as overriding behavior. Then, we examine how reliance behavior translates to distributive fairness. Finally, we assess the role of fairness perceptions. For all statistical comparisons, we conduct nonparametric tests because we cannot confirm the prerequisites (normal distribution and equal variance) of their parametric counterparts. Specifically, we conduct Kruskal-Wallis omnibus tests [64] whenever applicable, and two-tailed Mann-Whitney U tests [81] for pairwise comparisons. We report p-values for omnibus tests and pairwise comparison tests between the baseline and each condition with explanations (task-relevant and gendered), respectively, in the corresponding figures.
corrective to detrimental overrides) did not improve through the provision of explanations.

4.2 Interplay Between Explanations, Reliance, and Distributive Fairness

Accuracy by gender. Consistent with our findings at the aggregated level (see Figure 3), we do not observe any accuracy changes through explanations over the baseline in Figure 6, neither for men \( (p = 0.199) \) nor women \( (p = 0.151) \) bios. This means that both in the task-relevant and the gendered condition, explanations did not enable people to improve decision-making accuracy, neither for men nor women bios. From Figures 7 and 8, we see why this is the case: for men bios, overrides overall went down in the task-relevant condition, with corrective overrides decreasing even stronger than detrimental overrides; and overrides went up in the gendered condition, with only detrimental overrides increasing. For women bios, detrimental overrides increased and corrective overrides did not change in the task-relevant condition, whereas both corrective and detrimental overrides went up equally in the gendered condition.

Types of overrides by gender and occupation. When looking at effects of explanations on overriding behavior by gender in Figures 7 and 8, no intervention improved participants’ ability to perform corrective vs. detrimental overrides of AI recommendations compared to the baseline—i.e., the ratio of corrective to detrimental overrides did not improve—neither for men nor women bios. This is consistent with our findings at the aggregate level (see Figure 5). Notably, we see that detrimental overrides in the gendered condition marginally increase for men bios (Figure 7) over the baseline \( (p = 0.078) \), and in the task-relevant condition they significantly increase for women bios (Figure 8) compared to the baseline \( (p = 0.013) \). At the same time, corrective overrides remain unchanged in either case.

From comparing Figures 7 and 8, it also appears that participants generally overrode more recommendations for women than men bios: both corrective and detrimental overrides are higher across all conditions in Figure 8 compared to Figure 7. However, because the AI system mostly predicts men as professors and women as teachers, Figures 7 and 8 alone do not allow us to disentangle whether participants override women bios more often because of (i) the bios’ associated gender or (ii) because of the fact that they were predicted to be teachers. Figures 14 and 15 in Appendix C allow a more nuanced conclusion: here, we show that there are more overrides for men when they are correctly predicted by the AI model as teachers (MTT) than for women when they are correctly predicted by the AI model as professors (WPP). Together, these results suggest that participants did not generally override women bios more often than men bios, but instead people were overall more prone to do promoting overrides; which means that participants overrode AI recommendations more often when someone was suggested to be a teacher vs. a professor.

Importantly, people’s likelihood to override conditioned on gender and predicted occupation did vary across conditions. By virtue of our study design, we are able to observe stereotype-countering corrective overrides, and both stereotype-aligned and stereotype-countering detrimental overrides. As explained in Section 3.2, the motivation for this design is our focus on studying whether explanations allow humans to correct for stereotype-aligned incorrect AI predictions, which would be the most frequent errors of an occupation prediction model that exhibits gender bias [30]. We see that in the task-relevant condition, people performed fewer corrective overrides for men \( (p = 0.011) \) and the same amount for women \( (p = 0.834) \) in comparison to the baseline, as shown in Figures 7 and 8. Meanwhile, in the gendered condition participants performed marginally more corrective overrides for women \( (p = 0.083) \) and the same amount of such overrides for men \( (p = 0.588) \). This means that participants in the gendered condition were more likely to perform stereotype-countering corrective overrides than

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9 We assume here that the occupation of professor is associated with a higher societal status than that of teacher. Hence, promoting refers to predicting someone to be a professor, whereas demoting means to predict someone to be a teacher.

