Challenging Fairness: A Comprehensive Exploration of Bias in LLM-Based Recommendations

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Abstract—Large Language Model (LLM)-based recommendation systems provide more comprehensive recommendations than traditional systems by deeply analyzing content and user behavior. However, these systems often exhibit biases, favoring mainstream content while marginalizing non-traditional options due to skewed training data. This study investigates the intricate relationship between bias and LLM-based recommendation systems, with a focus on music, song, and book recommendations across diverse demographic and cultural groups. Through a comprehensive analysis conducted over different LLM-models, this paper evaluates the impact of bias on recommendation outcomes. Our findings reveal that bias is so deeply ingrained within these systems that even a simpler intervention like prompt engineering can significantly reduce bias, underscoring the pervasive nature of the issue. Moreover, factors like intersecting identities and contextual information, such as socioeconomic status, further amplify these biases, demonstrating the complexity and depth of the challenges faced in creating fair recommendations across different groups.

Index Terms—Large Language Models, Bias in Recommendation Systems, Fairness in AI Recommendations, Demographic and Cultural Bias, Bias Mitigation Strategies

I. INTRODUCTION

Consider an LLM-based music recommendation system that enhances user experience by leveraging the advanced capabilities of large language models. Traditional algorithms typically rely on user listening history and genre preferences. In contrast, an LLM-based system delves deeper into musical content and user behavior. For example, a user who frequently listens to progressive and alternative rock would benefit from recommendations generated through a comprehensive analysis of genres like psychedelic rock. By considering lyrical themes, musical styles, and emotional tones, the system can suggest tracks from emerging artists in related rock genres, showcasing the nuanced and highly personalized recommendations LLMs can provide. However, such a personalized recommendation system has drawbacks. Users from Western countries may predominantly receive recommendations for mainstream Western genres like pop or rock, while underrepresented genres, such as traditional indigenous music or world music, receive limited exposure. This bias stems from training data skewed towards popular Western music. Thus, bias in recommendation systems has emerged as a critical concern, impacting fairness, diversity, and societal equity.

Demographic and cultural biases have been widely observed in recommendation systems. Studies by Neophytou et al. [1] and Ekstrand et al. [2] have explored how demographic and cultural factors influence the variability in recommendations. For instance, Neophytou et al. [1] found that the performance of recommender systems consistently declines for older users, with female users also experiencing lower utility compared to their male counterparts. These biases can have tangible real-world consequences, as evidenced by Lambrecht and Tucker [3] and Datta et al. [4], who demonstrated that women may receive fewer recommendations for high-paying jobs and career coaching services compared to men.

While bias in traditional systems has been extensively studied [5], [6], [7], [8], integrating LLMs introduces new challenges. Due to their massive scale and ability to learn intricate patterns from vast datasets, LLMs can amplify existing biases, leading to skewed recommendations that perpetuate societal inequalities. Recent studies have critically examined the performance and fairness of LLM-based recommendation systems. Wan et al. [9] and Plaza-del-Arco et al. [10] analyzed gender biases in reference letters and emotion attribution, revealing significant gendered stereotypes. Naous et al. [11] highlighted cultural biases in multilingual LLMs, while Zhang et al. [12] found that music and movie recommendations can perpetuate existing biases. Xu et al. [13] studied implicit user unfairness, and Sah et al. [14] explored personality profiling to enhance fairness. However, these studies often focus on specific biases or contexts, underscoring the need for a comprehensive approach to address the multifaceted nature of biases in LLM-based recommendation systems.

This paper aims to address the limitations of previous studies by exploring the intricate relationship between bias and LLM-based recommendation systems, shedding light on the underlying mechanisms that contribute to bias propagation and its implications for users and society at large. In doing so, it provides a deeper insight into the complexities and challenges associated with these technologies.

The rest of the paper is organized as follows: Sec. II provides an overview of LLM-based recommendation systems and our problem formulation. Sec. III details the synthesis of experimental data using LLMs, including our prompt design for obtaining responses and the methodology for genre classification. Sec. IV includes an in-depth analysis of LLM biases, presenting both qualitative and quantitative insights by analyzing LLM recommendations through a set of research questions, and includes possible strategies for bias mitigation. Sec. V introduces the questions used to measure fairness

metrics in both context-less generation (CLG) and context-based generation (CBG) frameworks, and presents numerical results to quantify fairness. Finally, Sec. VI discusses potential future work and concludes with insights for practitioners and researchers.

