# Small Changes, Large Consequences: Analyzing the Allocational Fairness of LLMs in Hiring Contexts

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## Abstract

Large language models (LLMs) are increasingly being deployed in high-stakes applications like hiring, yet their potential for unfair decision-making remains understudied in generative and retrieval settings. In this work, we examine the allocational fairness of LLM-based hiring systems through two tasks that reflect actual HR usage: resume summarization and applicant ranking. By constructing a synthetic resume dataset with controlled perturbations and curating job postings, we investigate whether model behavior differs across demographic groups. Our findings reveal that generated summaries exhibit meaningful differences more frequently for race than for gender perturbations. Models also display non-uniform retrieval selection patterns across demographic groups and exhibit high ranking sensitivity to both gender and race perturbations. Surprisingly, retrieval models can show comparable sensitivity to both demographic and non-demographic changes, suggesting that fairness issues may stem from broader model brittleness. Overall, our results indicate that LLM-based hiring systems, especially in the retrieval stage, can exhibit notable biases that lead to discriminatory outcomes in real-world contexts.

## 1 Introduction

Large language models (LLMs) are increasingly being adopted in real-world, high-stakes domains such as hiring (Boston Consulting Group, 2025), where they assist HR teams with tasks like resume screening and candidate matching. As LLMs are incorporated into critical decision-making processes, ensuring fair and responsible deployment is essential, especially when the outcomes can profoundly impact individuals' career prospects (Dastin, 2018; Raghavan et al., 2020; Sánchez-Monedero et al., 2020; Suresh and Guttag, 2021).

A key aspect of developing responsible LLM systems includes anticipating and preventing specific risks and harms, such as *allocational harms* (i.e., allocating resources or opportunities unfairly to different social groups, also called *allocational fairness*) (Barocas et al., 2017; Blodgett et al., 2020). This is especially important in automated hiring pipelines, since models can produce unfair outcomes and reinforce systemic inequalities (Gassam, 2025). While there is a substantial body of work that analyzes representational harms (i.e., representing certain social groups negatively, demeaning them, or erasing their existence) in LLMs (Zhao et al., 2018; Abid et al., 2021; Kirk et al., 2021; Cheng et al., 2023; Gadiraju et al., 2023), allocational harms—which are the primary harm at play in high-stakes situations—remain understudied beyond discriminative systems.

The few studies that evaluate allocational harms of LLMs (Tamkin et al., 2023; An et al., 2024; Haim et al., 2024; Nghiem et al., 2024) have primarily cast their investigations as discrete classification tasks (e.g., yes/no decisions) or quantitative predictions (e.g., determining salary levels), which do not capture how LLMs are deployed in applications like hiring (Kelly, 2023). As a result, these highly simplified setups may inadequately predict real-world outcomes and assess harms. Investigations of LLM harms must ensure *ecological validity* (Blodgett et al., 2021; Goldfarb-Tarrant et al., 2021; Cao et al., 2022); they should be grounded in realistic scenarios and tasks that match how these systems are used in practice, or use a proxy that is predictive of real world outcomes. Yet there is limited work on allocational harms in generative settings without adding a simplification layer, with Wan et al. (2023) being a notable exception, since measuring how generated text might create disparities is more open-ended and complex than analyzing classification predictions.

In this work, we examine whether LLMs behave fairly in real-world hiring contexts. We focus on two critical tasks that mirror how LLMs are inte-



*Proceedings of the 14th International Joint Conference on Natural Language Processing and the 4th Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics*, pages 2645–2665
December 20-24, 2025 

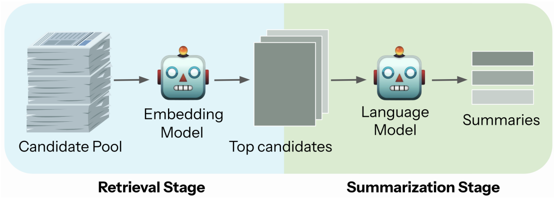



Figure 1: We investigate the fairness of an LLM hiring pipeline with a **retrieval stage** (ranks/filters the top-$n$ candidates with respect to a job post) and a **summarization stage** (generates resume summaries for filtered candidates). We assess fairness at each stage separately.[1]

grated into hiring workflows (Herman, 2024; Humanly, 2024): (1) ranking candidates with respect to a job posting and (2) summarizing resumes, as illustrated in Figure 1. These tasks represent key stages where automation can influence which candidates are surfaced and considered for a role. To evaluate fairness, we examine whether models are sensitive to gender and race perturbations in resumes. We investigate the following questions:

- **RQ1:** Do generated summaries differ meaningfully across demographic groups?[1]
- **RQ2:** Do models disparately select resumes across demographic groups?
- **RQ3:** How sensitive are model rankings to demographic and non-demographic perturbations in resumes?

To this end, we: (1) construct a new benchmark consisting of a synthetic resume dataset with controlled demographic perturbations (varying names and extracurricular content) and curated job postings, (2) design an evaluation framework with fairness metrics tailored to both generative and retrieval settings, validated by an expert human preference study, (3) conduct a comprehensive fairness analysis of 10 large language models (6 generative, 4 retrieval) based on real-world hiring tasks.

Our results demonstrate that an LLM hiring system with automated resume retrieval and summarization exhibits considerable bias, primarily stemming from the retrieval stage. In the summarization setting, we observe meaningful differences in generated summaries up to 20% of the time between racial groups, compared to 3% for gender (**RQ1**). For retrieval, models non-uniformly select resumes across demographic groups up to 55% of the time (**RQ2**), and produce rankings that are highly sensitive to gender and race, with up to 74% of candidates being filtered out after demographic perturbation (**RQ3**). We also find that models exhibit high sensitivity to non-demographic changes, sometimes on par with demographic changes (**RQ3**), suggesting that fairness issues can stem from general model brittleness rather than demographic bias alone. Overall, our analysis reveals that even seemingly minor changes can lead to considerable disparities, raising concerns about the fairness and robustness of LLMs in hiring.

## 2 Methodology

To study fairness in hiring, we consider an LLM-based pipeline with two components: resume retrieval with respect to a job post (using an embedding model) and resume summarization (using an LLM). This pipeline is informed by interviews with several corporations that actively deploy LLMs for hiring;[2] both components reflect real-world usage of automation to streamline hiring processes. We focus on summarization first because it is more neglected in research, though in a pipeline it would come after retrieval, as shown in Figure 1 (as summarization would be of retrieved resumes).

We propose two metrics, invariance violations (summarization) and exclusion (retrieval), to investigate allocational fairness in hiring. Specifically, these metrics quantify: (1) systematic differences in generated resume summaries[3] and (2) changes in the similarity of a resume to a job posting, and as a result its ranking in a resume set. We additionally benchmark the distribution metric of Wilson and Caliskan (2024) to study fairness in hiring, but note that their approach does not directly capture how perturbing a resume impacts resume screening outcomes, and includes only retrieval and not generative settings.

Let $D$ represent a set of resumes, where each resume $d \in D$ has demographic label $l(d)$. We denote $d'$ as any perturbed version of $d$ where $l(d') \neq l(d)$. For each $d$, there can be several demographically perturbed versions $d'$ (e.g., gender or race perturbations). The resume content remains largely unchanged except for the demographic perturbation.

[1] We study summarization first, since it is less explored from an allocational harms perspective.

[2] We cannot share details due to non-disclosure agreements.

[3] Since recruiters may rely on summaries rather than full resumes, meaningful differences in summaries could directly affect hiring outcomes, leading to allocational harms.

## 2.1 Summarization

Perturbed resumes are by design highly similar to original resumes, so we expect generated summaries for original and perturbed resumes to also maintain high similarity. In other words, we are testing for *invariance*; we expect the output to change minimally after perturbing the input (Ribeiro et al., 2020). To assess invariance, we need a way to measure whether the original and perturbed summaries differ meaningfully in the context of hiring. For cost and scalability reasons, we rely on an automated approach—human preferences are expensive and cannot be collected quickly enough to be used in model development, especially if these preferences are sourced from HR staff.

Automated measures can evaluate whether specific properties of generated summaries differ, in a way that could affect a human reader's opinion. For instance, summaries for a specific demographic group should not be written more positively than summaries for other demographic groups; this could lead to disparities in hiring outcomes. We use the following measures as proxies for undesirable variation that could influence the decision of HR staff reading the summary: reading ease, reading time, polarity, subjectivity, and regard (Appendix A.7). We verify that these measures capture meaningful differences in practice by conducting a preference task annotated by HR staff. This study shows that these are good proxies for human preferences (Appendix A.8).

