Exploring User Opinions of Fairness in Recommender Systems

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Abstract
Algorithmic fairness for artificial intelligence has become increasingly relevant as these systems become more pervasive in society. One realm of AI, recommender systems, presents unique challenges for fairness due to tradeoffs between optimizing accuracy for users and fairness to providers. But what is fair in the context of recommendation—particularly when there are multiple stakeholders? In an initial exploration of this problem, we ask users what their ideas of fair treatment in recommendation might be, and why. We analyze what might cause discrepancies or changes between user’s opinions towards fairness to eventually help inform the design of fairer and more transparent recommendation algorithms.

Author Keywords
fairness; multistakeholder recommendation algorithms; consumers; providers; trust; bias; transparency; explanation; user study;

Introduction
Historically the term fairness has been difficult to define. People’s opinions of what constitutes fair or unfair treatment differ between cultures and throughout time [9]. As algorithms become more deeply embedded into social contexts like education, healthcare, policy, and the internet, the issue of defining fair treatment is also increasingly interdis-

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In the discipline of computer science - and more specifically machine learning - researchers have begun to tackle these problems. Previous work has made an effort to turn philosophical definitions of fairness into metrics that machine learning models can optimize for [5, 2]; however, these definitions may not be sufficient for diverse users and groups [10]. In this project we focus on one specific realm of machine learning, recommender systems with multiple stakeholders, as we explore what it means for these algorithms to be fair or unfair - from the viewpoint of those who consume the recommendation. Multistakeholder recommender systems are unique to issues of fairness, because of an inherent tradeoff for fairness between multiple sets of users [1]. For example, two types of users for a multistakeholder recommendation algorithm could be (1) those who provide items to be recommended (providers), and (2) those who consume the recommended items (consumers).

In the case of a company like Kiva, a micro-lending platform, the providers would be borrowers who are seeking funding for their loans, and the consumers would be those who are looking to lend money to others. If Kiva began to provide loan recommendations for consumers, there would need to be a decision for how fair the recommender system should be for the providers. In this example, provider-fairness is a type of recommendation diversity. As recommendations represent a more diverse set of providers (e.g., both over-funded and under-funded borrowers on Kiva), they tend to become less personalized (less accurate) for the consumer [7]. Thus, recommendation algorithms with multiple stakeholders will need to draw a line between how diverse versus how personalized the system should be. It is apparent that consumers and providers will have different opinions about where this line should be drawn. In this work, we ask the consumers for their opinion.

**What do the Consumers Think is Fair?**

For this exploratory study, we conducted interviews with 30 participants (majority college students) in which we asked them to reflect on fairness issues in the context of recommender systems, using both systems they are familiar with (e.g., Netflix, Amazon) and Kiva as examples. We analyzed our data using thematic analysis [4], and arrived at a number of overarching themes, a subset of which we discuss here.

**I. Consequences of the System**

First, participants tended to want more provider-fairness (diversity) and less accuracy (personalization) when they recognized that recommendations could have a noticeable, harmful effect on certain stakeholders in the system. Though most participants preferred less personalization as provider risk became higher, none indicated wanting to completely omit personalization. In the context of recommendations, this viewpoint makes sense on platforms like Netflix or Spotify, where the user expects some level of personalization to derive utility from the platform. However, most participants still expected accuracy for recommendations that do not always require personalization, such as popular/trending items, which struggle with issues of provider-fairness as well.

Many participants expressed that certain kinds of recommendations (such as housing, job recommendations, healthcare, or finances) should include fairness as a central goal, due to potential for harmful consequences in an unfair system. For example, P15 contrasted Netflix and Spotify with Zillow and Indeed.com, noting that for the former it doesn’t really “matter,” but it would, e.g., for housing or employment (see sidebar).
II. Nonprofits Versus For-Profit Companies

Another important influence was the kind of organization that was providing recommendations. Specifically, participants tended to trust nonprofit fairness goals (e.g., Kiva's) more than for-profit companies, which led them to indicate a preference for less personalization and more diversity on nonprofit platforms. For example, multiple participants described differences between for-profit companies and nonprofits, in terms of both motives and consequences (see sidebar for examples from P11-1 and P8).

P8: "Kiva has really big consequences if someone doesn't get that funding, you know, versus Amazon doesn't have as big of a consequence cause Amazon's more detached thoroughly. Like if you buy it, that's great, they get more money. But if you don't buy it... they're still getting money. Versus Kiva, if you buy it, that's great, somebody gets clean water, if you don't buy it, somebody is not getting clean water."

P22: "I feel like right now, the way things are, it's kind of capitalistic and promotes the wealthy getting wealthier. And people who are struggling to start off a business, and maybe failing - with a fairness goal it would be better."

P11-2: "I think a fair algorithm, if such a thing is even possible, would be something that really, I guess is non-biased. But of course, everything's biased in some way."

IV. Transparency / Explanations

Explanation also plays a role in opinions towards fair treatment in recommendations. Recent work has highlighted that people's perceptions of algorithmic justice are altered when the algorithm's decisions are explained in different ways [3], and in our study participants indicated that while they would like to have some transparency through explanation when recommendations are altered for provider-fairness, they did not want the explanations to be meant to convince the consumer to change their mind, as described by P12-2 (see sidebar).

Conclusion and Future Work

Overall, this work is a starting point to build a better understanding of where to draw the line between recommendation personalization and provider-fairness in multistakeholder recommender systems. While it is important to keep in mind the preferences of the consumer, as this study has done, future work could dive into the preferences of providers (such as Spotify musicians or Amazon sellers), as well as the preferences of the designers of these systems. In multistakeholder environments, it is very important to appropriately balance the interests of every member of the system in order to build trust, maintain accuracy, and promote equality. The indication that many consumers have different preferences for recommendation fairness is somewhat alarming, but also important evidence that this work is necessary to ensure greater fairness in the future, and to understand the necessary tradeoffs. A greater understanding of what stakeholder's preferences are will allow for more
transparency of these tradeoffs in the future, to ensure that every stakeholder’s interests in recommender systems are taken into consideration.

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