User Acceptance of Gender Stereotypes in Automated Career Recommendations

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Abstract

Currently, there is a surge of interest in fair Artificial Intelligence (AI) and Machine Learning (ML) research which aims to mitigate discriminatory bias in AI algorithms, e.g. along lines of gender, age, and race. While most research in this domain focuses on developing fair AI algorithms, in this work, we show that a fair AI algorithm on its own may be insufficient to achieve its intended results in the real world. Using career recommendation as a case study, we build a fair AI career recommender by employing gender debiasing machine learning techniques. Our offline evaluation showed that the debiased recommender makes fairer career recommendations without sacrificing its accuracy. Nevertheless, an online user study of more than 200 college students revealed that participants on average prefer the original biased system over the debiased system. Specifically, we found that perceived gender disparity is a determining factor for the acceptance of a recommendation. In other words, our results demonstrate we cannot fully address the gender bias issue in AI recommendations without addressing the gender bias in humans.

Introduction

Artificial Intelligence (AI) is increasingly used in consequential decision making, but recent discoveries have shown that AI systems often exhibit discriminatory bias in their behavior, particularly along gender, age, and racial lines (Dastin 2018; Noble 2018; Angwin et al. 2016). For example, an AI tool that helps judges assess the risk of an incarcerated individual committing a crime in the future was found to be biased against African Americans (Angwin et al. 2016). In other domains including personalized search, ads and recommendation, AI systems lead to skewed outcomes (Ali et al. 2019). AI models trained on text data have been found to encode gender stereotypes such as associating computer programming with men and homemaking with women (Bolukbasi et al. 2016), which could potentially impact automated career counseling and hiring decisions. Indeed, Amazon had to scrap its AI recruiting tool because it was found to be biased against women (Dastin 2018).

Since biased AI systems can be discriminatory against vulnerable populations in our society and/or reinforce harm-

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ful stereotypes, there are strong motivations to develop AI debiasing interventions (Campolo et al. 2017). We argue that there are two aspects which must be considered when it comes to mitigating AI bias: the algorithmic aspect and the human-AI interaction aspect. Most existing approaches in the AI community focus on the algorithmic aspect. The mission of the field has primarily been to develop (a) new metrics that quantify fairness (Dwork et al. 2012; Kusner et al. 2017), and (b) new machine learning techniques that remove bias (Zhang, Lemoine, and Mitchell 2018; Dev and Phillips 2019; Foulds et al. 2020a). On the other hand, the humanfair AI interaction aspect as well as its broader social context is equally important and significantly understudied. For example, in many contexts such as targeting ads on search and social network platforms it is well understood that there is a tension between building a fair system and achieving the platform's own revenue goals (Miller and Hosanagar 2010), and this tension cannot be resolved by algorithms alone. As bias in AI may arise from the human side of the sociotechnical system via systemic bias and/or human prejudice encoded in data (Barocas and Selbst 2016), will bias mitigation be effective if we focus only on removing the bias in AI without addressing the bias in humans?

In this research, we systematically study the interplay between AI debiasing techniques and humans, using AI career recommendation as a case study. Career choice is a major part of human life, as it often defines one's economic success, social standing, and quality of life. Humans have a tendency to associate masculine and feminine traits with specific careers, which results in the perception that certain genders are better suited for certain occupations (White and White 2006). Machines that learn from career data are thus expected to be influenced by the resulting gender gaps in career choices unless bias mitigation techniques are performed (Dastin 2018).

We first dive into the algorithmic aspect of the problem, using machine learning to systematically mitigate bias in AI systems so that they do not reinforce harmful stereotypes. Second, we examine the human-fair AI interaction aspect of the problem. We perform a user study to investigate whether users will typically prefer a fair AI system over a biased one. Users may have their own biases, and our results show that

users' acceptance of a debiased AI system can be influenced by their own biases. The following are the main contributions of the paper.

- To the best of our knowledge, this is the first study on how human bias interferes with the effectiveness of a fully implemented fair AI career.
- As a case study, we develop a debiased recommender system which mitigates gender bias in career recommendations (authors 2019). Our offline evaluation shows that the debiased recommender is fairer than the gender-aware (biased) recommender without any loss of prediction accuracy.
- We conduct an online user study with over 200 participants (college students) to understand their acceptance of the debiased system. The results indicate that participants in general prefer the gender-aware (biased) career recommender over the gender-debiased one. We analyzed the role a participant's own bias plays in his or her acceptance of the recommendations. Our results indicate that the perceived gender disparity in a recommended career is significantly correlated with its acceptance.

In the rest of the paper, we describe related literature, the implementation of a debiased machine learning algorithm for fair career recommendation, an offline evaluation of the system, an online user study for understanding the relationship between human bias and the acceptance of a fair AI system.

Related Work

In this section, we summarize recent work on fair AI and ML, review social science studies on the relationship between gender bias and career decisions, and briefly discuss the work in the Human-Computer Interaction (HCI) community on AI bias/fairness.

Fair AI and ML Research

Recently, there has been a sharp focus in the AI community on how to prevent AI from perpetuating or, worse, exacerbating social unfairness. Most efforts concentrate on (1) developing metrics to quantify the bias in data as well as in ML algorithms, and (2) developing fair ML algorithms that mitigate these biases.