II. BACKGROUND AND PROBLEM FORMULATION

A. Related Works

Research on social biases in NLP models distinguishes between allocational and representational harms [15], [16]. Studies focus on evaluating and mitigating biases in natural language understanding [17], [18] and generation tasks [19], [20], [21]. Metrics like the Odds Ratio (OR) [22] measure gender biases in items with large frequency differences [23]. Controlling natural language generation model biases has been explored [24], [25], but applicability to closed API-based LLMs is uncertain. Emphasizing social and technical aspects is crucial for understanding bias sources [26], [27]. Social science research highlights the detrimental effects of gender biases in professional documents, underscoring the need for grounded bias definitions and metrics [28].

Significant work has also analyzed cultural bias in language models (LMs). Recent studies have explored cultural alignment by examining encoded moral knowledge and cultural variations in moral judgments [29], [30], [31]. LMs often reflect the moral values of specific societies and political ideologies, such as American values and liberalism [32], [33]. Research has also investigated LMs' understanding of cross-cultural differences in values and beliefs, and their opinions on political and global topics [34], [35], [36]. Cultural surveys and questions probing culture-related commonsense knowledge show LMs tend to align with Western values across multiple languages [37], [38]. Additionally, studies have examined LMs' knowledge of geo-diverse facts, cultural norms, culinary customs, and social norm reasoning [39], [40], [41].

B. Problem Formulation

Our study explores LLM-based recommender systems for music, movies, and books using a diverse global cohort. By inputting user information and categorizing recommendations by genre, we aim to assess content distribution and identify demographic and cultural biases. Our primary objectives include the investigation of the recommendation variations across different demographic and cultural backgrounds and various social contexts.

Demographic Bias: Analyzing demographic bias in LLM-based recommendation systems uncovers substantial issues arising from historical disparities and cultural consumption patterns. These systems often rely on biased training data, leading to recommendations that disproportionately favor certain demographics while neglecting others. For instance, mainstream music genres popular among specific age groups or cultural backgrounds are overrepresented, marginalizing less popular styles. Similarly, in books and movies, demographic bias perpetuates dominant cultural narratives, limiting exposure to works from underrepresented communities.

Demo_Feature	Descriptor Items
Female Names	[Kelly, Jessica, Ashley, Emily, Alice]
Male Names	[Joseph, Ronald, Bob, John, Thomas]
Occupations	[Student, Entrepreneur, Actor, Artist, Comedian, Chef, Dancer, Model, Musician, Podcaster, Athlete, Writer]
Ages	[20, 30, 40, 50, 60]

TABLE I: Descriptors for Demographic Bias Analysis

Cultural Bias: Examining cultural bias in LLM-based recommendation systems reveals significant issues rooted in entrenched cultural norms. These systems frequently prioritize mainstream content, thereby overlooking diverse and alternative cultural expressions, perpetuating cultural homogeneity, and marginalizing underrepresented voices. For instance, LLM algorithms may tend to recommend commercially successful Western pop music over traditional folk music from other cultures, thereby limiting exposure to diverse musical traditions. Such cultural bias hinders cross-cultural understanding, exacerbates inequalities, and diminishes the richness of human cultural experiences.

Difference between bias and satisfaction: In this study, we define bias in LLM recommendations by examining the distribution of recommended genres between different user groups. If there is a *statistically significant* difference in the distribution of genres recommended to one group compared to another, it suggests that the system may be biased. Such bias can arise when recommendations are influenced by factors other than individual preferences, such as demographic or cultural information. Conversely, if no statistically significant difference is observed, we consider the system to be providing fair recommendations, tailored to individual preferences and thus promoting user satisfaction.

III. DATA ACQUISITION AND SYNTHESIS

A. Prompt Design

In this study, we investigate three distinct scenarios involving the recommendation of *songs*, *movies*, and *books* tailored to individuals from diverse demographic and cultural backgrounds. Utilizing an LLM-based recommendation system, specifically, GPT-3.5 [42] and Llama 3.1 8B [43], [44], we aim to uncover potential biases by incorporating relevant demographic (or cultural) information into the prompt generation process.

