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 settings like hiring, yet their potential for unfair decision-making remains understudied in generation and retrieval. 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), using a synthetic resume dataset with demographic perturbations and curated job postings. Our findings reveal that generated summaries exhibit meaningful differences more frequently for race than for gender perturbations. Additionally, retrieval models exhibit high ranking sensitivity to both gender and race perturbations, and can show comparable sensitivity to both demographic and non-demographic changes. Overall, our results indicate that LLM-based hiring systems, especially in the retrieval stage, can exhibit notable biases that lead to discriminatory outcomes.

1 Introduction

Large language models (LLMs) are increasingly being adopted in high-stakes domains like hiring [1], where their decisions can directly shape career opportunities. Responsible deployment requires anticipating risks such as *allocational harms* (i.e., allocating resources or opportunities unfairly to different social groups) [2, 3], since automated hiring systems may produce unfair outcomes and reinforce systemic inequalities. While prior work has extensively examined representational harms (i.e., representing certain social groups negatively, demeaning them, or erasing their existence) in LLMs [4, 5, 6, 7, 8], allocational harms—the primary harm at play in high-stakes situations—remain understudied beyond discriminative systems.

The few studies that evaluate allocational harms for LLMs [9, 10, 11, 12] focus on simplified classification or prediction tasks (e.g., binary hiring decisions, salary estimates), which do not reflect real-world deployment [13]. These setups risk poor *ecological validity* [14, 15, 16], since harms must be evaluated in realistic contexts or with predictive proxies. Yet there is limited work on allocational harms in generative settings without adding a simplification layer, with [17] being a notable exception, since measuring how generated text might yield disparities is more complex than analyzing classification predictions.

In this work, we examine whether LLMs behave fairly in real-world hiring contexts. We focus on two core tasks that mirror how real-world usage in hiring workflows [18, 19]: (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 model sensitivity to gender and race perturbations in resumes by

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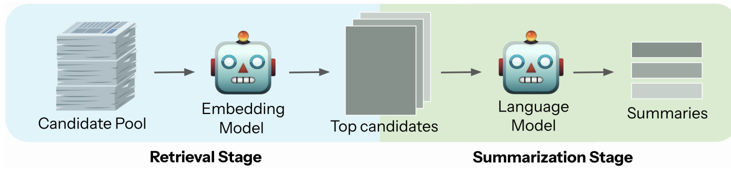


Figure 1: We investigate the fairness of an LLM hiring pipeline with a **retrieval stage** (filters the top-n candidates with respect to a job posting) and a **summarization stage** (generates resume summaries for filtered candidates). We assess fairness issues at each stage separately.

asking: **RQ1)** Do generated summaries differ meaningfully across demographic groups? **RQ2)** 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 a holistic 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. We will make all data and code publicly available.

Our findings show that LLM hiring systems display substantial bias, primarily in the retrieval stage. Summaries differ across racial groups in up to 20% of cases versus 3% for gender (**RQ1**), while retrieval is highly brittle, excluding up to 74% of candidates after demographic perturbations (**RQ2**). Models are also highly sensitive to non-demographic changes, indicating fairness concerns arise from general brittleness rather than demographic bias alone (**RQ2**). Overall, even small changes can yield major disparities, raising concerns about the fairness and robustness of LLMs in hiring.

2 Methodology and Setup

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 reflects real-world practices, as informed by interviews with corporations using LLMs for hiring.[1] 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).

Since perturbed resumes are highly similar to original resumes by design, we expect resulting summaries and rankings for original and perturbed resumes to also be similar. Based on this idea, we propose two metrics to assess allocational fairness: *invariance violations* for summarization and *exclusion* for retrieval. These metrics quantify systematic differences in generated resume summaries and meaningful changes in resume rankings with respect to job postings, respectively. While [20] also studies hiring fairness in a retrieval setting, their approach does not explicitly capture how perturbing a resume impacts resume screening outcomes.

2.1 Summarization

We examine whether demographic perturbations to resumes (e.g., changing names or extracurricular content associated with gender or race) lead to systematic differences in generated summaries. Since recruiters may rely on summaries rather than full resumes, disparities here could directly affect candidate evaluation. To capture meaningful differences in the context of hiring, we use automated proxy measures such as reading ease, polarity, and subjectivity. These proxies are validated through a preference task annotated by HR staff, confirming their effectiveness in capturing human preferences.

Fairness Metric Invariance violations are calculated by performing paired t-tests between original and perturbed summaries across all proxy measures ($\alpha = 0.05$), and computing the proportion of tests where the null hypothesis (no difference) is rejected. See Appendix A.7-A.9 for more details.

[0] We study summarization first, since it is less explored from an allocational harms perspective.
[1] We cannot share details due to non-disclosure agreements.

2.2 Retrieval

For retrieval, we rank resumes based on their similarity to a job posting using dense embeddings and cosine similarity. We then measure how often the top-ranked resumes are excluded from consideration after demographic perturbation.