It is difficult to develop a universal definition of fairness because fairness/bias is a complex, multifaceted concept whose definition heavily depends on the social, culture and application context. Consequently, many definitions have been proposed. In fact, AIF360, the IBM open source platform for fair machine learning, has several dozen metrics for fairness/bias (Bellamy et al. 2019). Among them, some are about *individual fairness* and others are about *group fairness*.

Individual fairness seeks to ensure similar individuals get similar outcomes. Widely used individual fairness measures include *Fairness Through Awareness* ("An algorithm is fair if it gives similar predictions to similar individuals") (Dwork et al. 2012), *Fairness Through Unawareness* ("An algorithm is fair as long as any protected attributes such as race, age,

gender are not explicitly used in the decision-making process") (Gajane and Pechenizkiy 2017), and *Counterfactual Fairness* ("a decision is fair towards an individual if it is the same in both the actual world and a counterfactual world where the individual belonged to a different demographic group") (Kusner et al. 2017).

Group fairness partitions a population into groups defined by protected attributes (or intersections of protected attributes) and seeks to ensure that statistical measures of outcomes are equal across groups/subgroups. Widely used group fairness measures include Demographic Parity ("The likelihood of a positive outcome should be the same regardless of whether the person is in the protected group") (Dwork et al. 2012), Equalized Odds ("the probability of a person in the positive class being correctly assigned a positive outcome and the probability of a person in a negative class being incorrectly assigned a positive outcome should both be the same for the protected and unprotected group members") (Hardt, Price, and Srebro 2016), Equal Opportunity ("the probability of a person in a positive class being assigned to a positive outcome should be equal for both protected and unprotected group members") (Hardt, Price, and Srebro 2016) and Differential Fairness ("the probabilities of the outcomes will be similar with respect to different subgroups defined by the intersections of multiple protected attributes such as race, gender and race") (Foulds et al. 2020b). Most fairness measures are defined for classification tasks. There are fairness measures for other tasks. For example, Non-parity Unfairness (Yao and Huang 2017) is designed to evaluate the fairness of recommender systems.

In terms of mitigating bias in AI systems, one focus is to remove the bias from the data that is used to train the AI models. For example, vector projection-based bias attenuation method is used to remove bias from word embeddings (Dev and Phillips 2019). Since word embeddings are widely used as features to train downstream natural language processing models, debiased word embedding improves the fairness of the applications. There is also a large body of work that optimizes ML models under both traditional accuracy-based and new fairness-based objectives (Woodworth et al. 2017; Zafar et al. 2017; Agarwal et al. 2018; Foulds et al. 2020a). Furthermore, adversarial learning is used to improve model accuracy and at the same time minimize an adversary's chance of finding out protected attributes (e.g., gender and race) (Zhang, Lemoine, and Mitchell 2018).

Social Science Research on Gender Bias and Careers

According to Glick et al (Glick and Fiske 1999), gender, or the cultural construction of sex differences, is the "most automatic, pervasive and earliest learned" categorization that shapes social relations and identities. Social science research on gender bias and stereotypes in career choices consistently finds that gender-based differences in career selection exist even when controlling for measured competency and ability (Correll 2001). Career-related gender bias exists across country, culture and age. For example, even as kindergartners, girls select mostly traditional female ca-

reers such as teaching and nursing (Stroeher 1994). Scottish pupils were found to perceive Truck Driver, Engineer, Plumber/Electrician, Laborer, Armed Forces as "male" jobs while Nurse and Care Assistant "female" jobs. Boys, but especially girls, have strong preferences against working in sectors and industries that are traditionally the domain of the opposite sex (McQuaid and Bond 2004).

Many theories have been developed to explain why gender bias exists in career selection. Some of them focus on psychological constructs (i.e., variables at the level of individuals), while others focus on socioeconomic conditions and cultural understandings of gender roles.

Social Cognitive Theory (Bandura 1977) and Social Cognitive Career Theory (Lent, Brown, and Hackett 1994) are the most influential social cognitive frameworks for understanding individual human behavior as well as career decisions. They posit that human behaviour is primarily explained through self-efficacy beliefs, outcome expectations, and goal representations. Self-efficacy beliefs refer to "people's judgment of their capabilities to organize and execute courses of action required to attain designated types of performances." Outcome expectations concern a "person's estimate that a given behaviour will lead to a certain outcome." Goal representations are defined as "determinations of individuals to engage in a particular activity." Of the three determinants, self-efficacy has the strongest influence on behavior. Gender difference in self-efficacy beliefs may explain observed gender bias in career choice. For example, it was found that women possess lower levels of mathematics confidence than men because women had fewer learning possibilities and role models to stimulate them (Bandura 1978; Lent, Brown, and Hackett 1994).

In addition to psychological constructs, social and cultural beliefs about gender may also influence career choice of men and women. For example, gender beliefs are cultural schemas for interpreting or making sense of the social world. They represent what we think "most people" believe or accept as true about the categories of "men" and "women." Substantial evidence indicates that certain careers (e.g., mathematics) are often stereotyped as "masculine" (Meece et al. 1982; Hyde, Fennema, and Lamon 1990). This cultural belief about gender channels men and women in substantially different career directions since it impacts the self-efficacy of individuals (e.g., belief about their own mathematical competence) (Correll 2001).