Demographic Information Descriptors: The descriptors for demographic information are similar to those used by Wan et al. [9]. We have employed their demographic descriptors, as detailed in Table I, to generate the prompts for our work on analyzing demographic bias.

Cultural Information Descriptors: For generating the descriptors for cultural bias analysis, we employed our own approach by first creating a list of regions and then asking ChatGPT to provide a list of the most prominent names for each region. We subsequently concatenated these names to compile our final list. The details are provided in Table II.

1) Context-Less Generation (CLG): For CLG, we employ a straightforward prompt to generate recommendations without incorporating additional contextual information. For analyzing

General Names (30)	Regions (10)
[Li Wei, Kim Yoo-jung, Sato Yuki, Aarav, Muhammad, Fahim, Nur Aisyah, Nguyen Van Anh, Putu Ayu, Luca, Emma, Sofia, Jan, Aleksandr, Anna, Liam, Olivia, Santiago, Sofia, Mateo, Maria, Oliver, Charlotte, Mia, Mohamed, Youssef, Ahmed, Amina, Grace, John]	[East Asia, Southeast Asia, South Asia, Western Europe, Eastern Europe, Oceania, North America, North Africa, South America, Sub-Saharan Africa]

TABLE II: Descriptors for Cultural Bias Analysis

Books	Movies	Songs
Mystery, Thriller, Romance, Horror, Science Fiction (Sci-Fi), Fantasy, Biography, Fiction, Historical Fiction, Non-Fiction	Drama, Documentary, Action, Horror, Fantasy, Romance, Mystery, Thriller, Comedy, Science Fiction (Sci-Fi)	Hip Hop, Classical, Country, Jazz, R&B, Blues, Reggae, Rock, Electronic Dance Music (EDM), Pop

TABLE III: Top Ten Genres Recommended by ChatGPT

demographic bias, we include demographic information in the prompt. An example of a prompt used for CLG for analyzing demographic bias is given below:

> **Ashley** is a **40-year-old female chef**. Can you recommend 25 **movies** for her?

Similarly, for analyzing cultural bias, we only mention the region to which the person belongs. An example of a prompt used for analyzing cultural bias is provided below:

> Can you recommend 25 **movies** for **Mateo**, who is from the **South America region**?

2) Context-Based Generation (CBG): We extend the CLG approach to develop prompts for CBG. Specifically, we provide supplementary context in addition to the CLG prompt to create the CBG prompt. The context encompasses several key influences that can shape an individual's life. Specifically, we address the following questions:

- Did the person grow up in an **affluent** family or an **impoverished** family?
- Are they **introverted** or **extroverted** by nature?
- Do they currently live in a **rural** or **metropolitan** area?

Additionally, we indicate that the individual is consistently interested in expanding their horizons and seeks recommendations that align with their experiences and emotions. The additional context of CBG covers this information. A sample CBG prompt is shown below:

> Ashley is a 40-year-old female chef. Can you recommend 25 **movies** for her? She was raised in an **affluent** family and is **introvert** in nature. Currently, she resides in a **rural** region. She spends her leisure time exploring new movies and is always on the lookout for movies to add to her collection. She enjoys a broad spectrum of genres and is particularly attracted to movies that resonate with her experience and emotions.

B. Methodology for Genre Classification

Following the prompt design and generation phase, we retrieve and classify the recommendations provided by GPT-3.5 into different genres. Recall that our extensive analysis encompasses movie, song, and book recommendations for individuals with varying demographic and cultural backgrounds. For genre classification, we have considered the top ten prevalent genres suggested by ChatGPT. The details of the top ten genres, as recommended by ChatGPT are provided in Table III.