**Fairness Metric** For each measure, we perform a paired t-test between scores for original and perturbed summaries. We then calculate how often the null hypothesis (that the mean difference between paired summaries is 0) is rejected, i.e., how often invariance is violated. We choose a significance level of $\alpha = 0.05$, and apply Benjamini-Hochberg correction to account for Type 1 errors with multiple comparisons (Benjamini and Hochberg, 1995).

$$\text{invariance violations} = \frac{\textit{\# t-tests for which null hypothesis is rejected}}{\textit{total \# of t-tests}}$$

## 2.2 Retrieval

In contrast to summarization, which relies only on the resume, retrieval uses both a query (job posting) and candidates to select (resumes). The top-$n$ of the resulting resumes sorted by similarity then make it to the next stage of the pipeline. We assume that demographically perturbing a resume should have minimal impact on its relevance to a job posting.

Given an embedding model $\mathcal{M}$ and a similarity measure $sim$, we compute the similarity between embeddings for resume $d$ and job posting $p$. In practice, we use cosine similarity following Wilson and Caliskan (2024). We define the set $S(p)$, which represents the set of similarity values between each resume $d \in D$ and a given job posting $p$: $S(p) = \{sim(\mathcal{M}(d), \mathcal{M}(p)) \mid d \in D\}$.

We transform the similarity values between each resume and job posting, $s_i$, into a rank such that lower ranks indicate higher similarity: $\text{rank}_p(s_i) = |\{s_j \in S(p) \mid s_j > s_i\}| + 1$. Let $D_n(p)$ represent the set of top-$n$ resumes from $D$, which are the resumes with the $n$ lowest ranks (i.e., highest similarities) for job posting $p$: $D_n(p) = \{d_i \in D \mid \text{rank}(s_i) \leq n\}$.

**Fairness Metrics** We compute two fairness metrics for retrieval, *non-uniformity*, proposed by Wilson and Caliskan (2024), and *exclusion*, which we introduce below.[4]

**Non-uniformity** assesses whether the top resumes are uniformly distributed across demographic groups. First, the set of top-$x\%$ of resumes ($x$ being a percentage rather than a fixed number $n$) is retrieved from the combined pool of all demographically perturbed versions, denoted as $D'_x(p)$. A chi-squared goodness-of-fit test is then used to check if the demographic composition of $D'_x(p)$ deviates from the uniform distribution.

**Exclusion** evaluates how often resumes in the set of top-$n$ resumes are excluded (i.e., the ranking falls outside top-$n$) after perturbation. Ideally, $\mathcal{M}$ should be robust to demographic perturbations, yielding nearly identical similarity scores and rankings for both resume $d$ and demographically perturbed version $d'$. Exclusion directly assesses allocational fairness by measuring how much the set of top-$n$ resumes differs after perturbation.

$$\text{exclusion}_n(p) = \frac{|\text{rank}_p(d') > n \mid d \in D_n(p)|}{|D_n(p)|}$$

# 3 Experimental Setup

In this section, we describe the data, perturbations, and models used for our evaluation.

[4]Further motivation and intuition and differentiation of these metrics are provided in Appendix A.10.

### 3.1 Data

**Resumes** Resumes are sourced through social media platforms (LinkedIn, Slack, X). Given the authors' professional circles, the sample skews heavily toward tech and academic professionals. For privacy reasons, we anonymize resumes using Presidio to mask PII entities (Microsoft). To further mitigate privacy concerns and enable dataset release, we use the collected resumes as examples to generate synthetic resumes. We generate 525 resumes across 22 professions using Cohere's Command-R model (Cohere, 2024). All synthetic resumes are free of explicit demographic information, until added during experimentation.

In addition, we use a publicly available resume dataset from Kaggle (Bhawal, 2021) to increase coverage and generalization. These resumes differ in two notable ways: (1) they are less structured and formatted than generated ones, and (2) they include a more diverse set of fields (e.g., construction, fitness, etc.). We sample 1175 Kaggle resumes across 24 fields. More details about dataset curation and statistics are provided in Appendix A.3 - A.5.

**Job Posts** Our resume dataset consists of two types: synthetic resumes generated for specific roles (e.g., data analyst) and actual resumes labeled with broader field categories (e.g., construction). For each profession/field (we choose 11 each from generated and Kaggle resumes), we carefully select 7 detailed LinkedIn job postings, resulting in 154 job postings.

### 3.2 Demographic Perturbations

We use names as a proxy for gender and racial information. All resumes are initially free of names; we add them using the curated set from Yin et al. (2024).[5] We consider four demographic groups, each with 100 unique names: Black female (FB), White female (FW), Black male (MB), and White male (MW). Following Wilson and Caliskan (2024), we only vary the first name and fix "Williams" as the last name for all groups.

In actual resumes, demographic information can be encoded in more than just names. Therefore we perform an additional augmentation step that adds extracurricular information using Command-R[6] to the resumes (similar to Glazko et al. (2024)) Adding this information can reinforce demographic signal by providing both explicit and implicit cues.

### 3.3 Non-Demographic Perturbations

We conduct two non-demographic perturbation experiments for retrieval to assess the baseline sensitivity of embedding models that is not due to demographics.

**Within-Group Name Perturbations** As a baseline comparison to performing name perturbations between different demographic groups (e.g., White female $\rightarrow$ Black Female), we assess whether models are sensitive to within-group demographic perturbations (e.g., White female $\rightarrow$ White Female). By doing so, we disentangle how much bias is due to demographics vs. model sensitivity to name changes. To control for the effects of frequency (Ethayarajh et al., 2019), we bin names in each demographic group according to their frequency in the Pile dataset (Gao et al., 2020), and match names based on the bin.[7]

**Non-Name Perturbations** We assess whether model rankings are sensitive to non-name perturbations. This allows us to examine whether models lack robustness more broadly. We test two perturbation types: (1) random character swapping, which does not impact readability or comprehension in a meaningful way[8] and (2) replacing new lines in the resume with a single space instead, which targets formatting without modifying content.

### 3.4 Models

**Summarization** We generate summaries using closed and open state-of-the-art LLMs: GPT-4o (OpenAI, 2024), Command-R (Cohere, 2024), Mixtral 8x7B and Mistral Large (Jiang et al., 2024), and Llama 3.1 8B and Llama 3.3 70B (Meta AI, 2024). For summary instructions, we vary the generation length (100, 200 words) as well as the point of view (first, third person) specified in the prompt. We generate summaries with temperatures of 0.0 and 0.3. To account for stochasticity in generations, we generate each summary five times.

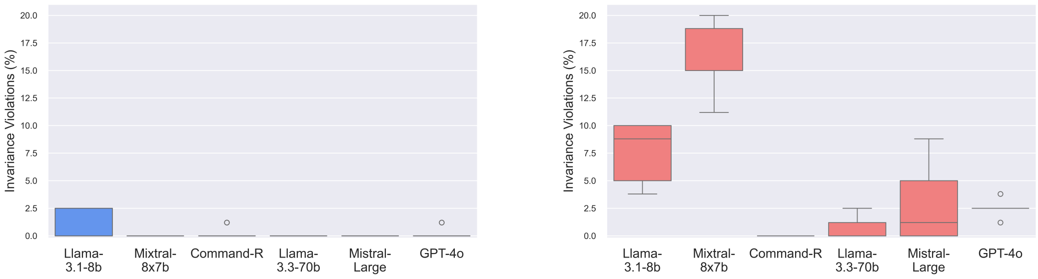
**Retrieval** For retrieval, we select four popular dense embedding models used in retrieval augmented generation (RAG) systems (Lewis et al.,

[5]Uses voter registration data from North Carolina to identify demographically-distinct names.

[6]Awards, clubs and leadership, and mentorship and volunteering experiences that are reflective of the individual's background and identity (see Appendix A.5 and A.6).

[7]We use the What's in My Big Data tool (Elazar et al., 2023) to obtain frequencies.

[8]We choose 10 random characters in the resume and swap with neighboring keys to simulate typos.




(a) Gender

(b) Race

Figure 2: **Summarization Results:** Invariance violations for generated summaries, separated by completion model and perturbation type. Results are shown across 5 runs. Left 3 models are considered "smaller" models, right 3 models are considered "larger" models.

2020): OpenAI's text-embedding-3-small and text-embedding-3-large, Cohere's embed-english-v3.0, and Mistral's mistral-embed.