In terms of overcoming gender bias in career decisions, the most commonly cited interventions include the availability of role models in the same social circle, especially same sex role models for women (Lockwood 2006; Hill and Giles 2014; McQuaid and Bond 2004). Encouragement from friends and family (Leaper and Starr 2019) also improves self-efficacy.

HCI Research on AI Fairness/Bias

Recent work on AI fairness/bias in the HCI community mostly focuses on identifying and analyzing biases in existing AI systems such as image search (Otterbacher, Bates, and Clough 2017; Kay, Matuszek, and Munson 2015), social media analysis (Johnson et al. 2017), image and per-

sona generation (Salminen, Jung, and Jansen 2019; Salminen et al. 2020), sentiment analysis (Díaz et al. 2018), text mining (Cryan et al. 2020) and natural language generation (Strengers et al. 2020).

There are also some work on fairness perception and definition. Wang et al (Wang, Harper, and Zhu 2020) and McDonald et al (McDonald and Pan 2020) conducted studies to better understand the perception of fairness. Hou et al (Hou et al. 2017) and Woodruff et al (Woodruff et al. 2018) explored how intended users, especially those marginalized by race or class, feel about algorithmic fairness. Dodge et al (Dodge et al. 2019) conducted an empirical study on how people judge the fairness of ML systems and how explanations impact that judgment. Chen et al (Chen et al. 2020) tried to quantify fairness/biases by measuring the difference of its data distribution with a reference dataset using Maximum Mean Discrepancy.

There is a rich body of work on mitigating bias in AI systems through the use of better system designs. One principled approach is known as equitable and inclusive codesign, which is about engaging diverse stakeholders especially underrepresented minorities directly in the design process (Madaio et al. 2020; Skinner, Brown, and Walsh 2020; Vorvoreanu et al. 2019; Metaxa-Kakavouli et al. 2018). Furthermore, better tooling (Cramer et al. 2019; Yan et al. 2020) and better algorithms (Strengers et al. 2020; Barbosa and Chen 2019) also help address the problem.

So far, there is little work focusing on what happens *after* biases in AI systems are identified and systematically removed. Does it automatically achieve its intended societal impact? Our work explores this domain.

Debiasing Career Recommendations

We use an AI career recommendation as a case study to illustrate how an AI recommender which uses state-of-the-art debiasing techniques to systematically remove gender stereotypes from its recommendation, may not produce intended outcomes. In this study, we focus on college major recommendation because the current subjects of our study were college students, to whom the choice of a major is one of the most consequential career decisions they make.

Recommender systems have gained widespread acceptance in the era of the internet, social network, and ecommerce. The basic idea of recommender systems is to infer user interest based on user-generated data. For example, collaborative filtering, a key method used in recommender systems, is based on the assumption that similar users have similar preferences of items (Sarwar et al. 2001). Thus, an ecommerce recommender will recommend a product to a customer if it was purchased by customers who gave similar ratings to other products in the past. Following the same idea, an AI career recommender suggests similar college majors to people who share similar interests.

A major source of bias/unfairness in machine learning outcomes arises from biases in the data (Barocas and Selbst 2016; Mehrabi et al. 2019; Suresh and Guttag 2019). A machine learning model trained on biased data may lead to unfair/biased predictions. For example, user preference data may encode real-world human biases (e.g., gender or racial

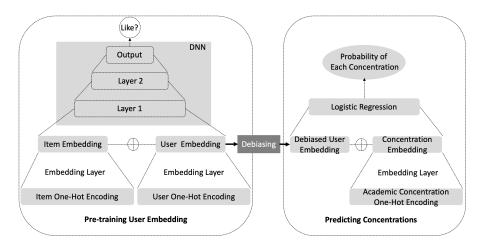


Figure 1: The Architecture of a Gender-Debiased Career Recommender

biases). As a result, the system may inherit the bias into its recommendations. In the following, we describe the methodology used to implement a debiased algorithm for fair college major recommendation.

Backend Algorithm Implementation

The system is designed to make career recommendations based on an individual's interests. The input to the system is a user's interests indicated on Facebook. We chose the Facebook data because it contains a wide range of items a person can like such as books, hobbies, thoughts, movies, music and sports. The output contains the top college major recommended by our system such as computer science, biology and psychology. We employed an existing Facebook dataset widely used in social media research (Matz et al. 2017; Youyou, Kosinski, and Stillwell 2015; Schwartz et al. 2013; Kosinski et al. 2015).

Since the academic concentrations in our data are declared by Facebook users, they are quite noisy (e.g., "Defense Against the Dark Arts" is a declared academic concentration). To prepare the Facebook data to train our recommender, we filtered out academic concentrations that occurred less then 3 times in the data. The final data used in training and testing the backend system contains a total of 16,619 users (of which 60% are female, 40% are male and no gender non-binary individuals), 1,380 unique concentrations, 140K+ unique items that a user can like and 3.5 million+ user-interest pairs.