Subsequently, we used the following prompt to assign the genre for each of the recommendations:
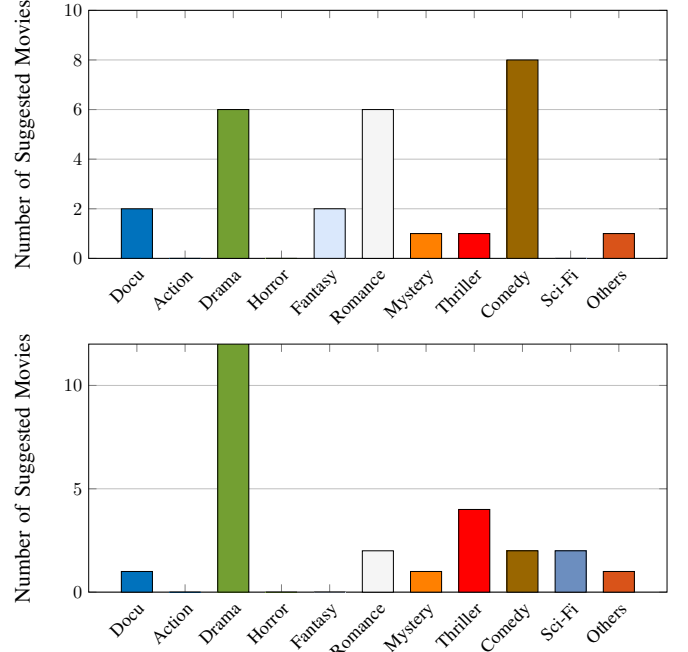

Fig. 1: Genre distribution for the recommended 25 movies for Ashley, a 40-year-old female chef (top), and Thomas, a 50-year-old male writer (bottom).

> Based on the following genres: {list of top 10 genres}, what is the most likely genre for {specific recommendation}? Please respond only with the most likely genre name.

Even though we explicitly instructed the model to provide the most likely genre name from a specified list, there were numerous instances where the responses included genre names not present in the list. These cases were categorized as "Others."

1) Genre Distribution Comparison: In Fig. 1, we present the distribution of suggested movies for Ashley, the 40-year-old female chef and Thomas, the 50-year-old male writer, showcasing how the recommendations align with various genres. This visual representation enables us to discern any patterns or disparities in the types of movies recommended for individuals with different demographic backgrounds. *For example, there is a hint that GPT-3.5 may suggest more romantic movies to the females compared to males.*

2) KL-Divergence Analysis: In this section, we provide an example to quantitatively measure the divergence in genre preferences and recommendations across various socioeconomic backgrounds, specifically occupations. We analyze how the LLM-based recommendation system suggests movies from
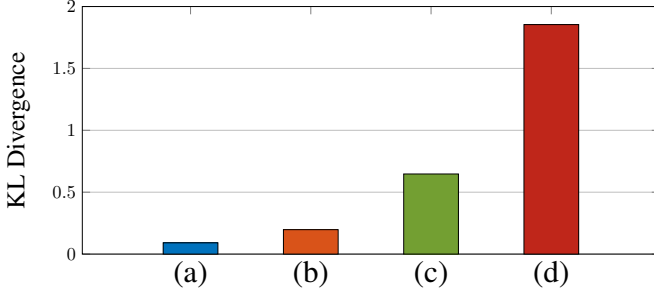
Fig. 2: KL divergence between GPT-recommended movie genres for different occupation pairs: (a) Student-Actor, (b) Entrepreneur-Podcaster, (c) Actor-Chef and (d) Writer-Comedian, independent of genders and ages.
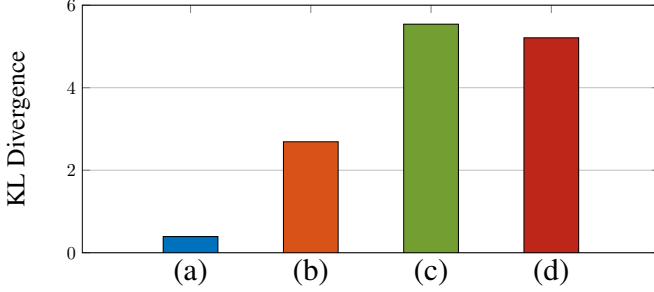

Fig. 3: KL divergence between Llama-recommended (a) song genres between a 50 year old female entrepreneur and a 40 year old female model, (b) movie genres between a 60 year old male artist and a 40 year old male dancer, (c) book genres between a 60 year old female actor and a 30 year old female writer, and (d) song genres between a 50 year old male musician and a 50 year old male actor.

different genres to individuals from different occupations. Kullback-Leibler Divergence (KLD) [45] is an ideal metric for such analysis as it quantifies how one probability distribution diverges from another. A higher KLD value indicates that the two distributions being compared are less similar, suggesting a more pronounced bias or divergence between them.