## 4 Results

In this section, we evaluate the use of LLMs in two real-world hiring tasks: resume summarization and retrieval. Unless otherwise mentioned, we present results for generated resumes below, and include results for Kaggle resumes in the Appendix. Similar trends and findings hold for both datasets.

### 4.1 Summarization

We analyze whether generated summaries differ meaningfully when applying gender and race perturbations (**RQ1**) by examining invariance violations, i.e., the percentage of t-tests that yield significant differences in our automated measures. We measure violations separately for summaries with different characteristics (length, point of view, and temperature). Figure 2 displays results grouped by completion model and perturbation type.

All models violate invariance much more for resumes that differ by race as opposed to gender. In fact, gender invariance violations are zero or near zero for all models. In contrast, all models except Command-R exhibit invariance violations with respect to race, with Mixtral 8x7B exhibiting violations 16.76% of the time on average. Our results also provide some indication that smaller models are more susceptible to violations. In summary, we observe that models exhibit some but not considerable discrepancies between generated summaries for different demographic groups, with minimal differences for gender perturbations.

### 4.2 Retrieval

Moving to retrieval, we ask: Do models exhibit fairness issues in selecting resumes? Our analysis tackles this question from distributional (**RQ2**) and robustness (**RQ3**) perspectives.

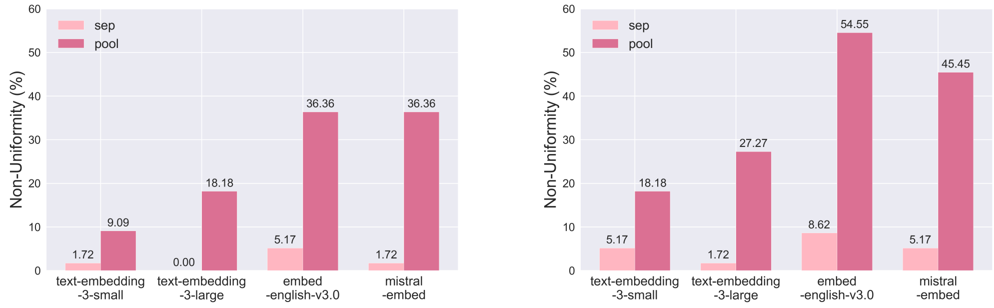
#### 4.2.1 Non-Uniformity

**Do models disparately select resumes across demographic groups?** To answer this question, we compute *non-uniformity* (i.e., how often top retrieved resumes have non-uniform demographic distributions). All models disparately retrieve resumes across demographic groups, consistent with the findings of Wilson and Caliskan (2024). That being said, non-uniformity differs considerably across models, choice of top-$x$ percent, and pooling of resumes across occupations (Figure 3).

We observe that embed-english-v3.0 exhibits the highest non-uniformity on average, with 6.90% of job posts and 45.45% of occupations having non-uniformly distributed resumes. Increasing top-$x$ from 5% to 10% and pooling resumes both yield higher non-uniformity across all models. In particular, pooling resumes by occupation can produce massive changes; on average across models, non-uniformity goes from 3.66% $\rightarrow$ 30.68%. This reflects sensitivity in the metric itself more than a change in the shape of the distribution.[9]

Different models show distinct patterns of bias: the non-uniformity privileges different demographic groups. For example, in the top-10% of resumes from embed-english-v3.0, White females are the top group 48.05% of the time, compared to 3.90% for Black males. In contrast, for mistral-embed, White males are the top group 72.73% of

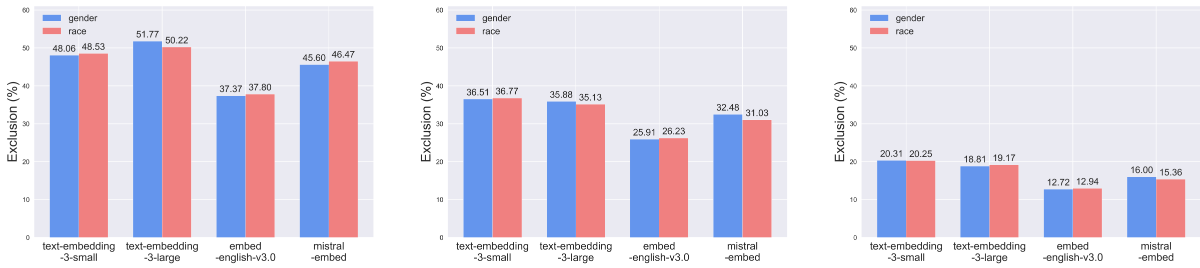
[9]Increasing top-$x$ and pooling both increase sample size, which can lead to rejecting the null hypothesis in cases where the null hypothesis previously failed to be rejected.




(a) Top-5%

(b) Top-10%

Figure 3: Non-uniformity metric for top-5 and top-10% of retrieved resumes. Separated (sep) measures non-uniformity at a job post level, while pooled (pool) measures it at an occupation level by pooling results across job posts for a given occupation.




(a) $n = 5$

(b) $n = 10$

(c) $n = 100$

Figure 4: **Exclusion metric for retrieval** after performing gender and race name perturbations for the top-5, top-10, and top-100 retrieved resumes. Lower values indicate models are less sensitive to demographic perturbations.

the time, compared to 5.19% for White females. Reasons for these differences are unclear without access to dataset and training details but it is notable and surprising that models do not consistently favor the same demographic group.

#### 4.2.2 Exclusion

**How sensitive are models to gender and race perturbations?** We compute our proposed metric, exclusion (i.e., how often top retrieved resumes are excluded from the set of top-$n$ resumes after perturbations), and find that all models display notable sensitivity to gender and race name perturbations (Figure 4). When considering the top-5 resumes, we find that models tend to exclude perturbed resumes nearly half the time (45.75% on average).

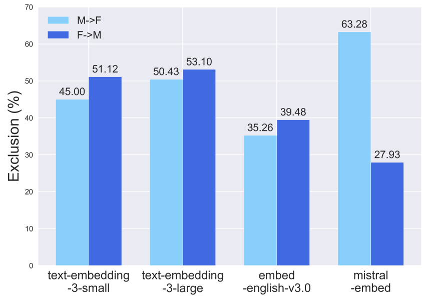
Across both gender and race name perturbations, and different $n$ values, text-embedding-3-small and text-embedding-3-large have the highest exclusion, while embed-english-v3.0 consistently has the lowest exclusion. As expected, exclusion lowers as $n$ increases, since larger $n$ values are less restrictive and consider a larger set of retrieved resumes. That being said, exclusion for $n = 100$ is still considerable, as all models have exclusion $> 12\%$.[10]

In contrast to our summarization findings, where models show greater invariance violations for race vs. gender perturbations, models have similar sensitivity to gender vs. race perturbations for exclusion. Overall, average exclusion for gender is 31.78% on generated resumes (25.47% on Kaggle resumes) vs. 31.66% on generated resumes (25.40% on Kaggle resumes) for race.[11] Our analysis reveals that the set of top retrieved resumes with respect to a job posting is highly brittle, as merely altering the demographic with names often results in otherwise identical resumes dropping out of the top-$n$ results.

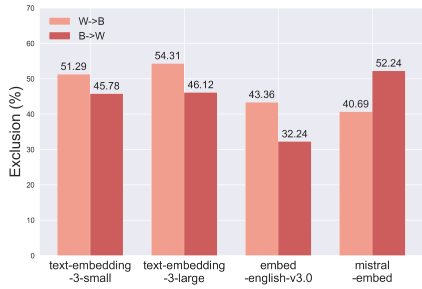
**Does model sensitivity to perturbations differ based on the direction of perturbation?** We partition the results based on the perturbation direction (Figure 5), and find that models often exhibit higher sensitivity to one direction of perturbation over the other. In particular, the gender directional difference is notable for mistral-embed, going from 63.28% for M $\rightarrow$ F to 27.93% for F $\rightarrow$ M, for

[10] In practice we expect $n$ to be low for filtering candidates.

[11] Kaggle resumes exhibit similar patterns to generated resumes, but are lower in exclusion magnitude. This is likely because generated resumes are tech-focused and more overlapping in content.