Fairness Metric Exclusion is calculated as the proportion of top-n original resumes that drop out of this set after perturbation, indicating the degree of model sensitivity to small variations.

2.3 Data, Perturbations, and Models

Our benchmark comprises of 525 synthetic resumes, paired with 154 curated job postings from LinkedIn. Resumes were generated using Command-R and seeded with actual resumes collected from social media platforms (LinkedIn, Slack, X) to produce realistic resumes. It is worth noting resumes are anonymized and free of explicit demographic information until added during experimentation.

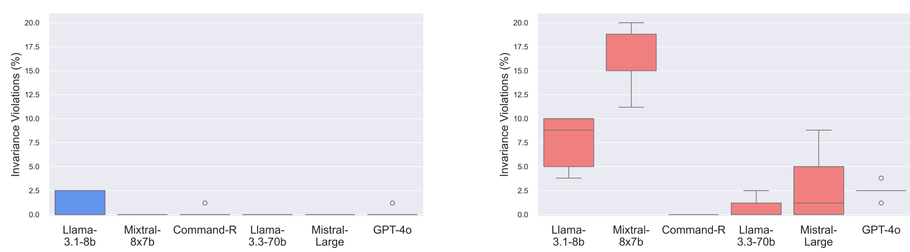
To assess fairness and robustness, we introduce targeted perturbations to resumes while keeping qualifications and professional experience constant: (1) **Names:** first names changed to names associated with different gender (e.g., Michael $\rightarrow$ Michelle) or racial groups (e.g., Emily $\rightarrow$ Lakisha). (2) **Extracurricular content:** additions such as "Black Student Union" or "Women in Engineering" to strengthen demographic cues. (3) **Non-demographic edits:** minor changes unrelated to demographics, such as spacing and typos (we only consider this for retrieval).

We evaluate 6 generative models (GPT-4o, Mixtral-8x7b, Mistral-Large, Command-R, Llama-3.1-8b, Llama-3.3-70B) and 4 retrieval models (text-embedding-3-small, text-embedding-3-large, embed-english-v3.0, mistral-embed). More details about experimentation can be found in Appendix A.2-A.6.

3 Results

We evaluate the use of LLMs in two real-world hiring tasks: resume summarization and retrieval.

3.1 Summarization

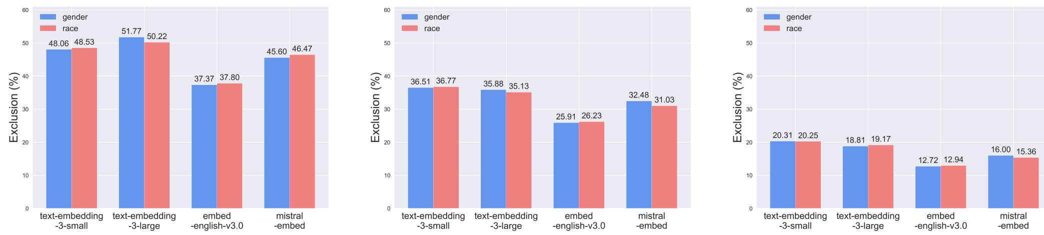


(a) Gender (b) Race

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.

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 across the 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.



(a) $n = 5$ (b) $n = 10$ (c) $n = 100$

Figure 3: **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.

3.2 Retrieval

How sensitive are models to gender and race perturbations? We find that all retrieval models display notable sensitivity to gender and race name perturbations (Figure 3). When considering the top-5 resumes, we find that models tend to exclude perturbed resumes nearly half the time (45.75% on average). 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 $> 12\%$ (in practice we expect n to be low for filtering candidates). 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.

We further partition the results based on the perturbation direction (Figure 5), and find that models often exhibit higher sensitivity to one direction of perturbation. 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 generated resumes with $n = 5$. We also observe that models exhibit opposite directional trends for gender and race, highlighting 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. 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. For example, W $\rightarrow$ B averages more than 5x the increase of B $\rightarrow$ W changes. These results suggest that models may encode and utilize various types of demographic signal differently.

More broadly, do models exhibit brittleness to non-demographic perturbations? To study this, we examine model sensitivity to two non-name perturbations: spacing and typos.

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 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). In summary, we observe that retrieval models lack overall robustness, which has fairness implications.

4 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 a holistic evaluation framework with new metrics. 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 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.

Acknowledgements

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A Appendix

A.1 Additional Background and Related Work

For background on the allocational fairness of LLMs in high-stakes domains, please see the Introduction.

Name Perturbations Performing name perturbations to study fairness is common practice in NLP fairness literature [21, 22, 23, 17, 10]. We go beyond this by perturbing resumes with extracurricular information, as done in [24], but largely focus on names because it is common practice. It is worth pointing out that [25] 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 [26].

Fairness Definitions We draw connections between the metrics we use and traditional ML fairness metrics [27]. 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 [28], which assesses whether similar individuals are treated similarly, and counterfactual fairness [29], which assesses whether outcomes are consistent for counterfactual individuals. Similarly, exclusion measures the stability of rankings under demographic perturbations.