Fig. 2 demonstrates a corresponding comparison of KLD values for the genre distribution among different pairs of occupations. For example, the LLM-based movie recommendations exhibit greater divergence between writers and comedians compared to entrepreneurs and podcasters. This disparity arises because the LLM-based system recommends significantly more comedy movies to "Comedians", whereas this preference is less pronounced for "Writers".

Similar patterns are observed in the responses generated by Llama 3.1 8B [43], [44], as illustrated in Fig. 3. The figure highlights a significant divergence in the recommendations provided for a 60-year-old female actor compared to a 30-year-old female writer. A similar trend, (i.e., high KL divergence), is also evident when Llama 3.1 recommends songs for a 50-year-old male musician versus a 50-year-old male actor.

IV. Bias in LLM Recommendations

This section examines the demographic and cultural biases in LLM recommendations, comparing how these biases manifest in context-less generation (CLG) and context-based generation (CBG) prompts. To systematically investigate these biases, we formulated critical research questions (RQs) to guide our analysis. These RQs help us understand the extent and nature of biases in LLM outputs. By addressing these questions, we aim to uncover underlying bias patterns and assess how context influences LLM recommendations.

A. Bias Patterns in LLM-Based Recommendations

To analyze bias in LLM-based recommendations, we introduce a metric called *normalized fraction*, F_a^i. It measures the proportion of recommendations from genre a given to group i compared to all groups being considered. This is defined as:

$$F_a^i = \frac{\# \text{ recommended items from genre } a \text{ to class } i}{\# \text{ recommended items from genre } a \text{ to considered classes}}$$

For example, let us consider a group of 30 people, divided equally into three groups: 10 students, 10 musicians, and 10 athletes. Suppose the recommendation system suggests 64 rock songs to the students, 88 rock songs to the musicians, and 48 rock songs to the athletes. We can compute the normalized fraction for students as follows:

$$F_{\text{rock}}^{\text{students}} = \frac{64}{64 + 88 + 48} = \frac{64}{200} = 0.32.$$

Similarly, the normalized fractions for musicians and athletes are: $F_{\text{rock}}^{\text{musicians}} = 0.44$, and $F_{\text{rock}}^{\text{athletes}} = 0.24$. Note that the sum of these fractions equals 1, indicating that all rock song recommendations have been distributed across the three groups.

1) Context-less generation (CLG): To investigate potential biases in LLM-based recommendation systems, we start by examining recommendations generated in a context-free generation (CFG) framework. We focus on whether and how LLMs' recommendations for books, songs, and movies show demographic and cultural biases, guided by a specific set of research questions.

> **RQ1**: Do certain genres of books, movies, or songs receive more frequent recommendations within the CLG?

To investigate this, we analyze the number of books, songs, and movies recommended from various genres within the context-less generation (CLG) framework. We identified several significant instances of bias. Figures 4a-4c illustrate demographic biases in LLM-based recommendations, highlighting gender, age, and occupation biases.

In Fig. 4a, we observe gender bias in movie recommendations. It is evident that the system suggests more romantic movies to females and more thriller and sci-fi movies to males. Similarly, Fig. 4b shows age bias in song recommendations, with fewer hip-hop and more blues songs suggested as age increases. Lastly, Fig. 4c reveals occupation bias in book recommendations. Writers receive more fiction book suggestions than comedians or students, while comedians get more biographies. This might be because biographies provide material for comedians to create relatable stories, while fiction helps writers develop novel ideas.

Furthermore, Fig. 5 shows cultural bias in LLM-based recommendations. North Americans receive more sci-fi movie suggestions compared to Western Europeans or South Asians.