To develop a college major recommender, first, we train a neural collaborative filtering (NCF) (He et al. 2017) model for predicting the items a user "likes," encoded as 1, or 0 if otherwise. A user's gender is not taken into account during the training of the NCF model. We also included 10% negative instances from those user-interest pairs marked as "0." In the input layer, the users and items are one hot-encoded. They are mapped into two separate embedding layers with embedding size of 100 (user and item embedding). Since NCF adopts two pathways to model users and items, the user and item embeddings are combined by concatenation. One

hidden layer with 10 linear units is added on the concatenated vector along with dropout regularization of probability 0.1, followed by a linear output layer. Finally, we train the model by optimizing MSE loss using *Adam* in batch mode with a learning rate of 0.001 for 20 epochs. Note that "relu" activation is used for the hidden and output layers. L2 regularization with tuning parameter 0.0001 is also used to optimize the loss for the NCF model.

We then study the use of the learned user embeddings to suggest academic concentrations by training a logistic regression classifier. We train the multi-class logistic regression model by minimizing a multinomial loss that fits across the entire probability distribution using stochastic average gradient descent in batch mode with a learning rate of 0.001 for 500 epochs. We further use L2 regularization with tuning parameter 0.0001 in the logistic regression model.

To gender-debias the recommendation, we add a debiasing step prior to applying logistic regression. Our debiasing approach adapts a recent work on attenuating bias in word vectors (Dev and Phillips 2019). Since traditional word embeddings are usually trained on massive text data, they inherit some of the human racial and gender biases from the data, as demonstrated by this well-known example, in which vector arithmetic on the embeddings solves an analogy task (Buonocore 2019):

$$doctor - man + woman = nurse$$
.

The user embeddings we have trained experience a very similar issue. Let p_u denote the embedding of a user, and let v_B , which is a unit vector in the same embedding space, denote the global gender bias in our system. We then debias p_u by removing p_u 's projection on the bias vector v_B :

$$p_u' = p_u - (p_u \cdot v_B)v_B. \tag{1}$$

The question is how to find v_B . We consider v_{female} , given below, is the representation of an average female user:

$$v_{female} = \frac{1}{n_f} (f_1 + f_2 + \dots + f_{n_f})$$

where $f_1, f_2, \cdots, f_{|n_f|}$ are the embeddings of female users. We define v_{male} in the same way. This allows us to derive the overall gender bias vector as:

$$v_B = \frac{v_{female} - v_{male}}{\|v_{female} - v_{male}\|} \ .$$

In the recommendation phase, the objective is to suggest top-N academic concentrations to a new user based on the user's preference/interests indicated on Facebook. First, we construct the user embedding of the new user by analyzing the liked items of the user using the pre-trained NCF model. Then the embedding of the new user is used as input features in the pre-trained logistic regression classifier directly. For the gender-debiased system, we dropped the intercept terms during prediction to further remove popularity bias (Steck 2011). Finally, the logistic regression model recommends top-N academic concentrations computed by sorting the probabilities of the 1380 concentrations for a given a user.

Offline Evaluation

To compare the performance of the gender-debiased recommender with a gender-aware recommender, we implemented two variations of the same system. The **gender-aware system** makes career recommendations based on the choices by the people of the same gender (e.g., recommending to girls based on the career choices of other girls) while the **gender-debiased system** employs the linear projection-based gender de-biasing strategy to systematically remove gender stereotypes from user embeddings.

Evaluation Metrics

We employ the following commonly used performance measures to evaluate the accuracy and fairness of each system.

Normalized discounted cumulative gain at K (NDCG@K) This is a well-known metric for assessing the quality of a *ranked* list of results (recommendations) (He et al. 2015). Since in our case there is only one ground truth recommendation (each Facebook user can only declare one career concentration), the metric can be simplified as:

$$NDCG@K = \sum_{i=1}^{N} \frac{relevance_K(n_i)}{\log_2(i+1)}$$

where n_i is the *i*-th recommendation and

$$relevance_K(n_i) = \begin{cases} 1 & \text{if } i \leq K \text{ and } n_i \text{ is the ground truth,} \\ 0 & \text{overotherwise.} \end{cases}$$

In general, the higher the NDCG score is, the higher the prediction accuracy is.

Non-parity unfairness (U_{PAR}) This metric is designed to evaluate the fairness of recommender systems (Yao and Huang 2017). It computes the absolute difference of the average ratings between two groups of users:

$$U_{PAR} = |E_q[y] - E_{\neg q}[y]|$$

where $E_g[y]$ is the average predicted score from one group of users, and $E_{\neg g}[y]$ is the average predicted score for the other group of users. In our case, we consider scores for N career concentrations for male and female subjects.

$$U_{PAR} = \frac{1}{N} \sum_{n=1}^{N} |E_{female}[y_n] - E_{male}[y_n]|$$

In general, the lower U_{PAR} is, the fairer the system is.

Experimental Settings and Results

To train an AI model to predict career concentrations, we need negative examples as well, that is, an academic concentration that is not a good fit for a user. We generate random pairs (u,c) as negative training instances, where c is any academic concentration not explicitly declared by u. Furthermore, we split the data and use 70% of it for training and the remaining 30% for evaluation.

Table 1 shows the evaluation results. Since the NDCG scores at position 3, 10 and 20 for the gender-debiased system are consistently higher than those for the gender-aware system, the gender-debiased system is considered more accurate than the gender-aware system. In addition, since the gender-debiased system also has lower U_{PAR} score, it is considered fairer than the gender-aware system.