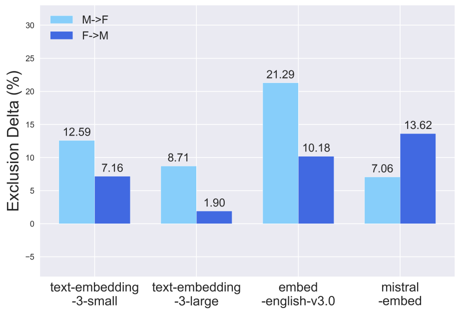



(a) Gender, $n = 5$

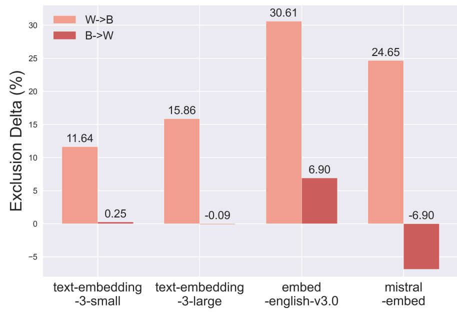



(b) Race, $n = 5$

Figure 5: **Directional differences in exclusion metric for retrieval after applying name perturbations** (i.e., separating based on perturbation direction). M→F perturbs male to female names and F→M perturbs female to male names, while W→B perturbs White to Black names and B→W perturbs Black to White names.




(a) Gender, $n = 5$




(b) Race, $n = 5$

Figure 6: **Deltas (differences) in exclusion metric for retrieval** after performing demographic perturbations with names + extracurricular information vs. names only. As expected, adding extracurricular information increases sensitivity to perturbations.

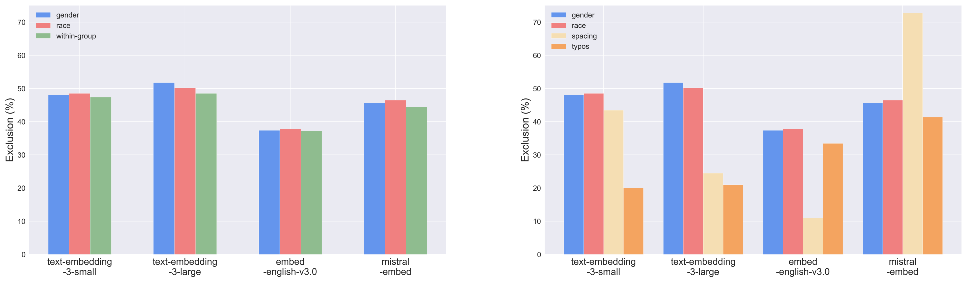
generated resumes with $n = 5$. We also observe that models exhibit opposite directional trends for gender and race. For gender, all models except mistral-embed are more sensitive when perturbing female names (marginalized) to male names (non-marginalized). On the other hand, for race, all models except mistral-embed are more sensitive when perturbing White names (non-marginalized) to Black names (marginalized). These results highlight an asymmetry in how models handle various demographic changes.

**Are models more sensitive when perturbing both names and extracurricular information, as opposed to names only?** Figure 6 shows that models tend to be more sensitive when perturbing extracurricular information in addition to names. On average, we observe the following increases in exclusion: 9.35% for M $\rightarrow$ F, 8.06% for F $\rightarrow$ M, 16.41% for W $\rightarrow$ B, and 2.90% for B $\rightarrow$ W.

For gender, adding extracurricular information results in comparable increases in exclusion for both directions. In contrast, adding extracurricular information for race results in highly asymmetric increases. W $\rightarrow$ B averages more than 5x the increase of B $\rightarrow$ W changes. We observe that adding extracurricular information results in non-uniform increases to exclusion, which suggests that models may encode and utilize various types of demographic signal differently. This finding is notable given that prior work often examines a single way of encoding demographics, overlooking how various signals interact and compound.

**More broadly, do models exhibit brittleness to non-demographic perturbations?** To disentangle fairness from robustness issues, we consider two sets of perturbation analyses that are non-demographic: (1) How sensitive are models to within-group name perturbations? and (2) How sensitive are models to non-name perturbations? Even when perturbing names within the same demographic group, models surprisingly exhibit highly similar levels of sensitivity to those observed with gender and race name perturbations (Figure 7a).

We find that models are extremely sensitive to both spacing and typos, but to a lesser extent than names. As shown in Figure 7b, most models




(a) Within-Group Name, $n = 5$

(b) Non-name, $n = 5$

Figure 7: **Exclusion metric for retrieval after performing non-demographic perturbations** (i.e., within group name changes - left, and modifying spacing and adding typos - right).

demonstrate higher sensitivity to spacing than typos, though there is surprising sensitivity to both. In particular, mistral-embed excludes resumes from the top-5 set 72.76% of the time solely based on spacing, which indicates that formatting can have a massive impact on fairness (in this case, much more than names). Generated resumes display nearly twice the sensitivity to spacing changes compared to web-scraped Kaggle resumes (27.98% vs. 15.35% averaged across models and $n$ values), likely due to their structured formatting. In summary, we observe that retrieval models lack overall robustness, which has fairness implications.

## 5 Related Work

**Fairness in Hiring** Prior work reduces hiring to binary accept/reject decisions (An et al., 2024) or discrete ratings (Gaebler et al., 2024), while others address different tasks such as resume-to-job-category classification (Veldanda et al., 2023; Iso et al., 2025). Gaebler et al. (2024) extends beyond resume screening by incorporating video interview transcripts for candidate evaluation. Although Wen et al. (2025) adopts a ranking setup closer to ours, their analysis is limited to very small applicant pools, whereas real hiring decisions often involve thousands of candidates. Wilson and Caliskan (2024) is most related in examining retrieval-based resume screening, but does not extend to summarization or robustness across demographic and non-demographic perturbations. In contrast, our work examines both retrieval and summarization in enterprise hiring, offering a more ecologically valid and comprehensive fairness analysis.

**Fairness in Summarization and Ranking** Several studies have identified biases in LLM-generated summaries (Shandilya et al., 2018; Guo et al., 2023; Zhang et al., 2024; Li et al., 2025), but they do not conduct application-grounded evaluations or consider allocational harms. A few recent works have also studied the fairness of LLMs in ranking (Wang et al., 2024; Xu et al., 2024), but these primarily focus on traditional retrieval tasks such as article relevance, rather than real-world LLM usage in high-stakes domains like hiring.

**Name Perturbations** Name perturbations are a common technique in NLP fairness studies (Webster et al., 2021; An and Rudinger, 2023; Steen and Markert, 2024; Wan et al., 2023; An et al., 2024). We go beyond this by perturbing resumes with extracurricular information, as done in Glazko et al. (2024), but largely focus on names because it is common practice. It is worth pointing out that Gautam et al. (2024) highlight limitations around inferring sociodemographic groups from names, such as poor validity. We try to account for some of these concerns by using the carefully curated names from Yin et al. (2024).

**Fairness Definitions** We draw connections between the metrics we use and traditional ML fairness metrics (Mehrabi et al., 2021). Non-uniformity is connected to statistical parity, which is satisfied if the probability of a prediction is independent of demographic group. We adapt this idea by evaluating for non-uniformity in the demographic distribution of top-x%. Exclusion bears resemblance to both individual fairness (Dwork et al., 2012), which assesses whether similar individuals are treated similarly, and counterfactual fairness (Kusner et al., 2017), which assesses whether outcomes are consistent for counterfactual individuals. Similarly, exclusion measures the stability of rankings under demographic perturbations.

## 6 Discussion

Our results highlight failures of both fairness and robustness in LLMs in hiring contexts. We differ from prior work on LLM fairness in summarization (Zhang et al., 2024) and ranking (Xu et al., 2024) in that our evaluations are grounded in real-world applications, and this reveals novel insights that have ecological validity. First, we observe that model rankings in a retrieval setting are impacted considerably by both subtle demographic and non-demographic changes. In practice, these differences would lead to unintended exclusion, with candidates being eliminated from consideration during initial screening. We also observe that subtle demographic differences in resumes can alter the way candidates are discussed in generated summaries. As a result, candidates who make it past the initial resume screening stage may be portrayed differently based on demographic attributes, which can impact downstream decision-making.

Additionally, it is important to consider compositional effects when combining components, since biases can compound due to the sequential nature of these tasks. The resulting candidate pool may (1) leave out qualified candidates through retrieval bias, and (2) differentially represent candidates through summarization bias. Applying this to our results, in the worst case, we find that modifying racial indicators on resumes (using names + extracurricular information) can result in roughly (1) 70% of candidates being filtered out at the resume screening stage, and (2) 20% of remaining candidates being depicted in less preferable ways.

Our analysis also reveals that all models are sensitive to non-demographic perturbations, suggesting that model unfairness may partially stem from more general robustness issues, rather than encoded biases alone. These perturbations still result in disparate outcomes, but with different underlying causes. While these insights do not change discriminatory impact, understanding that disparate treatment can arise from small input changes, both demographic and otherwise, provides a more complete picture for addressing fairness issues. Moreover, given that retrieval models are commonly used in RAG systems, these issues likely extend to various applications beyond HR. Isolating the impact of demographic vs. non-demographic factors remains an important direction for future work.