10 Recall that societal stereotypes typically associate men with being professors and women with being teachers [85].
in the baseline, while participants in the task-relevant condition were less likely to do so.

As for detrimental overrides, we see that they marginally increase in the gendered condition for men bios (p = 0.078), compared to the baseline (Figure 7). We also see that they are higher for women bios in the gendered condition (Figure 8), even though not statistically significant (p = 0.110). Considering that we do not observe differences in stereotype-aligned detrimental overrides between conditions (Figures 14 and 15 in Appendix C), we infer that people in the gendered condition performed more stereotype-countering detrimental overrides, by predicting more men to be teachers and women to be professors. It is noteworthy that when contrasting corrective and detrimental overrides, we observe that no condition improved participants' ability to make stereotype-countering corrective overrides vs. stereotype-countering detrimental overrides. In the gendered condition, this means that participants became more likely to override an AI recommendation when it predicted that a woman is a teacher, irrespective of her true occupation. Overall, we observe reliance behavior in the gendered condition that counters societal stereotypes, whereas in the task-relevant condition people tend to rely on AI recommendations in a way that reinforces stereotypes. We elaborate on the implications of this for distributive fairness below.

Implications for distributive fairness. We now examine how the observed reliance behavior relates to distributive fairness with respect to disparities in errors between men and women. First, we note that in the baseline condition, people tend to make more errors that promote men vs. women (58.9% vs. 39.9% in Figure 9), and erroneously demote women more than men (41.3% vs. 21.9% in Figure 10). Note that in the case of men, promoting behavior is stereotype-aligned, whereas in the case of women such behavior is stereotype-countering; and vice versa for demoting behavior. The resulting absolute error rate disparities between men and women for the baseline are, hence, 19.0% (promotions) and 19.3% (demotions), as depicted in Figure 11. From the previous paragraph we know that people in the task-relevant condition showed a tendency of reinforcing stereotypes, meaning that promotions of men increased more than those of women, which increased disparities in promotions even further over the baseline (Figure 11, left). Similarly, demotions of men decreased much more than demotions of women, leading to increased disparities in demotions over the baseline (Figure 11, right). In conclusion, we note that people's stereotype-aligned reliance behavior in the task-relevant condition exacerbated existing disparities in the baseline condition and, hence, hindered distributive fairness.

In the gendered condition, on the other hand, people countered stereotypes, meaning that promotions of women increased more than for men, reducing existing disparities (Figure 11, left). The most drastic reduction in disparities happens for demotions (Figure 11, right), since demotions increased for men and decreased for women (Figure 10). This results in a reduction of disparities in demotions from 19.3% (baseline) to 9.7% (gendered condition). Hence, people's stereotype-countering reliance behavior in the gendered condition mitigated existing disparities and, hence, fostered distributive fairness. It is important to stress that while disparities in error types decreased in the gendered condition compared to the baseline, this was due to a shift in the types of errors, as opposed to an increased ability to override mistaken AI recommendations.

4.3 The Role of Fairness Perceptions

Effects of explanations on fairness perceptions. Recall that we measure three items regarding fairness perceptions on 5-point Likert scales, ranging from 1 (unfair) to 5 (fair), as outlined in Section 3.3. We confirm good scale reliability at a Cronbach's alpha [121] value of 0.77. We then take the average of the three item ratings for each participant to obtain a single measure of fairness perceptions. From the distribution in Figure 12, we see that participants in the
**5 DISCUSSION**

In this section, we discuss our findings more broadly. We begin by summarizing our main findings, then acknowledge limitations of our study, and finally provide implications and recommendations for the design of socio-technical systems for decision support. In this section, we also discuss several directions for future work.