During the offline evaluation with well-established evaluation metrics for recommendation accuracy and fairness, we have demonstrated that the gender-debiased recommender is fairer without any loss of prediction accuracy, a criteria frequently used in the fair machine learning community to indicate the success of a fair AI algorithm. In the following, we describe a user study to investigate whether the gender-debiased career recommender can achieve the desired outcome with intended users, especially when gender-bias still exists in our society and even the most fairness-conscious individuals may still hold unconscious bias.

Online User Study

The goal of the user study was to investigate (a) whether users prefer a gender-debiased career recommender over a gender-aware recommender, and (b) whether their own belief/bias play a role in their preferences.

We adopted a between-subject design. We randomly assigned participants to use either a gender-debiased or a gender-aware career recommender (except for those who declare themselves gender non-binary or decline to disclose their gender, in which case the gender-debiased recommender was used). For participants assigned to the gender-aware recommender, we further assigned them to interact with either a "female" model or a "male" model, based on whether they were identified with the female or male gender. Here, the "female (or male)" model means a gender-aware career recommender trained on female (or male) data only.

We invited students from all majors at a mid-size university in the U.S. to participate in the online user study. Prior to the study, the survey protocol received the IRB approval, and participants confirmed that they were 18 years or older and agreed to an informed consent before they could proceed. After taking the survey, each participant was entered

	NDCG@3↑	NDCG@10↑	NDCG@20↑	$U_{PAR} \downarrow$
GenderAware	0.0009	0.005	0.007	1.1445
GenderDebiased	0.0050	0.010	0.013	1.1188

Table 1: Offline Evaluation on the Facebook dataset. Higher Values are better for NDCG; lower values are better for U_{par} .

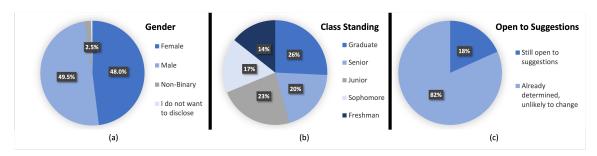


Figure 2: Participant Demographics: (a) Gender, (b) Academic Standings and (c) Open to Suggestion.

in a raffle for \$50 Amazon Gift Cards. Overall, we received responses from 202 participants. The entire survey took 5-10 minutes to complete.

In the following, we describe the questionnaire used in the study. The questionnaire included five sections: demographics, user interests, beliefs about gender-bias in career choice, recommendation acceptance and general system usability.

Demographics

We collected minimal personal information (such as gender) needed for the study.

- 1. What gender do you identify as (female, male, non-binary, or do not want to disclose)?
- 2. What is your class standing (freshman, sophomore, junior, senior, or graduate students)?
- 3. How "set" is your choice of major / minor / concentration (still open to suggestions, or already determined, unlikely to Change)?

As shown in Figure 2, 48% of the participants were females and 49.5% males. Unlike the Facebook dataset used to train the backend algorithm, our online user study includes 2% participants who were gender non-binary and 0.5% who did not want to disclose their genders. In terms of academic standing, 14.4% were freshmen, 16.8% were sophomore, 23.3% were juniors, 19.8% were seniors and 25.7% were graduate students. Of all the participants, only 18.3% were open to career suggestions. The rest were set on their chosen majors.

User Interests and Preferences

Users have varied interests and preferences. Accurately capturing their interests and preferences is critical to build a good recommender. In our work, we used a Facebook dataset to model user interests and preferences. The dataset stored 16K Facebook users' likes of 140K items. Given the large variety of the items, the set of items liked by a user could be a good representation of his or her interests and preferences.

Unfortunately, our participants were not among the 16K users in the Facebook dataset. In fact, many of them did not even use Facebook. It was certainly impossible to ask our participants to indicate whether they like each of the 140K items in our dataset. In order to model our participants' interests and preferences, we first used a dimension reduction technique to group the 140K items into a small number of categories. We then selected representative items from each category, and finally we asked our participants how they liked those representative items.

Specifically, the Facebook dataset we used can be considered as a (sparse) user-item matrix with 16, 619 rows (users) and 143, 303 columns (items). An entry is 1 if a person liked the item and 0 otherwise. We considered each item as a "word," and for each person, all the items he or she liked form a "document." We then performed a 100-topic Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003) analysis to automatically identify 100 latent topics in all the documents. Each of the latent topic was represented by a bag of "words", or in our case, a set of items (e.g., a latent topic related to high fantasy novels may contain representative items such as *The Lord of the Rings, The Hobbit, J.R.R. Tolkien, The Well at the World's End*, and *The Chronicles of Prydain*).

From each of the 100 topics, we asked three volunteers to individually select one representative item from the top 10 items identified by LDA. We then picked the common items selected by the three volunteers to ensure most participants of our study are familiar with the items. We finally decided on 48 well-known items, which are not too many to elicit a participant's interests in them during the user study.

Personal Belief on Gender Roles in Career Choice

We asked two questions to help us understand a participant's beliefs about gender roles in career selection.

4. (**Q-Stereotype**) Please indicate whether you agree with the following statement or not: "A gender stereotype in career selection is undesirable since it limits women's and men's capacity to develop their personal abilities."

5. (Q-DisparityPersonal) Please indicate whether you agree with the following statement: "If I am a female, I do not want to choose a career that is male-dominated" (for female participants), or "If I am a male, I do not want to choose a career that is female-dominated" (for male participants).