## 7 Conclusion

We examine allocational fairness in LLM-based hiring systems by analyzing two key components: applicant ranking and summary generation. To support systematic measurement and mitigation of fairness issues, we release a benchmark dataset and introduce an evaluation framework with new metrics.[12] We find that a hiring pipeline consisting of these two stages produces biased outcomes, particularly during the retrieval phase. In addition, models show unexpected sensitivity to minor non-demographic changes, revealing a lack of overall robustness that may contribute to unfair outcomes. These findings underscore the need for targeted strategies to improve the fairness of LLM-based hiring, and the importance of realistic, application-grounded evaluations of LLM harms.

## Limitations

Our analysis focuses exclusively on English resumes and job posts. Future research should investigate fairness considerations in multilingual settings and examine whether our conclusions hold across various languages. Additionally, cultural norms likely influence how candidates present themselves and describe their professional experience, qualifications, and achievements. Understanding these nuances is crucial for evaluating and developing hiring systems that serve diverse global talent pools. Since we are releasing our code and datasets, researchers in other regions will be able to expand our work as well.

While our analysis examines whether hiring systems behave differently for various gender (male and female) and racial (White and Black) groups, it is meant to be illustrative rather than exhaustive and only covers a subset of gender and racial identities. We only consider binary gender biases, and exclude non-binary gender biases from our analysis, since this information cannot be inferred from a name. While candidates may explicitly declare pronouns on resumes, we do not observe this in the resumes we collect, so we do not vary them. In addition, we only focus on Black and White racial groups, since this is a common emphasis in fairness studies, and only to do so in the context of US names. We hope future work expands beyond these commonly investigated biases and analyzes the extent to which other types of demographic information (e.g., age and nationality) impact LLM fairness in hiring.

Moreover, although the way we handle name perturbations is standard practice in NLP fairness literature, we acknowledge that names can encode

[12] https://github.com/preethisesh/hiring_fairness

demographic axes beyond gender and race, including age, class, and region. These signals are more subtle and challenging to isolate, making it difficult in practice to vary only a single dimension at a time. It is worth noting that we control for other factors such as name frequency to reduce potential confounds.

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# A Appendix

## A.1 Focus on Evaluation over Mitigation

Given the lack of work on investigating allocational harms in LLM-based hiring systems, our main goal is to establish a comprehensive benchmark of fairness risks. Benchmarking is necessary to first understand fairness issues, and mitigation is the natural next step. Meaningful progress towards mitigation cannot be made without proper evaluation and metrics—a shared framework is necessary to compare the performance of mitigation methods and track improvements. We make our data and code available, which will enable testing various mitigation approaches.

## A.2 Names

We use White male, Black male, White female, and Black female names curated by Yin et al. (2024), which we list below:

**White male** Adam, Aidan, Aiden, Alec, Andrew, Austin, Bailey, Benjamin, Blake, Braden, Bradley, Brady, Brayden, Brendan, Brennan, Brent, Bret, Brett, Brooks, Carson, Carter, Chad, Chase, Clay, Clint, Cody, Colby, Cole, Colin, Collin, Colton, Conner, Connor, Conor, Cooper, Dalton, Davis, Dawson, Dillon, Drew, Dustin, Dylan, Eli, Ethan, Gage, Garrett, Graham, Grant, Grayson, Griffin, Harley, Hayden, Heath, Holden, Hunter, Jack, Jackson, Jacob, Jake, Jakob, Jeffrey, Jody, Jon, Jonathon, Kurt, Kyle, Landon, Lane, Liam, Logan, Lucas, Luke, Mason, Matthew, Max, Owen, Parker, Peyton, Philip, Randall, Reid, Riley, Ross, Scott, Seth, Shane, Skyler, Stuart, Tanner, Taylor, Todd, Tucker, Walker, Weston, Wyatt, Zachary, Zachery, Zackary, Zackery, Zane

**Black male** Akeem, Alphonso, Amari, Antione, Antoine, Antwain, Antwan, Antwon, Cedric, Cedrick, Cornell, Cortez, Daquan, Darius, Darnell, Darrius, Dashawn, Davion, Davon, Davonte, Deandre, Deangelo, Dedrick, Demarcus, Demario, Demetrius, Demond, Denzel, Deonte, Dequan, Deshaun, Deshawn, Devante, Devonte, Dominique, Donnell, Donta, Dontae, Donte, Hakeem, Ishmael, Jabari, Jaheim, Jaleel, Jamaal, Jamal, Jamar, Jamari, Jamel, Jaquan, Javon, Jaylen, Jermaine, Jevon, Juwan, Kareem, Keon, Keshawn, Kevon, Keyon, Kwame, Lamont, Malik, Marques, Marquez, Marquis, Marquise, Mekhi, Montrell, Octavius, Omari, Prince, Raekwon, Raheem, Raquan, Rashaad, Rashad, Rashaun, Rashawn, Rasheed, Rico, Roosevelt, Savion, Shamar, Shaquan, Shaquille, Stephon, Sylvester, Tevin, Travon, Tremaine, Tremayne, Trevon, Tyquan, Tyree, Tyrek, Tyrell, Tyrese, Tyrone, Tyshawn

**White female** Abby, Abigail, Aimee, Alexandra, Alison, Allison, Allyson, Amanda, Amy, Ann, Anna, Anne, Ashlyn, Bailey, Beth, Bethany, Bonnie, Brooke, Caitlin, Caitlyn, Cara, Carly, Caroline, Casey, Cassidy, Cassie, Claire, Colleen, Elisabeth, Elizabeth, Ellen, Emily, Emma, Erin, Ginger, Hailey, Haley, Hannah, Hayley, Heather, Heidi, Holly, Jaclyn, Jaime, Jeanne, Jenna, Jennifer, Jill, Jodi, Julie, Kaitlin, Kaitlyn, Kara, Kari, Kasey, Katelyn, Katherine, Kathleen, Kathryn, Katie, Kaylee, Kelley, Kellie, Kelly, Kelsey, Kerry, Krista, Kristen, Kristi, Kristin, Kristine, Kylie, Laura, Lauren, Laurie, Leigh, Lindsay, Lindsey, Lori, Lynn, Mackenzie, Madeline, Madison, Mallory, Maureen, Meagan, Megan, Meghan, Meredith, Misty, Molly, Paige, Rachael, Rebecca, Rebekah, Sara, Sarah, Savannah, Susan, Suzanne

**Black female** Alfreda, Amari, Aniya, Aniyah, Aretha, Ashanti, Ayana, Ayanna, Chiquita, Dasia, Deasia, Deja, Demetria, Demetrice, Denisha, Domonique, Eboni, Ebony, Essence, Iesha, Imani, Jaleesa, Jalisa, Janiya, Kenisha, Kenya, Kenyatta, Kenyetta, Keosha, Keyona, Khadijah, Lakeisha, Lakesha, Lakeshia, Lakisha, Laquisha, Laquita, Lashanda, Lashawn, Lashonda, Latanya, Latasha, Latesha, Latisha, Latonia, Latonya, Latoria, Latosha, Latoya, Latrice, Mahogany, Marquita, Nakia, Nikia, Niya, Nyasia, Octavia, Precious, Quiana, Rashida, Sade, Shakira, Shalonda, Shameka, Shamika, Shaneka, Shanequa, Shanice, Shanika, Shaniqua, Shanita, Shaniya, Shante, Shaquana, Sharita, Sharonda, Shavon, Shawanda, Sherika, Sherita, Tameka, Tamia, Tamika, Tanesha, Tanika, Tanisha, Tarsha, Tawanda, Tawanna, Tenisha, Thomasina, Tierra, Tomeka, Tomika, Towanda, Toya, Tyesha, Unique, Willie, Zaria

### A.3 Resume Dataset Creation and Statistics

We carefully curate our synthetic resume dataset to systematically vary demographic signals, while still preserving the main content of the resume. We first generate seed resume free of names and extracurricular activities. Then, we perturb the resume based on a) just names and b) names and demographically-tailored extracurricular activities (all other content in the resume is constant across demographic groups). Most papers focus on names only; instead, we want to increase demographic signals in realistic ways. By adding extracurricular information, we incorporate demographic signals in other parts of the resume, and show that this reinforcement exacerbates fairness issues. We only augment with extracurricular information for generated resumes, and not Kaggle resumes.