### 5.1 Summary of Findings

In this work, we conducted a first holistic analysis of the effects of feature-based explanations on distributive fairness in AI-assisted decision-making. We also studied the mediating roles of reliance behavior and fairness perceptions, which have been the focus of prior work. Our findings suggest that feature-based explanations can have different effects on people’s perceptions, their reliance behavior, and distributive fairness—depending on whether they highlight the use of task-relevant words vs. words that are proxies for sensitive attributes. Specifically, we observe that for the task of occupation classification based on bios, a highlighting of gendered

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**Figure 12:** Fairness perceptions are higher in the *task-relevant* condition compared to the *gendered* condition. Fairness perceptions are averages of three items measured on 5-point Likert scales, resulting in values between 1 (“unfair”) and 5 (“fair”) with 0.33 increments.

**Figure 13:** Significant negative relationship between fairness perceptions and overrides, both corrective and detrimental, as well as overall. Ratio of corrective to detrimental overrides is independent of fairness perceptions.
words led to lower fairness perceptions, which are associated with more overrides of AI recommendations.

These findings relate to algorithm aversion theory [33], which postulates that humans tend to reject advice from algorithms (e.g., AI systems) and instead favor human judgment after they see the algorithm err. Jussupow et al. [59] frame algorithm aversion more generally as “negative behaviours and attitudes towards the algorithm,” and discuss several reasons for it, including algorithm agency, performance/capabilities, and human involvement. Our findings might be seen as an extension to this theory as they suggest perceived unfairness as another driver of human aversion towards AI systems. These findings can also be related to recent work by Vasconcelos et al. [124], who argue that the effects of explanations on reliance behavior depend on the degree to which they reduce the cognitive effort of verifying AI recommendations. While we do not observe that explanations actually enabled humans to verify the correctness of AI recommendations, a speculative reason why explanations in the gendered condition triggered more overrides is that they enabled participants to easily see that the AI system was considering sensitive information, which then resulted in low fairness perceptions and an increase in overrides. On the other hand, when task-relevant words are highlighted, this led to higher fairness perceptions, which translate to fewer overrides. In no case, however, do we observe that explanations improved people’s ability to perform corrective vs. detrimental overrides, compared to a scenario with no explanations.

Finally, we show that feature-based explanations can improve or hinder distributive fairness by fostering shifts in errors that counter or reinforce stereotypes: in the gendered condition, participants displayed stereotype-countering reliance behavior, while in the task-relevant condition, they displayed stereotype-aligned behavior. In both these cases, the respective reliance behavior affected both corrective and detrimental overrides. This means that the conditions affected the likelihood to perform an override conditioned on the predicted occupation and a bio’s associated gender, but with no relationship to the true occupation. For instance, the gendered condition fostered more overrides of AI recommendations when a woman was predicted to be a teacher, irrespective of whether this prediction was correct; meanwhile, in the task-relevant condition participants were less likely to override AI recommendations where a man was predicted to be a professor, irrespective of his true occupation.

5.2 Limitations

Our study setup assigned participants to either the gendered or the task-relevant condition; i.e., participants saw either only explanations with highlighting of gendered words or task-relevant words. We made this choice because we wanted to measure perceptions of fairness, but eliciting perceptions at an instance level could lead people to anchor their decisions to their expressed perceptions (or vice versa), which would compromise external validity. Assigning people to different conditions enabled us to measure perceptions at the aggregate level. In practice, an AI model might sometimes highlight only sensitive features, sometimes only task-relevant features, and at other times a mix of both. Future work that studies how instance-level perceptions relate to aggregate-level perceptions, and how these interdependencies shape reliance behavior could complement our findings. While our study design does not explicitly account for this, even if perceptions vary at the instance level, our findings suggest that reliance would depend on the inclusion of sensitive features, which research has shown to be an unreliable signal for assessing algorithmic fairness [7, 36, 63, 69, 88, 94, 101]. In particular, previous research has shown that “fairness through unawareness,” i.e., the exclusion of information that is evidently indicative of a person’s demographics, is neither necessary nor sufficient for an algorithm to be procedurally fair [69, 88, 101] or to not display bias in terms of distributive fairness [7, 36, 63, 94]. Our paper complements these works by showing that feature-based explanations may foster stereotype-aligned reliance behavior, therefore hindering distributive fairness in AI-assisted decisions.