Both questions were rated on a 5-point Likert scale from strongly disagree to strongly agree.

Recommendation Acceptance

For each of the top-3 career recommendations, we asked a participant (a) (Q-Acceptance) whether he/she will consider it as a possible future career choice (yes, no, I don't know) and (b) (Q-DisparityCareer) whether they perceive it to be a female- or male-dominated career or I do not know. The main difference between (Q-DisparityCareer) and (Q-DisparityPersonal) is that (Q-DisparityPersonal) expresses a general personal belief, while (Q-DisparityCareer) is a perception specific to a major.

General System Usability

We also asked about a participants' agreement with two general usability-related statements: (a) (**Q-UseAgain**) "I would like to use a career recommendation system like this in the future," and (b) (**Q-RecommendToOthers**) "I would like to recommend the system to my friends if it is available." Both are rated on a 5-point Likert scale.

Result Analysis

We summarize the main findings of the user study, with a focus on (a) user acceptance of gender-debiased versus gender-aware recommendations, and (b) whether a user's own belief or bias plays a role in the acceptance of a recommended career.

Summary of Recommendations by Each System

The AI recommender gave each participant a recommendation of three concentrations (606 recommendations in total for 202 participants). Figure 3 summarizes the recommendations by the gender-aware and the gender-debiased systems. It shows the top 13 most recommended career concentrations by both systems and the probabilities (on the x-axis) they are recommended for male and female participants respectively. As the left side of the chart shows, among all the career concentrations recommended by the genderaware system, Psychology had 10% chance of being recommended to females and 7.7% chance of being recommended to males. Overall, the most frequently recommended careers by the gender-aware system for males were Psychology, Mechanical Engineering, History, Computer Science, and Criminal Justice; while the most frequently recommended careers for females were Psychology, English, Nursing, Biology and Accounting. Moreover, Computer Science and Mechanical Engineering were exclusively recommended to males by the gender-aware system. In contrast, the recommendations made by the gender-debiased system showed

less gender stereotypes. As shown in the right chart of Figure 3, Computer Science was recommended to both males and females with similar probability (4.8% versus 4.1%). Based on this analysis, it seems the gender-debiased system is capable of mitigating some existing gender biases in its recommendation.

Do People Prefer a Debiased Recommender?

To test this, for each of the top 3 recommended concentrations, if a user indicated that they would consider it as a possible future career choice, the system received 1 point. The system received 0 points if the user said "no" and 0.5 if the user said "I don't know." Based on an independent sample t-test, the mean acceptance score for the genderdebiased system was 0.279 while that for the gender-aware system was 0.372. The difference is statistically significant with p < 0.01. Despite the results from the offline evaluation that showed the gender-debiased recommender was more fair while maintaining the same level of recommendation accuracy, users in general did not seem to prefer the recommendations made by the gender-debiased system more than those by the gender-aware system. In fact, the acceptance score for the gender-aware system was significantly higher than that for the gender-debiased system.

In the following, we try to explore whether a participant's own belief/bias plays a role in explaining the finding.

Self-reported Belief and Acceptance

Here we focus on a participant's responses to Q-Stereotype and Q-DisparityPersonal. Both responses were rated on a 5 point Likert scale, 5 being the most biased (strongly disagree with Q-Stereotype or strongly agree with Q-DisparityPersonal), 1 being the least (strongly agree with Q-Stereotype and strongly disagree with Q-DisparityPersonal) and 3 being neutral. Figure 4 shows the distribution of the responses. The majority of the participants received a score of either "1" or "2", Very few people scored more than 3. In fact, only 4% of the participants scored 4 and 1.5% scored 5 in Q-Stereotype. Only 2% scored 4 and 0% scored 5 in Q-DisparityPersonal. In summary, based on self-reported user responses to Q-Stereotype and Q-DisparityPersonal, only a small number of the participants exhibited some degree of gender bias in college major selection.

To test whether a participant's self-reported belief impacts his/her acceptance of a recommendation, we employed a Generalized Linear Model (GLM) where the dependent variable was his/her acceptance score regarding a recommended major and the independent variables were his/her responses to Q-Stereotype or Q-DisparityPersonal. We also controlled the variation of demographics such as age, gender and academic standings as they could be confounders.

The GLM results indicate that the main effect for Q-Stereotype on Q-Acceptance is not statistically significant (p < 0.667). In contrast, the main effect for Q-DisparityPersonal on Q-Acceptance is significant (p < 0.050).

Note the self-reported bias measures such as Q-Stereotype and Q-DisparityPerosnal may not accurately capture a person's true belief/bias. Prior research has demonstrated that

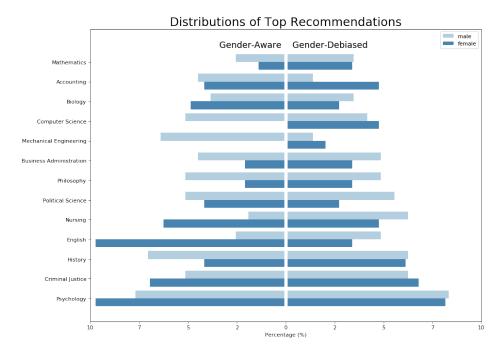


Figure 3: Distributions of Career Recommendations by Gender from the Gender-Aware and Gender-Debiased Systems.

social desirability bias is common in self-report surveys when the survey topics are sensitive (e.g., related to illegal acts such as drug use, income, ability and prejudice) (Krumpal 2013). Due to social desirability concerns, there is a tendency for people to overreport socially desirable behaviors or attitudes and underreport socially undesirable behaviors or attitudes. Since gender bias is considered a sensitive topic, it is likely that our participants may have responded in a way that show less bias.