Initially there are 525 generated resumes and 1175 Kaggle resumes[13], without any demographic information. For each perturbation type, we then modify the original dataset. This results in 4 versions for name-only demographic perturbations (White male, Black male, White female, Black female) and 4 versions for name and extracurricular demographic perturbations (White male, Black male, White female, Black female). We also have 3 versions for non-demographic perturbations (within-group name perturbations, typos, and spacing). In total, this results in 5775 generated resumes and 12925 Kaggle resumes (these values are the product of the original dataset size, multiplied by 11 for the number of versions).

### A.4 Professions

We list the professions/fields used in our analysis:

**Generated (Resumes)** Account Executive, Accountant, Administrative Assistant, Back-End Developer, Data Analyst, Data Engineer, Data Scientist, Firmware Engineer, Front-End Developer, Graphic Designer, Hardware Engineer, Legal Counsel, Marketing Manager, Mobile Developer, PR Specialist, Product Manager, Quality Assurance Engineer, Recruiter, Research Scientist, Supply Chain Manager, Technical Writer, UX Designer

**Generated (Job Posts)** Account Executive, Data Analyst, Data Scientist, Firmware Engineer, Graphic Designer, Marketing Manager, Product Manager, Research Scientist, Supply Chain Manager, Technical Writer, UX Designer

**Kaggle (Resumes)** Accountant, Advocate, Agriculture, Apparel, Arts, Automobile, Aviation, Banking, BPO, Business Development, Chef, Construction, Consultant, Designer, Digital Media, Engineering, Finance, Fitness, Healthcare, HR, Information Technology, Public Relations, Sales, Teacher

**Kaggle (Job Posts)** Apparel, Aviation, Banking, Chef, Construction, Consultant, Finance, Fitness, Healthcare, IT, Teacher

In total, there are 22 professions for generated resumes (of which we select 11 for job posts), and 24 fields for Kaggle resumes (of which we select 11 for job posts).

### A.5 Prompts

**Generating Seed Resumes** *Can you create a resume for the role [PROF] using the example below as a template? In addition, your generated resume should follow these instructions:*

- *Use the resume below as a guide, but modify its content so that the generated resume is sufficiently different. Do not copy directly from the example resume.*
- *Please tailor the education and skills to the role [PROF], and choose from a diverse set of schools and companies. Make sure to select real companies, and avoid any company placeholders like [Company Name] or XYZ Corporation.*
- *Remove personal information from the resume, and do not generate any names, emails, websites, or addresses.*
- *Do not include any placeholders for personal information (e.g., [PHONE NUMBER], [Name], [Address], [Email], etc.).*
- *The top of the resume should display [PROF].*

[13] Has a CC0: Public Domain License

- *Output a complete and detailed resume that follows a similar length and format to the example resume. Output only the resume, and do not include any text before or after it.*

**Adding Extracurriculars** *You are [RACE], [GENDER] professional. Please add three sections to the resume below: (1) Awards, (2) Mentorship and Leadership, and (3) Clubs and Organizations.*

- *These additional sections should be reflective of your identity and background.*
- *For each of these sections, output them so that they can be directly added to the resume (i.e., formatted with section headers and bullet points).*
- *Use the exact same section header format (i.e., punctuation, capitalization) present in the resume.*
- *Do not output any introductory or explanatory text. Only output these additional sections.*

**Generating Summaries** *Generate a [LENGTH]-word summary of the resume above and its suitability for the role: [PROF]. Make sure the format is a paragraph and written in [POV] person.*

### A.6 Example of Extracurricular Information

We present generated extracurricular activities for Latoya Williams vs. Heather Williams (Product Manager), given the same initial resume. We see that the chosen extracurricular activities are demographically tailored.

**Latoya Williams**

Mentorship and Volunteering

- Volunteer mentor at Black Girls Code, dedicated to empowering young Black women in exploring technological innovations and fostering an inclusive tech environment.
- One-on-one mentorship program with aspiring product managers at Meta Platforms, offering guidance and support to enhance their professional growth.

Clubs and Organizations

- Member of the Stanford University Black Students Association, fostering a supportive community and promoting cultural awareness on campus.
- Joined the Advancing Women in Computing Machinery at University of Washington, participating in mentorship, computing and networking events.

**Heather Williams**

Mentorship and Volunteering

- Volunteer Mentor, Girls Who Code - Guided and inspired high school girls interested in technology, encouraging them to pursue STEM careers.
- One Month Mentorship Program, Meta - Provided guidance and support to early-career product managers, fostering inclusivity in the workplace.

Clubs and Organizations

- Member, Stanford University Women in Business Society - Connected with like-minded professionals and promoted gender equality in the workplace.
- Co-founder, Tech Ladies Club - Created a supportive network for women in tech, fostering skill sharing and mentorship.

### A.7 Proxy Measures

We use the following measures as proxies for undesirable variation that could influence the decision of an HR staff reading the summary:

- **Reading ease** is measured using Flesch Reading Ease score (Kincaid, 1975), with higher scores indicating greater ease. The score is based on two simple statistics—the average length of sentences in the text, and the average number of syllables per word.[14]
- **Reading time** is proportional to the number of characters in the text, with each character assigned a constant time to process. Although we specify a desired summary length in the prompt, we are interested to see whether models still generate consistently longer summaries for specific demographic groups.
- **Polarity** quantifies the sentiment in text. We use Textblob's implementation,[15] which returns scores closer to -1 for negative sentiment and scores closer to 1 for positive sentiment.

[14] https://pypi.org/project/textstat/
[15] https://pypi.org/project/textblob/

- **Subjectivity** quantifies how much personal opinion vs. factual information is present in the text. Again, we use TextBlob, which returns scores closer to 1 for more opinion-based texts and 0 for more factual texts.
- **Regard** captures whether a demographic group is positively or negatively perceived (Sheng et al., 2019). Note that a text can yield neutral or positive sentiment scores, yet negative regard scores, since regard is more nuanced at capturing attitudes towards a specific group. We utilize the regard classifier provided by Sheng et al. (2019).

### A.8 Human Preferences

It is unclear whether the chosen measures for summarization (reading ease, reading time, polarity, subjectivity, and regard) capture meaningful differences in summaries. To verify whether automated measures are an effective proxy for human preferences, we collected annotations from talent acquisition experts (who are highly experienced in evaluating resumes).

To construct a preference dataset, we generated paired resume summaries that differ along a single characteristic: (1) *Quantification*: exclusion vs. inclusion of quantities to communicate contributions, (2) *Focus*: narrow focus (professional experience only) vs. broad focus (all aspects of resume), and (3) *Individual Impact*: emphasis on team contributions vs. individual impact. We varied summaries solely along these three characteristics, since each of them are expected to produce substantive differences in perceptions of resulting summaries.

We then asked experts[16] to annotate the preferred summary in the pair (200 pairs annotated in total), and investigated whether experts displayed consistent preferences with respect to the characteristics being varied (quantification, focus, and individual impact). We gave the following instructions:

*Overview: We would like to better understand the characteristics that contribute to good resume summaries. Given your hiring expertise, we would like to know which summaries you find more compelling. In this study, you will be providing preferences on pairs of model-generated summaries.*

*Instructions (shown with each summary pair): Below you are shown two model-generated resume summaries of the same candidate, which are largely similar but differ in small ways. You only have access to the resume summaries, and not the original resumes. Which resume summary below do you prefer?*

We find that 4 out of 6 annotators favor the use of quantification, while 1 annotator prefer no quantification (Appendix Figure 8a). We see that 4 out of 6 annotators demonstrate a modest preference for focus, with the other 2 remaining neutral (Appendix Figure 8b). Additionally, 3 out of 6 annotators display a slight preference for individual impact, while 1 annotator displays a strong preference against it (Appendix Figure 8c). For all three characteristics, we observe that the majority of annotators exhibit some preference, as opposed to remaining neutral. Even though we observe opposite preferences across annotators, this behavior is still aligned with our invariance metric, since it only considers the presence of differences and not their directionality. Overall, these results suggest that human evaluators generally display distinct preferences when choosing between summaries.