Importantly, our study does not claim that the observed effects should be taken for granted in any AI-assisted decision-making setup; rather, they should be carefully evaluated in future empirical studies. With this work, we aim to provide an important example that shows how unreliable feature-based explanations are when it comes to effects on humans’ reliance behavior and distributive fairness. Our hope is that this work will inform improved assessment and design of explainability techniques, leading to a nuanced understanding of when and how certain types of explanations can enable humans to improve fairness properties of a system.

5.3 Implications

Our work has several important implications for the design of socio-technical systems for decision support. In the following, we group them by theme.

Towards meaningfully evaluating explanations. A main argument of our work is that claims around explanations fostering distributive fairness must directly measure the impact of explanations on fairness metrics of AI-assisted decisions, which depend on humans’ reliance behavior. To this end, our study constitutes a blueprint that should be used to evaluate other types of explanations and tasks. Crucially, our research shows that the mechanism through which reliance behavior affects metrics of fairness matters. In particular, we show that distributive fairness may improve even in the absence of an enhanced ability to perform corrective overrides. In other words, appropriate reliance is not a necessary condition for improving distributive fairness in AI-assisted decision-making, but the presence of explanations may drive a change in fairness metrics by fostering over- or under-reliance for certain types of cases. Simultaneously, our work shows that an improvement in distributive fairness metrics does not necessarily mean that humans are overriding incorrect recommendations. For instance, we have seen in our study that overriding stereotype-aligned AI recommendations (e.g., when a woman is predicted to be a teacher) may decrease gender disparities in error rates, even if correct recommendations are being overridden. This finding may be particularly important from a design and a policy perspective, since a common motivation when providing humans with discretionary power to override decisions is an expectation that they will be able to correct for an AI system’s mistakes [43, 45].

These findings also have implications for the interpretation of studies focused on perceptions of fairness. Our work shows that
fairness perceptions have no bearing on people’s ability to correctly override AI recommendations. Instead, our study results suggest that low fairness perceptions are associated with more overrides of AI recommendations, irrespective of their correctness. This may still lead to improvements in distributive fairness but does not indicate that humans differentiate between correct and incorrect AI recommendations. This is important as perceptions are often used as proxies for trust and reliance [120].

Towards grounding explanations in concrete and realistic objectives. Previous work has emphasized that interpretability is not a monolithic concept, and the design of explanations should always be grounded on a concrete objective that it helps advance [74]. However, as also noted in previous research [32, 70], it appears that we have been overloading explanations with a plethora of vague and broad-brush expectations—especially in regards to fairness—which may promote a false sense of optimism with respect to the capabilities of existing techniques, and hinders the design of truly effective novel interventions. Prior work has claimed, e.g., that “explainability can be considered as the capacity to reach and guarantee fairness in ML models” [8]. However, such claims are misleading as they ignore the fact that both explainability and fairness are complex, multi-dimensional concepts that warrant a more nuanced perspective [32]. Our work emphasizes the importance of designing explanations with the explicit purpose of enabling human decision-makers to rely on AI recommendations in a way that enhances distributive fairness metrics, and it casts doubt over the reliability of popular feature-based explainability approaches to advance this goal—despite them being widely employed in both academic and practical settings [15, 46].