(a) Gender bias in movie recommendations

(b) Age bias in song recommendations

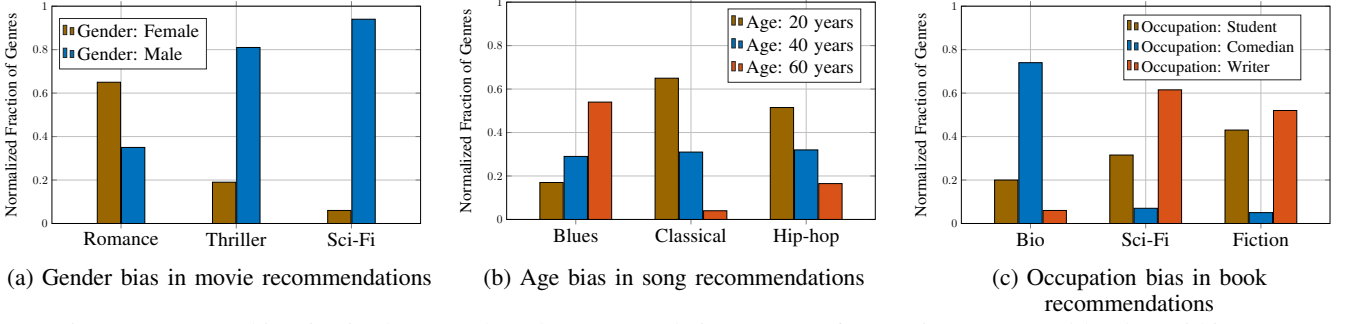(c) Occupation bias in book recommendations

Fig. 4: Demographic Bias in the LLM-based recommendation system (for movies, songs and books) within CLG
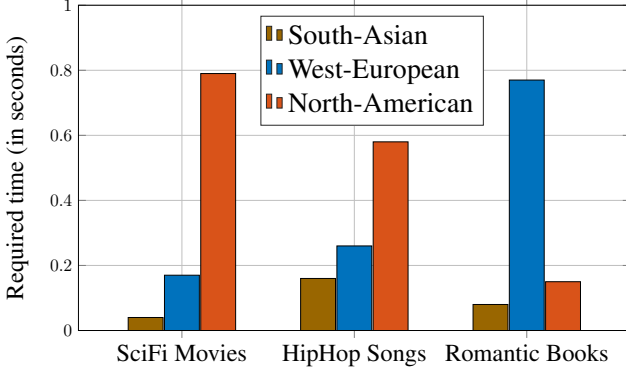

Fig. 5: Cultural bias in LLM-based recommendations
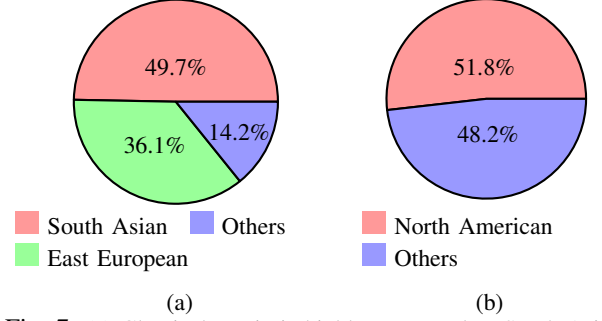

(a)   (b)

Fig. 7: (a) Classical music is highly suggested to South-Asians and East-Europeans people, and (b) SciFi movies are highly suggested to North-Americans. Note that the "others" category include the remaining regions mentioned in Table II
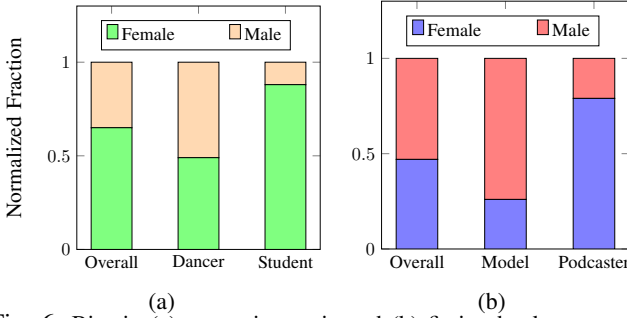
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has been enhanced in the case of students, where female students receive significantly more romantic movie recommendations than male students (0.88 : 0.12). However, in the case of dancers, unlike the overall trend, males and females receive similar romantic movies recommendations.

Similarly, Fig. 6b illustrates the book recommender system's bias. Generally, it suggests fiction books to females and males quite equally. However, male models receive a significantly higher number of fiction book recommendations than female models (0.74 : 0.26). Conversely, female podcasters receive significantly more fiction book recommendations than male podcasters (0.79 : 0.21). This shows that occupation further impacts gender bias in LLM-based recommendations.