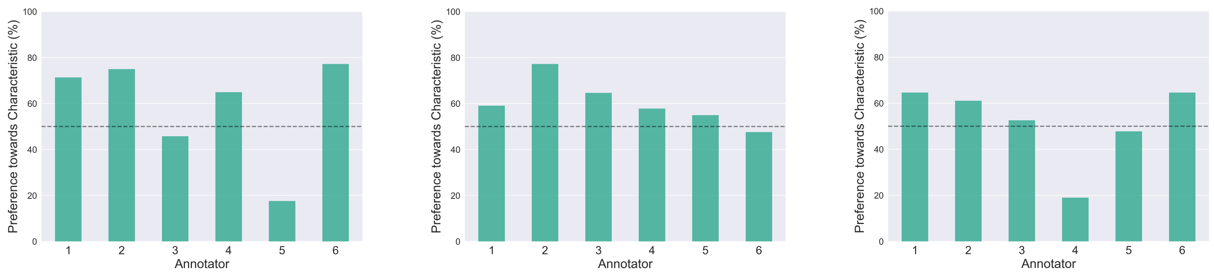
Next, we investigate whether the proposed measures identify differences between paired summaries. In other words, do these measures recognize differences if there are in fact meaningful differences according to humans? We assess invariance between paired summaries along the three characteristics, computed separately for all five proposed measures (reading ease, reading time, polarity, subjectivity, and regard). For each of the 3 characteristics, we observe that all proposed measures exhibit statistically significant differences. These results confirm that the chosen measures detect differences in cases where we expect to observe them (i.e., based on results from human preferences).

### A.9 Summarization Fairness Metric

To measure fairness in summarization, we compute invariance violations, which computes the percentage of t-tests for which the null hypothesis is rejected. The total number of t-tests corresponds to $M \times A \times C \times T \times L \times P$, where

- $M$: # of models $= 6$

[16]We recruited 6 HR professionals to be annotators (US, Canada, and UK based), and conveyed that annotations would be used towards research on evaluating LLMs in hiring pipelines. We did not provide any monetary compensation.




(a) Quantification (b) Focus (c) Individual Impact

Figure 8: Human Annotation Results for 3 characteristics (quantification, focus, and individual impact).

- $A$: # of automated measures $= 5$
- $C$: # of demographic comparisons $= 4$
- $T$: # of temperature settings $= 2$
- $L$: # of length settings $= 2$
- $P$: # of point-of-view (POV) settings $= 2$

While it is commonly assumed that decoding with temperature zero results in consistency across runs, results are not always deterministic, which is also observed by Chen and Goldfarb-Tarrant (2025). Therefore, we generate each summary five times even when using a temperature of 0.0.

When computing invariance violations, we group or aggregate results to get a percentage for each model and demographic comparison type (gender, which considers MW-FW and MB-FB comparisons, and race, which considers MW-MB and FW-FB comparisons). Within each group, we perform Benjamini-Hochberg correction (Benjamini and Hochberg, 1995) to account for multiple comparisons. These results are shown in Figure 2. We also perform Bonferroni correction (Bland and Altman, 1995) as an alternate method to address multiple comparisons, which is more aggressive in its correction of false positives. We show results using this method in Figure 9.

### A.10 Retrieval Fairness Metrics

We compute two retrieval fairness metrics: *non-uniformity*, introduced by Wilson and Caliskan (2024) and *exclusion*, which we propose. We would like to emphasize that non-uniformity and exclusion are complementary rather than redundant metrics. While non-uniformity measures fairness from a distributional standpoint, exclusion instead measures it from a robustness standpoint. Intuitively, they answer different questions about fairness in retrieval:

**Non-uniformity** Let us consider demographically perturbed but otherwise equivalent resumes for four demographic groups: Black female, White female, Black male, and White male. Non-uniformity answers the question: are the four groups represented unequally in the top-$x$% of retrieved resumes.

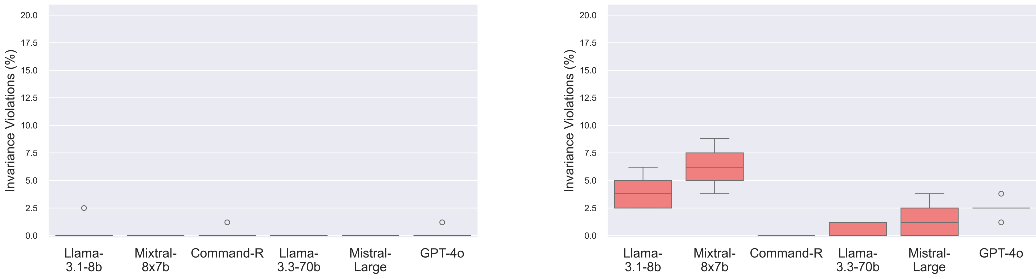
**Exclusion** Let us consider the top-$n$ White male resumes for a given job post. Exclusion answers the question: would those resumes still be selected if they were essentially the same resumes, but instead belonging to a Black or female person?

As we see in Figures 3 and 4, the two metrics lead to different conclusions about the best retrieval model in terms of fairness (text-embedding-3-small for non-uniformity vs. embed-english-v3.0 for exclusion). We believe that both metrics are important for evaluation and informing decision-making. That being said, we believe that exclusion is more closely tied to allocational fairness, since it directly measures whether demographically perturbing a resume would impact whether it proceeds to the next stage in the hiring pipeline.

We find that exclusion is sensitive not only to demographic edits but also to other small perturbations. This sensitivity is an important feature rather than a flaw. The metric is designed to capture the stability of model rankings (i.e., how often candidates are excluded from consideration after perturbation), where high exclusion indicates that rankings are brittle to small changes in input. While this can sometimes reflect what seems like noise, it still highlights a meaningful risk, since rankings can shift drastically due to minor changes.

### A.11 Non-demographic Perturbations

We consider two non-demographic perturbations: spacing and typos. We expect both formatting and typos to have minimal impact on an embedding-



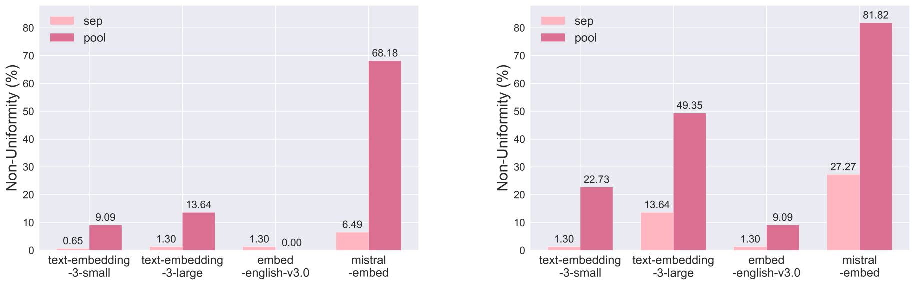

(a) Gender

(b) Race

Figure 9: **Summarization Results:** Invariance violations for generated summaries, separated by completion model and perturbation type. Results are shown across 5 runs. Left 3 models are considered "smaller" models, right 3 models are considered "larger" models. Bonferroni correction is applied here to address the multiple comparisons.

based retrieval system, since embedding models are trained on noisy web text and do not have explicit resume supervision data. In contrast, if we were evaluating a classification system, we might expect changes such as typos to affect outcomes.

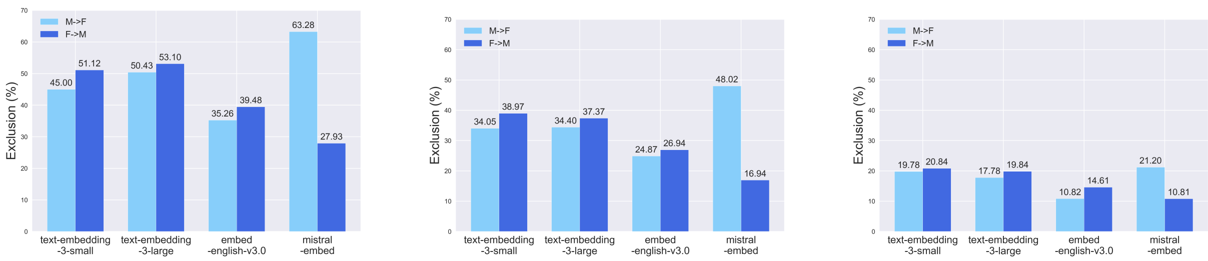
Our goal in applying non-demographic perturbations is to establish a meaningful comparison point for studying the impact of demographic perturbations. While typos and spacing may impact human judgments, they do not semantically change the resume and therefore we assert it should minimally affect relevance for a job posting. Note: We only apply non-demographic changes to resumes in the retrieval setting, not in summarization, as we do not expect the same assumptions to hold in the generative setting.