Towards providing relevant cues through explanations. Related to the previous theme, we argue that explanations must be designed to provide relevant cues to human stakeholders for them to be able to use their discretionary power effectively towards advancing any specified objectives. With respect to distributive fairness, our work suggests that feature-based explanations are not providing these relevant cues. Informing humans about whether or not an AI system considers sensitive information (e.g., gender) would only be relevant if it were desirable to override AI recommendations based thereon. However, previous research has shown that the disuse of sensitive information (“fairness through unawareness” [65]) is neither a necessary nor a sufficient condition for distributive fairness [27, 36, 63, 88, 94]. Moreover, it is known that the use of sensitive information by an AI system can be concealed: Lakkaraju and Bastani [69], e.g., construct misleading explanations by leveraging correlations between sensitive and seemingly legitimate features. This means that feature-based explanations are not a reliable mechanism to assess either procedural or distributive fairness. Instead, we propose that explanations must transcend a human-in-the-loop operationalization of the flawed idea of “fairness through unawareness” and instead enable the human decision-maker to ground their reliance behavior on information that is both relevant and reliable for improving distributive fairness metrics. A possible way forward might be to directly communicate relevant individual or group fairness properties of the AI system to the decision-maker, which has been recently studied by Ashktorab et al. [9].

Towards widening the scope of explanations. We also suggest moving towards a broader understanding of what algorithmic transparency might entail. We should aim to understand how to build a supportive ecosystem around AI systems, one that enables relevant human stakeholders to achieve their respective goals. One element of such an ecosystem could be an interface that allows individuals to query different pieces of information, based on their background and situational needs. To this point, novel findings from ethnographic work studying the use of AI have the potential to inform alternative designs of explanations. For instance, Lebovitz et al. [71] study the adoption of AI in three healthcare domains and emphasize the importance of interrogation practices, which are practices used by humans to relate their own knowledge to AI’s predictions. They note that if AI systems are to add value, they will sometimes make recommendations that conflict with experts’ knowledge. Therefore, what is needed are processes and tools that assist them in reconciling these differing perspectives. Moreover, it is not always clear that what is needed are explanations pertaining to the AI system’s inner workings, as opposed to explanations of the broader socio-technical system. For instance, interventions that assist humans in reasoning about the information that is and is not available to the AI system may help them reconcile disagreements and better integrate multiple information sources [55, 56]. In clinical decision-making, Elsan et al. [40] discovered that explanations could foster social interactions and reveal how different physicians respond to specific AI recommendations in the past. Auxiliary interventions such as cognitive forcing functions have also been demonstrated to encourage more effective reliance behavior [18].

Additional future directions. To design effective interventions for decision support, it is important to understand the psychological mechanisms at play when humans adhere to or override AI recommendations. One promising direction for follow-up work will be to study why the highlighting of gendered features results in AI aversion. On the other hand, we have also seen cases where humans perceive the use of gendered words for predicting occupations as fair (see Figure 12 in Section 4), and it will be interesting to analyze when and why this is the case.

Prior work has argued that people’s socio-cultural identity may relate to how they integrate AI recommendations into their decisions [44]. Empirically, Mallari et al. [80] found that self-reported gender affected decision-making behavior and also interacted with the demographics of decision-subjects in the realm of recidivism prediction. Moreover, Peng et al. [96] provide evidence that crowd-workers’ gender affected AI-assisted decisions, including biases. Studying how demographics influence the use of explanations with respect to distributive fairness is, however, an open and important research question that merits in-depth follow-up work.

6 CONCLUSION

Explanations have been framed as an important mechanism for better and fairer human-AI decision-making. In the context of fairness, however, this has not been appropriately studied, as prior works have mostly evaluated explanations based on their effects on people’s perceptions. To fill this gap, we conducted a first comprehensive study of the effects of popular feature-based explanations on distributive fairness in AI-assisted occupation prediction. We
find that the type of features that an explanation highlights matters: when explanations highlight only task-relevant words, people tend to reinforce stereotypical AI recommendations, ultimately increasing error rate disparities between women and men. On the other hand, when explanations highlight gendered words, people tend to override more AI recommendations to counter stereotypical AI recommendations, which decreases error rate disparities. Importantly, these effects on distributive fairness do not involve an enhanced human ability to override incorrect AI recommendations (i.e., “appropriate reliance”) but solely emerge from a shifting in error types. For instance, if an AI system predicts that a woman is a teacher and the explanation highlights the use of gendered words, human decision-makers are more likely to override the recommendation regardless of whether the woman is indeed a teacher.

