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AI Risks: A Fluctuated Bidding for Online Jobs' Ads to Mitigate Gender-Based Discrimination Risk

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Abstract

In the first stage of AI-based recruiting, AI is used to predict and then deliver job ads to the most relevant audience on online platforms. Empirical studies have shown that AI has discriminated based on gender during the job ads delivery process, and the literature discusses multiple reasons for this. This work focuses on one important reason: women are a more desirable demographic for many advertisers, making ad placements for women more expensive. Since recruiters are competing with commercial advertisers who bid high to secure ad placements for women, this reduces the likelihood that job ads will be delivered to both genders in an equally distributed manner. This paper proposes a framework specifically designed to conduct a controlled and supervised bidding process to deliver job ads in a near-equal distribution between males and females, separating it from the conventional, profit-driven logic of commercial ads delivery, where high bids are used to generate more revenue with skewed delivery.

Keywords: AI risks, Algorithmic advertising, AI Recruiting, AI Gender-based discrimination, Algorithmic bias.

1 Introduction

According to (Boyko & Kholodetska, 2022) 37% of organizations use AI tools to improve their productivity using algorithmic advertising through different online platforms like Facebook, Instagram, Snapchat, and Twitter. However, studies (Ali et al., 2019; Dastin, 2022; Datta et al., 2018; Datta et al., 2014; Deshpande et al., 2020; Lambrecht & Tucker, 2019; Wille & Derous, 2018) showed that AI tools discriminate. When it comes to the recruiting field, AI-based recruiting affects how people are exposed to and reach out to job opportunities. AI-based recruiting starts by using AI to market the available jobs using online algorithmic advertising on different social platforms; after receiving responses, AI tools are used to screen the potential candidates' CVs, then AI tools are used to assess the chosen candidates (Ali et al., 2019; Black & van Esch, 2020; Fabris et al., 2023). AI algorithms or assistants are playing a significant role in each of those stages, which could potentially make the recruiting process almost under the control of AI tools. In recent years, many studies investigated those steps and ended up proven the presence of gender-based discrimination risk as well as other types of discrimination such as discrimination based on race, age and ethnicity (Ali et al., 2019; Dastin, 2022; Datta et al., 2014; Deshpande et al., 2020; Fabris et al., 2023; Lambrecht & Tucker, 2019; Mehrjoo et al., 2024) which could undermine decades of human efforts toward enabling gender equality in labour markets. This paper proposes a farmwork to mitigate the risk of gender-based discrimination in online advertising for jobs using AI.

2 Related Work

2.1 Online Job Advertising

Firms and recruiters publish their job ads through huge online platforms such as Facebook and Google, where AI tools predict to whom a particular job ad will be delivered. From a high-level overview, there are two major stages that control job ads delivery process and could cause gender-based discrimination which are the targeting stage and the real-time bidding auctions (Ali et al., 2019; Datta et al., 2018; Datta et al., 2014; Fabris et al., 2023; Imana et al., 2021; Lambrecht & Tucker, 2019, 2021, 2024; Zeng et al., 2022).

At the targeting stage, many targeting strategies and players interact together in a complex interplay. The first player is the advertiser (the recruiter) who controls three main parameters: the ads' creation process, the targeting parameters that indicate the desirable audience and the ads' budget and the desirable bidding strategy. The second player is the platform that organizes job advertising campaigns and controls two main parameters: predictions about which user is a 'possible target' for a particular job ad and the advertising auctions. Facebook use "ad relevance diagnostics" (Facebook, 2019) whereas Google Ads use "quality score" (Google, 2024) to determine the likelihood that an ad is relevant to a user. Platform predictions use the advertisers' parameters mentioned above as well as other parameters such as users' browsing history, clicks history on ads and online habits which is known as Online Behavioural Advertising OBA (Plane et al., 2017).