Mitigating social desirability in self-report surveys remains a challenging topic in social psychology as people differ in their tendency to engage in socially desirable responding (Edwards 1953; Fordyce 1956). To overcome this problem, in the following, we measure a form of implicit bias based on perceived gender-disparity of an academic concentration. Since perceived gender-disparity of a major (e.g., to ask a person whether Computer Science is a male or female-dominated career) is a less personal and less sensitive topic, we expect to get a more accurate assessment of a participants' gender-related biases.

Perceived Gender Conformity and Acceptance

We define perceived gender conformity (PGC), an implicit bias measure based on a participant's own gender and his/her responses to Q-DisparityCareer. PGC is equal to "1" or "conform" if the perceived dominant gender of a major is consistent with the gender of the participant (e.g., a major is perceived to be male-dominated and the participant is a male or a major is perceived to be female-dominated and the participant is a female). PGC will be "0" or "conflict" if the perceived dominant gender of the major conflicts with the gender of the participant (e.g., the major is male-dominated and the participant is a female or the major is

female-dominated and the participant is a male). For all the other cases (where participants answered "I don't know" to Q-DisparityCareer or the gender of the participant is non-binary or non-disclose), the value of PGC is assigned to "0.5" or "neutral".

We built a GLM model to study the relation between a user's PGC and his/her acceptance of a recommended major. The dependent variable was Q-Acceptance and the independent variable was PGC. We controlled demographic factors such as age, gender and academic standing. Our analysis results show a positive correlation between PGC and user acceptance ($\beta = 0.104$, p;0.050). Figure 5(a) shows the average acceptance scores grouped by PGC. The mean acceptance score was the lowest (0.23) when the perceived "gender" of the recommended major differed from the gender of the participant (PGC=0). In contrast, when they were the same (PGC=1), the mean acceptance score was the highest (0.364). When there was no perceived genderdisparity or the participant was gender non-binary or nondisclose (PGC=0.5), the mean acceptance score was in between(0.342). Since the acceptance gap between PGC=0 and PGC=0.5 was much larger than between PGC=0.5 and PGC=1, the observed correlation seems mainly due to the avoidance of majors that were perceived to be dominated by the opposite gender. This may partially explain why our participants preferred the gender-debiased system less since it tried to overcome some of the gender stereotypes and was more likely to recommend majors dominated by the opposite sex.

Interaction Between Personal Belief and PGC

We also studied whether there was any significant interaction effect between a user's personal belief (Q-Stereotypes

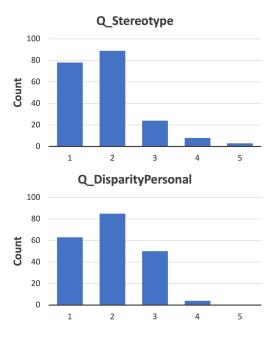


Figure 4: Self-reported belief about the Gender Role in Career Choices. Q-Stereotypes (1: strongly agree or least biased and 5 strongly disagree or most biased) and Q-DisparityPersonal (1: Strongly disagree or least biased and 5 Strongly Agree or most biased)

and Q-DisparityPersonal) and the perceived gender conformity of a major (PGC) on user acceptance. We performed two new GLM analyses where the dependent variable was Q-Acceptance and the independent variables were Q-Stereotype*PGC or Q-DisparityPersonal*PGC respectively. We also controlled for demographics such as age, gender and academic standing. Our results show that the interaction effect between a user's response to Q-Stereotype and PGC on Q-Acceptance was not significant (p < 0.9223). But there was a marginally significant interaction effect between a user's responses to Q-DisparityPerosnal and PGC on user acceptance (p < 0.052).

To understand the interaction effect between Q-DisparityPersonal and PGC on user acceptance, we grouped the responses to Q-DisparityPersonal into LOW (those with a score of 1 or 2) and MEDIUM/HIGH (those with a score of 3, 4, and 5). Since there were very few people with a score of 4 or 5 (only 2% of the participants), most of the people in the Medium/High group had a score of 3. Figure 5(b) shows the comparison between these two groups of people. When people did not mind selecting a major dominated by the opposite sex (in the Q-DisparityPersonal=LOW group), there wasn't much difference in their acceptance of majors conflicting or conforming to their genders. In contrast, people in the MEDIUM/HIGH group showed high preference to majors conforming to their genders (PGC=1) while avoiding majors conflicting with their genders (PGC=0).

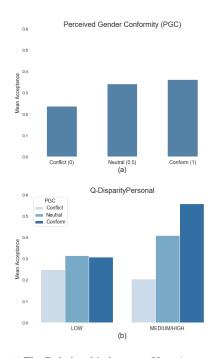


Figure 5: (a) The Relationship between User Acceptance (y-axis) and Perceived Gender Conformity (PGC) (b) The interaction between Q-DisparityPersonal and PGC.