Overall, our findings raise doubts about the reliability of feature-based explanations as a mechanism to improve distributive fairness in AI-assisted decision-making. Our work has important implications for the design of socio-technical systems for decision support, pertaining to (i) meaningfully evaluating explanations, (ii) grounding explanations in concrete objectives, (iii) providing relevant cues through explanations, and (iv) widening the scope of explanations. We hope that this work will inform improved assessment and design of novel explainability techniques, leading to a nuanced understanding of when and how certain types of explanations can enable humans to improve fairness properties of a system.

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After completing steps (1)–(3), we obtain the task-relevant vocabulary among others.

We constructed the task-relevant vocabulary that significantly change the classifiers’ predictions. We then constructed stop words. We inferred top-5000 most occurring words, after removal of (manually defined) 10 across the set of all bios. We chose task-relevant conditions.

Gendered vocabulary.

Let $W = \{w_1, \ldots, w_n\}$ be the set of $n$ words that occur most often across the set of all bios. We chose $n = 5000$, i.e., $W$ contains the top-5000 most occurring words, after removal of (manually defined) stop words. We inferred $W$ from applying a CountVectorizer [93]. In trial runs, we found that increasing $n$ beyond 5000 does not significantly change the classifiers’ predictions. We then constructed two logistic regression classifiers, $A_{el}$ and $A_{gen}$, with access to mutually disjoint vocabularies: task-relevant words ($W_{rel} \subset W$) and gendered words ($W_{gen} \subset W$).

Task-relevant vocabulary. We performed the following steps to construct the task-relevant vocabulary $W_{rel}$:

1. For all $i \in \{1, \ldots, n\}$, compute the average occurrence of word $w_i$ in bios of men and women professors and teachers. We call the results $\frac{w_i}{P,m}$, $\frac{w_i}{P,w}$, $\frac{w_i}{T,m}$, and $\frac{w_i}{T,w}$, where we use $P$, $T$ and $m$, $w$ as a shorthand for the respective occupations and genders. We also compute $\frac{w_i}{P}$ as the average occurrence of $w_i$ for any other occupation $\bullet$ that is not professor or teacher.

2. For given gender $g \in \{m, w\}$, check whether $\frac{w_i}{P g} > \frac{w_i}{P}$ or $\frac{w_i}{T g} > \frac{w_i}{T}$ for all other occupations $\bullet$, i.e., whether the average occurrence of word $w_i$ in professor or teacher bio of gender $g$ is greater than the average in any other occupation. If this condition is met, add $w_i$ to $W_{rel}^g$, the set of task-relevant words for gender $g$.

3. Compute $W_{rel}^m \cap W_{rel}^w = W_{rel}$ as the set of words that are task-relevant for both genders.

After completing steps (1)–(3), we obtain the task-relevant vocabulary $W_{rel}$ of 543 words, including faculty, kindergarden, or phd, among others.

Gendered vocabulary. Denote $|B^o|$ the amount of bios of occupation $o \in \{P, T\}$ and gender $g \in \{m, w\}$. We perform the following steps to construct the gendered vocabulary $W_{gen}$:

1. Sample equal amounts of bios for men and women professors and teachers. Since $\min\{|B^o|\} = |B^T| = 6440$, randomly sample 6440 bios for each combination of occupation and gender.

2. Extract features from bios by applying a CountVectorizer with TF-IDF weighting [93].

3. Train a logistic regression to predict gender from the extracted features.

4. Compute the importance of each (weighted) feature based on the absolute magnitude of their corresponding regression coefficient, and sort the resulting list of words by importance.

