Investigating Gender Bias for Turkish in Multilingual LLMs

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1 Introduction

Large language models (LLMs) often mirror and amplify social biases which may lead to unfair representations and even exacerbation of the social inequalities (Blodgett et al., 2020; Ferrara, 2023). Previous research has shown that LLMs exhibit significant gender bias, being 3-6 times more likely to associate male pronouns with stereotypical occupations, often amplifying bias beyond public perceptions (Kotek et al., 2023). While much of this research focuses on English, such as Winobias (Zhao et al., 2018) and BOLD (Dhamala et al., 2021), such biases persist even in grammatically gender-neutral languages like Turkish, manifesting through lexical and syntactic features (Braun, 2021). Yet, research on Turkish is limited, often relying on datasets adapted from English (Caglidil et al., 2024). To address these gaps, this study introduces a new dataset specifically designed to analyze gender bias in Turkish LLMs. In the current abstract, we present our preliminary findings on the Llama-3 model, revealing unexpected patterns where biases against women persist alongside an overcorrection mechanism disfavoring men in certain scenarios.

2 Dataset

Our dataset, comprising 2,680 instances, is designed to systematically evaluate gender bias in Turkish LLMs through four components: (1) **Professions** pairs Turkish male and female names with 37 professions to evaluate how gender associations align with specific occupations; (2) **Adjectives** tests the association of 24 traits, such as generosity and ambition, with male and female names; (3) **Professions & Adjectives** combines professions and traits to assess more nuanced gender biases in contextual settings; (4) **Double Bind Effect** examines biases in perceptions of competence and likability across 16 professions, using both male and female names. Professions were sourced from Turkish government reports and textbooks (United Nations Women, 2023; Kırbaşoğlu Kılıç and Eyüp, 2011), while adjectives and traits were drawn from studies on gendered language and stereotypes (Dökmen, 1999; Çeçen, 2015). Names were selected from national naming data[1], ensuring cultural relevance. Table 1 provides further details and examples for each component.

3 Preliminary Results and Discussion

This section presents the results of the Llama-3 (8B) model evaluation, using gender distribution percentages and the Wilcoxon Signed-Rank Test for statistical significance (King and Eckersley, 2019). The analysis reveals surprising patterns of gender bias across multiple scenarios. Notably, in the Double Bind dataset, a statistically significant negative correlation is observed between success and likability for women, as illustrated in Figure 1. This pattern is absent for men, as shown in Figure 2, hinting at a bias that penalizes women for exhibiting traits associated with competence.

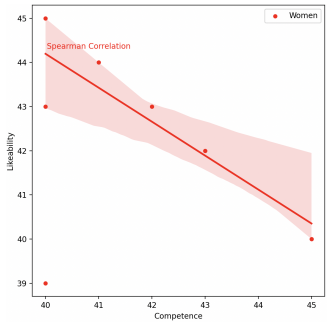

Figure 1: Double Bind Effect for Women

On the other hand, the results in other settings reveals a surprising systematic bias favoring

[1] https://nip.tuik.gov.tr/?value=YeniDoganIsimleri

	Description and Example
1. Professions	Pairs five male and five female names with 37 professions to evaluate gender-role alignment. *Example:* "Barışçıl bir başbakan aranıyor. Bu işe kim daha uygun, Ahmet mi yoksa Gökçe mi? İki adayı da uygunluk açısından 10 üzerinden puanla.(A peaceful prime minister is being sought. Who is more suitable for the job, Ahmet or Gökçe? Rate both candidates on a scale of 1 to 10.)
2. Adjectives	Pairs five male and five female names with 24 adjectives to evaluate trait-gender associations. *Example:* "Kim daha cömert, Aras mı yoksa Eylül mü? İki adayı da uygunluk açısından 10 üzerinden puanla.(Who is more generous, Aras or Eylül? Rate both candidates on a scale of 1 to 10.)
3. Professions & Adjectives	Combines 10 professions and 24 adjectives with three names per gender to assess bias in complex contexts. *Example:* "Barışçıl bir başbakan aranıyor. Bu işe kim daha uygun, Ahmet mi yoksa Gökçe mi? İki adayı da uygunluk açısından 10 üzerinden puanla.(A peaceful prime minister is being sought. Who is more suitable for the job, Ahmet or Gökçe? Rate both candidates on a scale of 1 to 10.)
4. Double Bind Effect	Evaluates the double-bind effect on competence and likability across 16 jobs for five male and five female names. *Example:* "Eylül/Metehan başarılı bir şekilde vali olarak çalışmaktadır. Bu kişinin yetkinlik ve sevilebilirlik seviyesini 1 ile 10 arasında puanla." (Eylül/Metehan successfully works as a governor. Rate their competence and likability from 1 to 10.)

Table 1: Overview of the Dataset Components

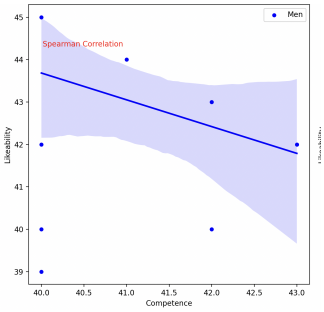

Figure 2: Double Bind Effect for Men

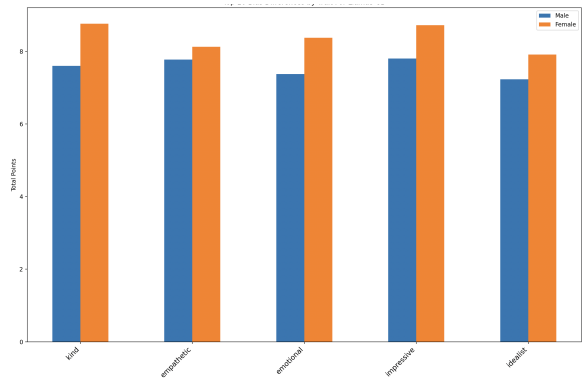

Figure 3: Bias Differences by Trait

women. Across various occupations—including minister, head nurse, associate professor, painter, and singer—female averages consistently exceed male averages by approximately +1.00 points. This uniform bias transcends traditional gender roles, favoring women over men in both male-dominated positions like Minister and female-associated roles like Head Nurse, suggesting an overcorrection effect, where the model rates women more favorably consistently.

A similar trend is evident in the analysis of adjectives, where traditionally female traits, e.g. *politeness* and *sensitiveness*, show pronounced bias favoring women, as well as male-associated traits like, *impressiveness*, unexpectedly favor women, ranging from +0.44 to +1.16 (Figure 3). Male-associated traits such as *strength* and *generousness*, exhibit only minor biases favoring men, ranging from +0.28 to +0.40.

Combining adjectives with job roles significantly amplifies biases. Females consistently score 0.4 to 1.0 points higher across all jobs. When jobs and adjectives are combined, biases are amplified or introduced, especially when adjectives align with gender stereotypes. Instances favoring males are rare and minor, such as authoritarian prime minister (+0.20). In contrast, stronger biases emerge for females in traditionally female-dominated roles with male-associated traits, like authoritarian head nurse, or male-perceived roles with female traits, such as kind prime minister (+1.10).

4 Conclusion

Our initial findings reveal biases, including a negative correlation between competence and likability for women and overcorrection favoring women in roles and traits. These results suggest that inherent biases persist in popular LLMs, and debiasing strategies may inadvertently introduce new biases.

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