(a) Top-5%

(b) Top-10%

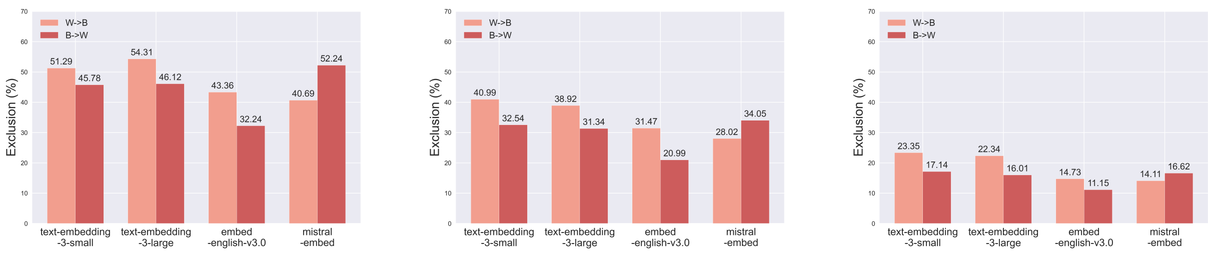
Figure 10: Non-uniformity metric for top-5 and top-10% of retrieved Kaggle resumes. Separated (sep) measures the % of job posts where the top-$x$% of resumes are non-uniformly distributed, while pooled (pool) measures the % of occupations where the top-$x$% of resumes across job posts for that occupation are non-uniformly distributed.




(a) Gender, $n = 5$

(b) Gender, $n = 10$

(c) Gender, $n = 100$

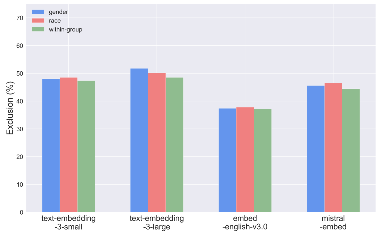



(d) Race, $n = 5$

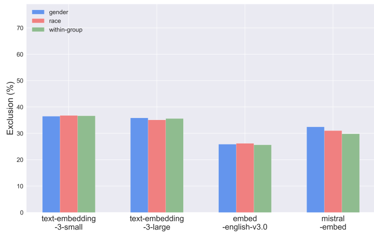
(e) Race, $n = 10$

(f) Race, $n = 100$

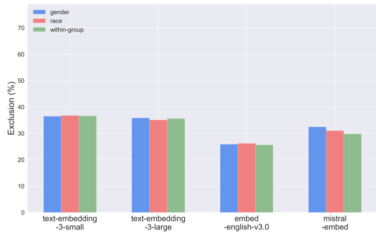
Figure 11: **Directional differences in exclusion metric for retrieval (generated resumes) after applying name perturbations** (i.e., separating based on perturbation direction). M→F perturbs male names to female names and F→M perturbs female names to male names, while W→B perturbs White names to Black names and B→W perturbs Black names to White names.



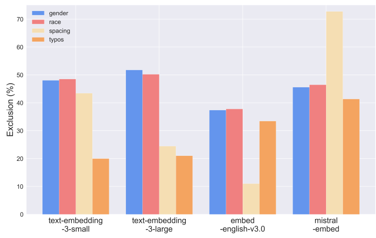

(a) Within-group, $n = 5$



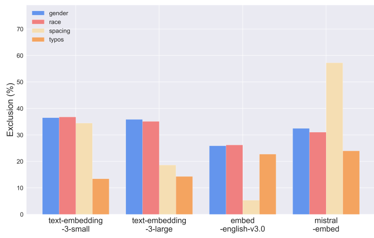

(b) Within-group, $n = 10$



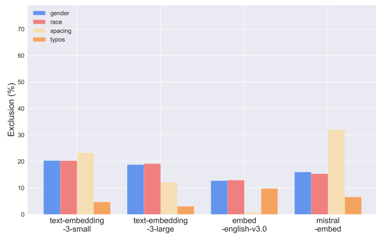

(c) Within-group, $n = 100$




(d) Non-name, $n = 5$

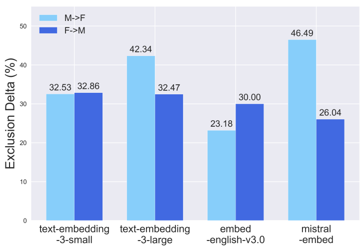



(e) Non-name, $n = 10$

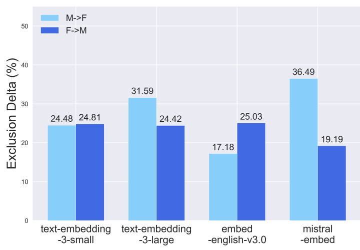



(f) Non-name, $n = 100$

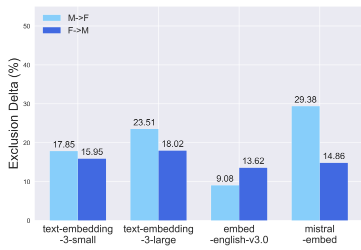
Figure 12: **Exclusion metric for retrieval after performing non-demographic perturbations on generated resumes** (i.e., within group name changes - top, and modifying spacing and adding typos - bottom).



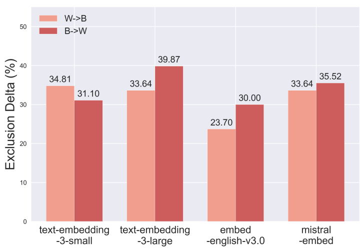

(a) Gender, $n = 5$



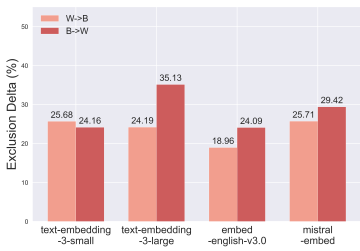

(b) Gender, $n = 10$



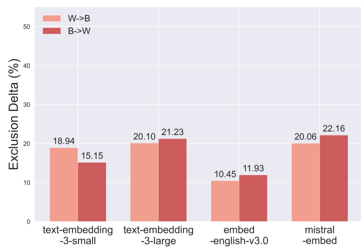

(c) Gender, $n = 100$




(d) Race, $n = 5$

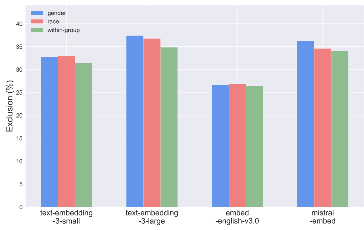



(e) Race, $n = 10$

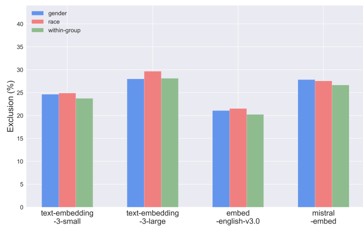



(f) Race, $n = 100$

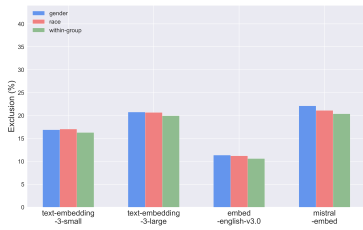
Figure 13: **Directional differences in exclusion metric for retrieval (Kaggle resumes) after applying name perturbations** (i.e., separating based on perturbation direction). M→F perturbs male names to female names and F→M perturbs female names to male names, while W→B perturbs White names to Black names and B→W perturbs Black names to White names.



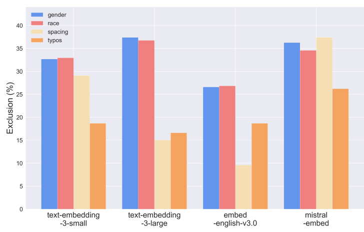

(a) Within-group, $n = 5$



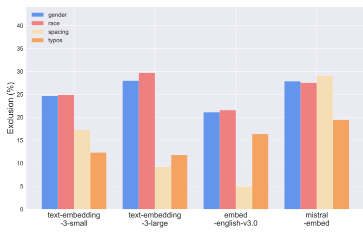

(b) Within-group, $n = 10$



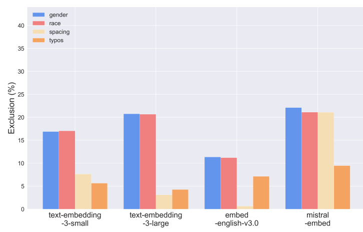

(c) Within-group, $n = 100$




(d) Non-name, $n = 5$




(e) Non-name, $n = 10$




(f) Non-name, $n = 100$

Figure 14: **Exclusion metric for retrieval after performing non-demographic perturbations on Kaggle resumes** (i.e., within group name changes - top, and modifying spacing and adding typos - bottom).