5. Include the top-5% most important words in $W_{gen}$ as the set of words that are highly predictive of gender. We choose the threshold of 5% so as to exclude words that are spuriously correlated with gender (e.g., towards).

After completing steps (1)–(5), we obtain the gendered vocabulary $W_{gen}$ of 214 words, which include—apart from gender pronouns and words such as husband and wife—words like dance, art, or engineering, which are not evidently gendered.

Deploying the classifiers. Having established our vocabularies $W_{rel}$ and $W_{gen}$, we proceed by training two logistic regression models on a balanced set of bios containing 50% professors and 50% teachers. Denote $|B^P|$ and $|B^T|$ the amounts of bios of occupations $P$ and $T$. Since $|B^T| = 16,221 < |B^P|$, we randomly sample 16,221 bios of professors, while preserving the gender distribution from the original data. This yields a dataset of 32,442 bios, 50% of which we use as a holdout set. We separate a relatively large holdout set because we will eventually use a specific subset of these bios in our questionnaires (see Appendix B). The resulting classifiers achieve $F_1$ scores of 0.87 ($A_{el}$) and 0.77 ($A_{gen}$). For generating dynamic explanations with highlighting of predictive words, we employ the TextExplainer from LIME [104].

A CONSTRUCTION OF TASK-RELEVANT AND GENDERED CLASSIFIERS

Here, we explain in more detail how we constructed the AI models that we use for generating recommendations and explanations in the task-relevant and gendered conditions.

Let $W = \{w_1, \ldots, w_n\}$ be the set of $n$ words that occur most often across the set of all bios. We chose $n = 5000$, i.e., $W$ contains the top-5000 most occurring words, after removal of (manually defined) stop words. We inferred $W$ from applying a CountVectorizer [93]. In trial runs, we found that increasing $n$ beyond 5000 does not significantly change the classifiers’ predictions. We then constructed two logistic regression classifiers, $A_{el}$ and $A_{gen}$, with access to mutually disjoint vocabularies: task-relevant words ($W_{rel} \subset W$) and gendered words ($W_{gen} \subset W$).

Task-relevant vocabulary. We performed the following steps to construct the task-relevant vocabulary $W_{rel}$:

1. For all $i \in \{1, \ldots, n\}$, compute the average occurrence of word $w_i$ in bios of men and women professors and teachers. We call the results $\frac{w_i}{P,m}$, $\frac{w_i}{P,w}$, $\frac{w_i}{T,m}$, and $\frac{w_i}{T,w}$, where we use $P$, $T$ and $m$, $w$ as a shorthand for the respective occupations and genders. We also compute $\frac{w_i}{P}$ as the average occurrence of $w_i$ for any other occupation $\bullet$ that is not professor or teacher.

2. For given gender $g \in \{m, w\}$, check whether $\frac{w_i}{P g} > \frac{w_i}{P}$ or $\frac{w_i}{T g} > \frac{w_i}{T}$ for all other occupations $\bullet$, i.e., whether the average occurrence of word $w_i$ in professor or teacher bio of gender $g$ is greater than the average in any other occupation. If this condition is met, add $w_i$ to $W_{rel}^g$, the set of task-relevant words for gender $g$.

3. Compute $W_{rel}^m \cap W_{rel}^w = W_{rel}$ as the set of words that are task-relevant for both genders.

After completing steps (1)–(3), we obtain the task-relevant vocabulary $W_{rel}$ of 543 words, including faculty, kindergarden, or phd, among others.

Gendered vocabulary. Denote $|B^o|$ the amount of bios of occupation $o \in \{P, T\}$ and gender $g \in \{m, w\}$. We perform the following steps to construct the gendered vocabulary $W_{gen}$:

1. Sample equal amounts of bios for men and women professors and teachers. Since $\min\{|B^o|\} = |B^T| = 6440$, randomly sample 6440 bios for each combination of occupation and gender.