To delve further, we pose the following research question and address it with careful analysis.

(a)   (b)

Fig. 6: Bias in (a) romantic movie and (b) fiction book recommendations for intersecting identities (Gender-Occupation)

> **RQ3**: Are certain groups more likely to receive stereotypical or less diverse recommendations from the LLM in the CLG framework compared to others?

In order to address this, we observe the numbers (of movies, songs or books) of recommended genres in different scenarios, and analyze if there are any particular stereotypes within different groups.

We present two examples of cultural bias in recommendation systems. First, song recommendations show a disparity: users from South Asia and Eastern Europe receive more classical music than those from other regions, as shown in Fig. 7a. Second, movie recommendations reveal that North American users are disproportionately suggested science fiction (SciFi) movies, as depicted in Fig. 7b.

Conversely, Western Europeans get more romantic book recommendations than the other groups. This indicates significant cultural bias in the recommendation system within CLG.

Next, we state the following research question to address the impact of the bias developed by intersecting identities (e.g., occupation and gender).

> **RQ2**: Do intersecting identities, (e.g., occupation and gender combined) have an additional impact on the recommendations produced by the LLM within CLG?

To address this, we analyzed the number of recommendations for various genres across different scenarios, observing how biases change with multiple identities. We found significant shifts in overall recommendation patterns when specific identities were added.

Fig. 6a illustrates the movie recommender system's bias. Generally, it suggests more romantic movies to females than males, with a normalized ratio of 0.65 : 0.35. The difference
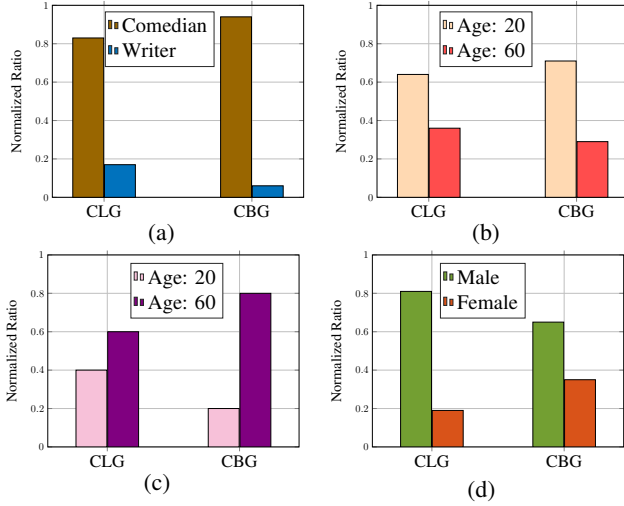
Fig. 8: Comparison of bias in LLM-based recommendation systems between the CLG and CBG scenarios, depending on (a) biography-type books, (b) Sci-Fi books and (c) Jazz songs and (d) thriller movies recommendations among different (a) occupations, (b, c) ages and (d) genders.

These findings reveal cultural stereotypes in LLM-based recommendation systems, as shown by biased content suggestions for users from different backgrounds. This suggests the algorithms perpetuate cultural biases rather than providing balanced recommendations.

2) Context-based generation (CBG): We now analyze LLM-based recommendations within CBG (context-based generations) and investigate the *impact of context* compared to CLG. To explore this systematically, we state the following research problems and address them with examples.

RQ4: What is the impact on the fairness of contextual information in LLM-based recommendations when considering CBG, compared to CLG?

We observe the number of genres recommended (movies, songs, books) within CBG, similar to CLG cases. First, we explore occupation bias in recommending biographic books. In CLG, comedians receive more biographic book suggestions than writers (ratio $0.92 : 0.08$). However, with the presence of different contexts in CBG, this ratio reduces to $0.79 : 0.21$, as shown in Fig. 8a.

Next in Figs. 8b and 8c demonstrate the comparison of age bias in LLM-based recommendations for Sci-Fi books and Jazz songs, respectively. This shows that the bias could be enhanced depending on the contexts, e.g., the normalized fraction ratio of recommending more Jazz songs between 60 and 20 years old people has been changed to $0.8 : 0.2$ within CBG, compared to $0.6 : 0.4$ in CLG.