The advertising auctions which run by the platforms to predict which advertiser will win a particular ad placement. Every time a user login to the platform, an auction runs in the background between different competitor advertisers. The advertiser will win based on the bids and the predicted "ad-to-user relevance" which indicate the value of the ad to the user and as a result the expected engagement level with the ad (Imana et al., 2021). According to (Lambrecht & Tucker, 2019; Mehrjoo et al., 2024; Silverstein & Sayre, 2009) females are considered the most appealing demographic for all advertisers due to two main reasons: females are more likely to engage with the online advertisements than males and females control the biggest share of the global consumer spending. This led to a high competitions among different advertisers to show their ads to females which raise bids' prices for ads placements when a female is the target. (Mehrjoo et al., 2024) refers to this as the Digital Marketing Pink Tax phenomenon (DMPT) and their results showed that advertisers in some sectors may pay up to 64% to deliver their ads to females. The DMPT affects online job ads delivery process. To make the job ads reach females, recruiters need to compete with all the commercial advertisers and give higher bids otherwise most of the job ads will be deliver to males due to the low bids regardless of if the "ad-to-user relevance" may suggest the ad more suitable to be delivered to a female. Facebook mentioned that clearly at their first article to explain how their relevance score works as: "Of course, relevance isn't the only factor our ad delivery system considers. Bid matters too. For instance, if two ads are aimed at the same audience, there's no guarantee that the ad with an excellent relevance score and low bid will beat the ad with a good relevance score and high bid" (Facbook, 2019). Upon this explanation, results from different studies are reviewed in the next section.

2.2 Evidence of Gender-Based Discrimination in Online Job Advertising

Many studies have investigated how fair online job advertising are when used in recruiting. (Lambrecht & Tucker, 2019) run an experiment over 191 countries to algorithmically deliver job ads in STEM fields (science, technology, engineering and math) in a gender-neutral manner using an algorithm that maintain cost-effectiveness and many online platforms as a test field. On Facebook the job ads had been shown to more than 20% males more than females, on Google AdWards the results were 51% ads impressions for males compared to 36% for females, and on Instagram 15% of ads impressions showed to females. (Lambrecht & Tucker, 2019) pointed out to the reason as that the ads allocation mechanism was affected by economic forces where advertisers in general should pay more to show their ads to females as females are considered a "prized demographic".

(Ali et al., 2019) conducted their study on Facebook platform and focused on studying two factors as possible reasons for the skewed delivery of job ads toward a specific gender. The first factor was the use of algorithmic financial optimization on the advertisers' budget when delivering the ads which has been referred to by (Lambrecht & Tucker, 2019) as maintaining cost-effectiveness. The second factor was the "ad- user relevance" which is mainly calculated by Facebook. To test the first factor, (Ali et al., 2019) used varied budgets to deliver identical ads to the same audience. The ads with low budgets was seen by over than 55% of males whereas ads with high budgets was delivered to less than 45% of males which reflecting exactly the results by (Lambrecht & Tucker, 2019) that imply females are more expensive to show ads to them. For the second factor (Ali et al., 2019) examined how the ads' content (image, text, headlines) will affect the delivery process by deliver ads with "different stereotypical interests" to the same audience. Results was that over than 80% of ads with content related to "bodybuilding" was delivered to males and 90% of ads with content related "cosmetics" delivered to females. (Ali et al., 2019) reported that ads for "lumber industry" jobs was delivered to 90% males, ads for "cashier positions in supermarkets" was delivered to 85% females which reflect how AI perpetuate gender stereotypes when delivering job ads.

(Datta et al., 2014) conducted a randomized controlled experiment using their own created tool AdFisher and Google Ad to find out if job algorithmic advertising are showed in the same rate for males and females. The experiment settings were mainly to create a one thousand simulated users, and to indicate the gender of half of them as male and the other half as female at their profiles on Google Ad settings then to make all the simulated users visit the top 100 websites related to employments in the United States. The results showed that job ads were delivered in a very skewed rate between the two genders where males were shown job ads in rate of 1852 times compared to only 318 times for females.

2.3 Research Question and Hypothesis

As discussed in the related work above, bids have had a significant impact on the ad delivery process, sometimes unintentionally steering ads toward a specific gender. The question is how the use of a highly fluctuating bidding strategy, specifically in advertising for jobs, will affect the distribution process. Based on the results of the aforementioned work, the initial hypothesis is that a highly fluctuating bidding strategy will result in a near-equal distribution of job ads between males and females.