Fairness in Summarization and Ranking Several studies have identified biases in LLM-generated summaries [30, 31, 32, 33], 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 [34, 35]. Similarly, these works mainly focus on traditional retrieval tasks such as article relevance, rather than real-world LLM usage in high-stakes domains like hiring.

A.2 Names

We use White male, Black male, White female, and Black female names curated by **(author?)** [26], 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.

Initially there are 525 generated resumes, free of 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 (this value is 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:

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

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

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].*
- *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

<u>Mentorship and Volunteering</u>

- 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

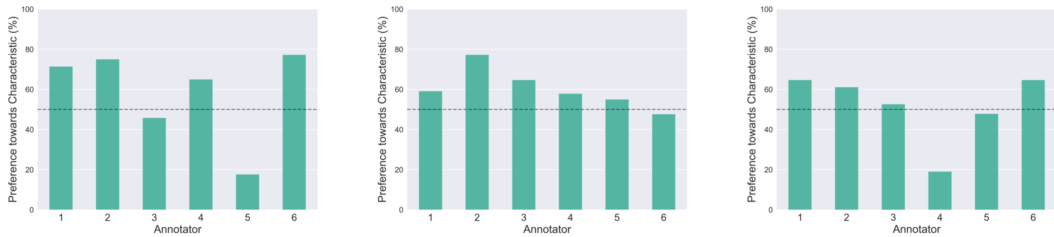
We use the following measures as proxies for undesirable variation that could influence the decision of an HR staff reading the summary:

- **Reading ease** is measured using Flesch Reading Ease score [36], 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.[2]
- **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,[3] which returns scores closer to -1 for negative sentiment and scores closer to 1 for positive sentiment.
- **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 [37]. 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 **(author?)** [37].

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).

[2] `https://pypi.org/project/textstat/`
[3] `https://pypi.org/project/textblob/`



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

Figure 4: Human Annotation Results for 3 characteristics (quantification, focus, and individual impact).

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[4] 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 4a). We see that 4 out of 6 annotators demonstrate a modest preference for focus, with the other 2 remaining neutral (Appendix Figure 4b). Additionally, 3 out of 6 annotators display a slight preference for individual impact, while 1 annotator displays a strong preference against it (Appendix Figure 4c). 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).

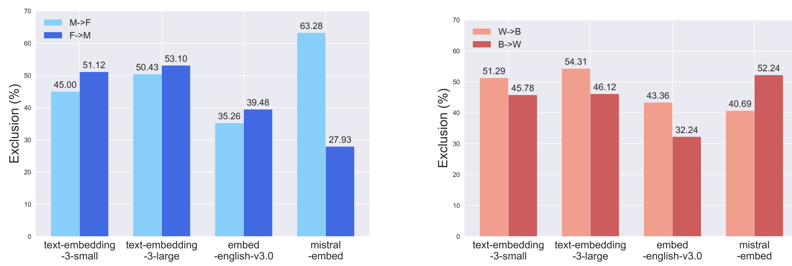
A.9 Summarization Fairness Metric

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

[4] 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.

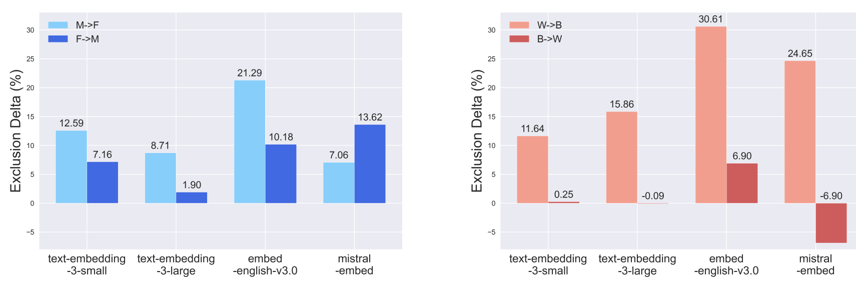
- M: # of models $= 6$
- A: # of automated measures $= 5$
- C: # of demographic comparisons $= 4$
- T: # of temperature settings $= 2$
- L: # of length settings $= 2$
- P: # of point-of-view (POV) settings $= 2$

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 [38] to account for multiple comparisons. These results are shown in Figure 2.



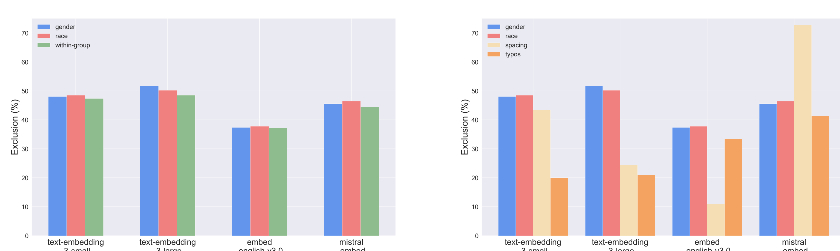
(a) Gender, $n = 5$ (b) Race, $n = 5$

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.



(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).