User Acceptance and Other Factors

Among the demographics of a participant, gender was found to be significantly correlated with recommendation acceptance (P < 0.017); the correlation between age and recommendation acceptance was marginally significant (p <0.063). Academic standing was not significantly correlated with the acceptance (p < 0.911). Moreover, among all the factors we tested, the one that was most predictive of whether someone would consider the recommended career a possible future career choice is whether someone was still open to career changes (p < 0.000). When asked the question "How 'set' are you on your choice of major / minor / concentration?", 82% chose "Already determined, unlikely to change", only 18% chose "Still open to suggestions" (see Figure 2c)). Unsurprisingly, most people would not accept the recommended careers, regardless of the quality of the recommendations.

General System Usability

Finally, based on user responses to two general system usability questions (Q-UseAgain and Q-RecommendToOthers), our participants were generally positive about the systems. The mean score for Q-UseAgain was 3.34 and the mean for Q-RecommendToOthers was 3.40, both are better than neutral (3). Figure 6 shows the response distributions by different systems (5 being the best). Since the response distributions for Q-UseAgain and Q-RecommendToOthers are very similar, they show a consistency between these two usability measures. In addition, since the darker bars skewed more toward right, the mean usability scores for the gender-aware system

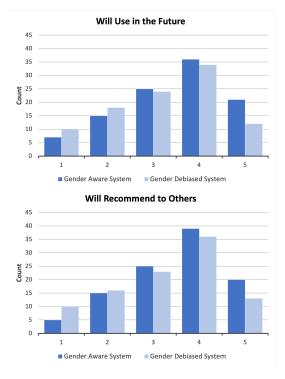


Figure 6: Distributions of (a) Q-UseAgain (left) and (b) Q-RecommendToOthers (right).

are generally higher than those of the gender-debiased system (for Q-UseAgain, the mean is 3.20 for the gender-debiased system and 3.47 for the gender-aware system; for Q-RecommendToOthers the mean is 3.27 for the gender-debiased system and 3.52 for the gender-aware system). The differences are marginally significant (for Q-UseAgain, p < 0.095, for Q-RecommendToOthers: p < 0.093). This result is consistent with the Q-Acceptance-based evaluation measure, which confirms our prior finding: the study participants preferred the gender-aware system more than the gender de-biased system.

Discussion

In this section, we discuss the findings we have discovered in this work, its implications on fair AI system design, and the limitations of our current study which could be addressed in future work.

What Have We Discovered?

Much effort in the AI and HCI community has focused on identifying and removing AI bias using algorithmic or design-based solutions. What we have discovered is that our participants prefer biased recommendations over debiased ones, despite both methods achieving similar prediction accuracy. For debiasing algorithms such as our fair career recommender to move the needle on equity in the real world, we may also need to find ways to "nudge" users to accept debiased recommendations.

To understand why participants did not prefer fair recommendations, our study results suggest that their unconscious bias may play a role. Our participants seemed to avoid careers that are dominated by the opposite sex. Similar results were found in previous research (Stroeher 1994) where, even as kindergartners, girls would select mostly traditionally female careers and avoid traditionally male careers. In other words, the bias is so deeply ingrained that people subconsciously shun a career dominated by the opposite gender regardless whether it matches their interests and skills. Societal bias may also play a role in the participants' preferences for gendered recommendation. Even supposing that a person is unbiased, they may still make a career choice that conforms to "social norms" if they believe that they might otherwise be disadvantaged in their career growth or subjected to discrimination on the job.

Since systemic bias and prejudice due to humans are root causes of inequities in our society (Crenshaw 1989) and hence in data, without addressing the human side of the issue, fair AI systems may not produce their intended societal impacts. Beyond addressing algorithmic issues, the AI and the HCI communities need to devote more attention to developing technologies that can help humans identify and overcome their own biases.

Implications on Fair AI Research

We believe in addition to debiasing algorithms, bias/fairness explanation and persuasion technology may play important roles in helping people overcome their biases. Educating people by explaining fairness/bias as well as its societal impact may help raise awareness and slowly nudge people toward a fairer society.

Limitations of the current study

One limitation of the current study is that over 80% of the participants are not open to new career suggestions, which significantly limits the statistical power of our analysis. As most of the participants are university students and have decided a career concentration, it would be better if most participants have not decided a career, and thus could benefit more from the recommendations. A future possibility is to revise the current IRB protocol to recruit minors (e.g., high school students) for the study.

Conclusions

In this paper, we demonstrated that it is not sufficient to simply rely on AI/ML debiasing algorithms to achieve the desired societal outcomes that the field of fair ML aims to produce, at least in the context of gender-debiased career recommendations. In fact, we found that on average our participants did not prefer career recommendations from a gender-debiased system, even though the system was just as accurate as the corresponding gender-aware system and participants generally self-reported that gender stereotypes in career selections are undesirable. Our results suggest that participants' own beliefs and unconscious biases are contributing factors to their acceptance of the AI recommendations (e.g., participants tended to avoid careers dominated by the opposite sex). To improve real-world equity in careers via a

debiased AI fairness system, it may be necessary to counter human bias as well as AI bias.

Going forward, it would be valuable to repeat our experiments in other problem domains, and with other protected dimensions such as race and disability status. To ensure that the impacts of fair AI technologies fulfil their potential benefits to society, more research on human-fair AI interaction, an understudied area, is urgently needed.

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