3 Proposed Solution: A Framework to Mitigate Gender-Based Discrimination in Online Job Advertising

The revenue-driven nature of online advertising campaigns makes it necessary for platforms to provide a specialized advertising strategy tailored for job ads. Bidding has been shown to be a substantial factor that can inadvertently skew job ads toward a specific gender. The proposed bidding strategy aims to achieve equal distribution of job ads by intentionally fluctuating bids during job ad campaigns. The high fluctuation in bids is expected to ensure equal delivery of job ads to both genders, as related work has demonstrated that higher bids are more likely to result in job ads being shown to women, while lower bids tend to show job ads to men. Lambrecht & Tucker (2021) recommends that platforms should offer advertisers the option to create campaigns designed to achieve equal distribution across desired demographics which is what this work aiming to achieve. A real-time auction between advertisers is triggered in the background every time a user visits an online platform. Commercial advertisers and employment recruiters compete to win ad placements for this user. The platform's "ad-to-user relevance" predictions may be quite similar, or even identical, for both commercial advertisers' and employment recruiters' ads, as they may target similar audiences. This leaves bidding as the primary factor in determining who wins the ad placement. Commercial advertisers are expected to bid higher, aiming to place ads for women to gain more revenue, while employment recruiters are expected to win placements equally for both males and females. As a result, females now have become the most appealing demographic for all types of advertisers. If employment recruiters place low to moderate bids to maintain algorithmic cost-effectiveness over the budget, they risk losing ad placements for females to commercial advertisers, skewing job ads delivery toward males and resulting in gender-based discrimination. Conversely, if employment recruiters place high bids to secure females' ad placements, the delivery process might skew against males, also leading to gender-based discrimination. The proposed strategy aims to maintain fluctuating bids, where higher bids secure ad placements for females and lower bids target males throughout the campaign as illustrated in Figure 1. Platforms should provide employment recruiters with the option to apply this fluctuating bidding strategy in job ad campaigns. Furthermore, while gender is a protected characteristic that cannot be used to target individuals in the case of job ads, it should be observed to assess the success of the fluctuating bidding strategy in delivering ads equally to both genders.

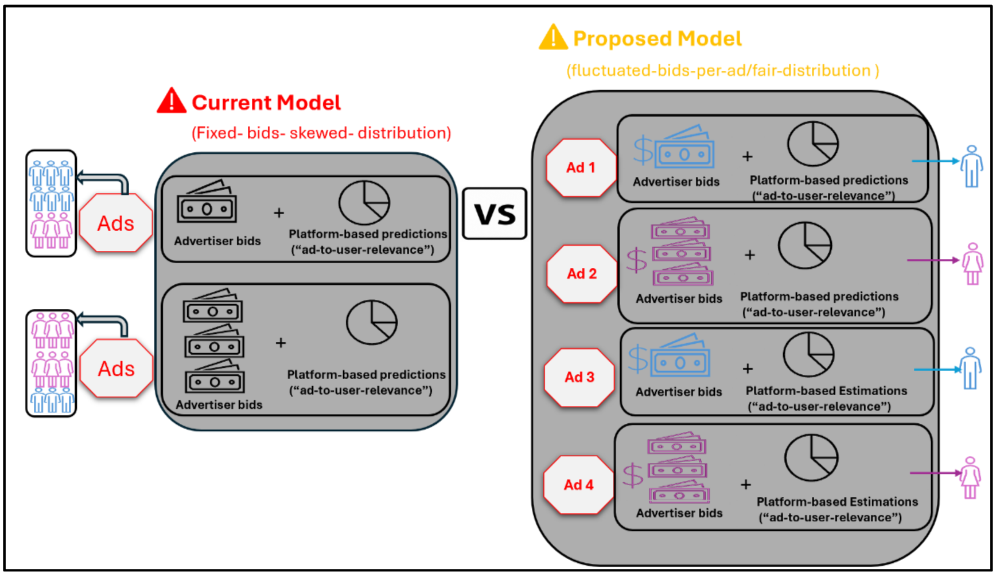

Figure1: The expected distribution of job ads when maintains a fluctuated bidding strategy.

4 Methodology

The experiment will be conducted using a computational Agent-Based Model (ABM) to simulate the behaviour of advertisers, ad-delivery platforms, and the platform users. The ABM will simulate a large population of agents, each with distinct characteristics and behaviours. The primary goal is to compare two bidding strategies in terms of how they affect the distribution of job ads between males and females. This model is expected to provide a better understanding of the effect of these two bidding strategies on the distribution of job ads:

Fixed bidding strategy: job ads will be delivered with a consistent bidding strategy that prioritizes cost-effectiveness while staying within a fixed budget. This strategy represents a more traditional, stable ad delivery approach.

Fluctuated bidding strategy: job ads will be delivered with a highly fluctuating bidding strategy, where the bid prices change with each job ad delivery, creating a more dynamic and potentially less stable ad distribution.

Agent-Based Model setup will include employment recruiter advertisers and commercial advertisers, the platform will simulate the auctions, and the delivery of the ads based on relevance and bidding amount. Also, the model will allow real time interactions between agents, simulating how changes in bidding strategies influence the distribution of the ads.