2. Extract features from bios by applying a CountVectorizer with TF-IDF weighting [93].

3. Train a logistic regression to predict gender from the extracted features.

4. Compute the importance of each (weighted) feature based on the absolute magnitude of their corresponding regression coefficient, and sort the resulting list of words by importance.

5. Include the top-5% most important words in $W_{gen}$ as the set of words that are highly predictive of gender. We choose the threshold of 5% so as to exclude words that are spuriously correlated with gender (e.g., towards).

After completing steps (1)–(5), we obtain the gendered vocabulary $W_{gen}$ of 214 words, which include—apart from gender pronouns and words such as husband and wife—words like dance, art, or engineering, which are not evidently gendered.

Deploying the classifiers. Having established our vocabularies $W_{rel}$ and $W_{gen}$, we proceed by training two logistic regression models on a balanced set of bios containing 50% professors and 50% teachers. Denote $|B^P|$ and $|B^T|$ the amounts of bios of occupations $P$ and $T$. Since $|B^T| = 16,221 < |B^P|$, we randomly sample 16,221 bios of professors, while preserving the gender distribution from the original data. This yields a dataset of 32,442 bios, 50% of which we use as a holdout set. We separate a relatively large holdout set because we will eventually use a specific subset of these bios in our questionnaires (see Appendix B). The resulting classifiers achieve $F_1$ scores of 0.87 ($A_{el}$) and 0.77 ($A_{gen}$). For generating dynamic explanations with highlighting of predictive words, we employ the TextExplainer from LIME [104].

B SELECTION OF BIOS

Pre-selection. As outlined in Section 3.2, participants are confronted with 14 bios of professors and teachers. We impose a series of constraints to select which bios from the holdout set we include in the questionnaires. In particular, for a given bio to be included in our questionnaires, we require it to satisfy the following:

- Both models $A_{el}$ and $A_{gen}$ must yield the same predicted occupation for the bio.
- The prediction probabilities of $A_{el}$ and $A_{gen}$ towards either occupation must be at most 20% different. This ensures that both models are comparably certain in their predictions for the given bio.
- The prediction probabilities of $A_{el}$ and $A_{gen}$ towards either occupation must be at most 80%. This aims at eliminating a large share of bios that are “too easy” to classify.
- To avoid any confounding effects of bios’ length on people’s behavior, we only consider bios of length between 50 and 100 words.

Enforcing these constraints on bios from the holdout set leaves us with 690 eligible bios (out of 16,221). In a next step, we decide on the final set for our questionnaires.

Final selection. The authors jointly screened these 690 bios and ruled out those that are trivial (e.g., because humans would easily be able to tell the occupation) or otherwise not suitable (e.g., because of misspellings or excessive use of jargon). We also discarded bios where explanations would highlight too few or too many words, or where the number of highlighted words was significantly different between the task-relevant and the gendered condition. This
Figure 14: Overrides of AI recommendations that correctly predict a man teacher to be a teacher (MTT).

Figure 15: Overrides of AI recommendations that correctly predict a woman professor to be a professor (WPP).

filtering narrows down the set of eligible bios to 38. The authors then independently screened the resulting 38 bios including the corresponding explanations, and assigned a rating of green ("in favor of using it"), yellow ("indifferent"), or red ("in favor of discarding it"), based on both a bio’s content as well as the associated explanation, favoring bios that were non-trivial but that contained enough information to make a correct prediction. We then decided on the final set of 14 bios based on majority vote, taking into account the required composition of scenarios, as outlined in Table 1 in Section 3.2.

C OVERRIDES OF ANTI-STEREOTYPICAL AI RECOMMENDATIONS

Figures 14 and 15 show participants’ overriding behavior for cases where AI recommendations are correct and anti-stereotypical; i.e., correctly suggesting men to be teachers (MTT) and women to be professors (WPP). We see that across conditions, overrides are much higher for the MTT case than for the WPP case. Together with the findings from Section 4 this suggests that participants were more prone to override AI recommendations whenever they suggested someone to be a teacher vs. a professor.