4.1 Experiment Design

A simulation as illustrated in figure 2 will be conducted to observe the distribution of job ads between genders as the dependent variable. The independent variables in this experiment are two bidding strategies: fixed bidding and fluctuated bidding. Agents in the simulation will be programmed to emulate a variety of preferences, online behaviours, and browsing histories. These factors will influence the relevance of the ads shown to each agent, providing insights into the effectiveness of the bidding strategies in achieving balanced ad distribution.

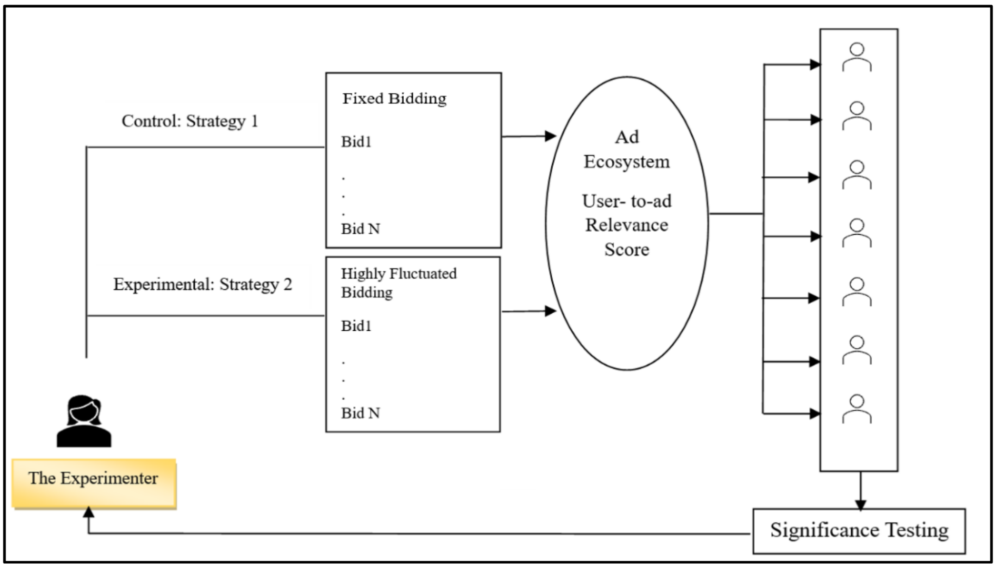

Figure 2: Experimental Design.

4.2 Significance Testing

To assess the impact of the two strategies, statistical significance testing will be used to compare the outcomes. The primary measure will be the proportion of ads delivered to males vs. females. The hypothesis is that there is a difference in ad distribution between genders across the two strategies. P-values will be used to determine whether the observed differences are statistically significant.

4.3 Model Validation and Evaluation

The results of the proposed agent-based simulation model will first be validated internally, followed by external validation using real-world online advertising platforms such as Facebook and Google Ads. Statistical techniques will be employed to compare the level of similarity between the model outputs and the real-world results, specifically regarding the distribution of job ads. According to (Bharathy & Silverman, 2013) a model should be evaluated based on its intended purpose. Therefore, the following performance metrics will be used to assess the model:

- The distribution of job ads across genders when using the proposed model.
- The relationship between the two bidding strategies employed in the experiment and the resulting outputs.
- The degree of correlation between near-equal gender-based distribution of job ads and the fluctuating bidding strategy.

5 Ethics, Expected Challenges and Limitations

To validate the ABM results in a real-world experiment, an ethical approval application will be submitted and obtained. All ads used in the real-world experiment will be real job ads that direct users to real job websites. To be inclusive and accurately observe the exact distribution of job ads, the experiment will include all possible gender values. This will involve users with self-reported binary gender values, as well as users identified with an uncategorized gender value or users with custom gender values.

6 Conclusion

As the field of recruiting became an intersecting field for multi disciplines among which AI is lead as an essential player, and as recruiting is hugely affect people's lives, assigning most of the recruiting process to AI tools impose a great responsibility on all parties involved in the process to ensure a fair, reliable and objective decisions towards all demographics. This research has proposed a framework to mitigate the risk of gender-based discrimination based on maintaining a fluctuated bidding strategy that expected to ensure an equal distribution for job ads between genders. As a future work, the proposed framework will be empirically examined in term of achieving an equal distribution of job ads.

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