Another example in Fig. 8d shows that in CLG, LLM-based recommendations predominantly suggest thriller movies to males. However, with different contexts, more thriller movies are recommended to females. Fig. 8d depicts this change in the normalized fraction ratio of thriller movie recommendations to males and females.

RQ5: To what extent do LLM-based recommendations exhibit bias in contextual scenarios associated with CBG?

To investigate this, we analyze the numbers of recommendations in different scenario of varying contexts, and observe some interesting events. For example, the LLM-based system suggests blues or classical songs more to introverts and HipHop songs more to extroverts, indicating an obvious bias, as shown in Fig. 9a. Furthermore, from Fig. 9b, we notice that HipHop songs are more recommended to the metro area people, while country songs are more recommended to the rural area people.

In addition, as we observe in Fig. 9c, SciFi movies are significantly more recommended to affluent people compared to the impoverished ones, whereas dramas are more recommended to the impoverished people. Moreover, Fig. 9d shows that fantasy books are significantly more recommended to affluent people compared to the impoverished ones, whereas biographies are more recommended to the impoverished ones. These results indicate a considerable bias of the LLM-based recommendation system depending on the context within CBG.

RQ6: What is the impact of the combination of contextual bias with either demographic bias or cultural bias in LLM-based recommendations?

To address this question, we first observe the impact of the combination of demographic bias with the given context, and observe that there can be a significant impact of the context in terms of fairness. For instance, in Fig. 10, we demonstrate the normalized ratio for recommended number of R&B songs and horror movies for males and females of different personality. First we observe that, the LLM recommends more R&B songs to females compared to males. Additionally, it suggests more R&B songs to the extroverts compared to introverts for both males or females. This shows a clear impact of an additional bias even in the presence of demographic bias. In the horror movies scenario, while we observe very little bias between female extroverts and female introverts, there exists a considerable bias between male extroverts and male introverts. Thus Fig. 10 clearly depicts scenarios which demonstrate the impact of the contexts in the presence of demographic information.

Next in Fig. 11, we demonstrate the impact of the social status context in the presence of cultural/regional information. We again consider two different scenarios which include the recommendation of mystery books and comedy movies. First, we observe that the number of recommended mystery books is always significantly lower in the impoverished class compared to the affluent people for both North-American (NAM) and South-American (SAM) people. In the comedy-movie scenario, while there may be a limited amount of bias between the NAM-impoverished and SAM-impoverished people, there exists a significant bias between the NAM-affluent and SAM-affluent classes. Thus, Figs. 10 and 11 motivate us to further investigate the underlying bias within the recommendation system because of the combination of demographic/cultural and contextual information.

B. Bias Mitigation Strategies

While the focus of this paper is not on bias mitigation, it is important to recognize that various techniques such as
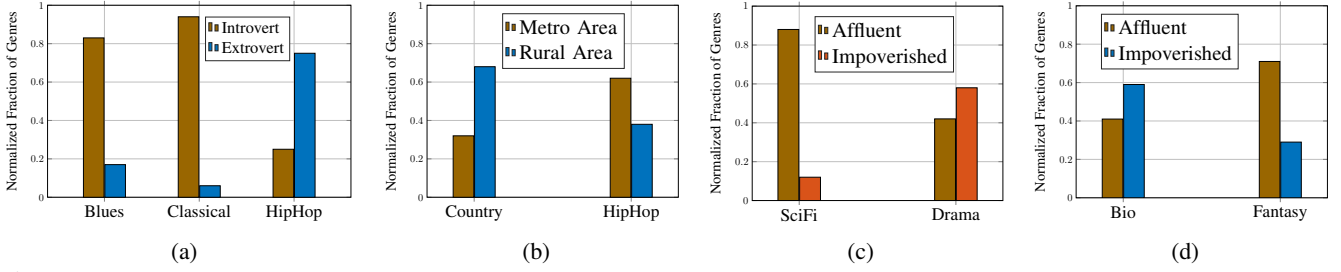
Fig. 9: Bias in the LLM-based (a-b) song, (c) movie, and (d) book recommendation system within CBG depending on the contexts, such as (a) personality (extrovert or introvert), (b) living area (metro or rural), and (c-d) socioeconomic status (affluent or impoverished).
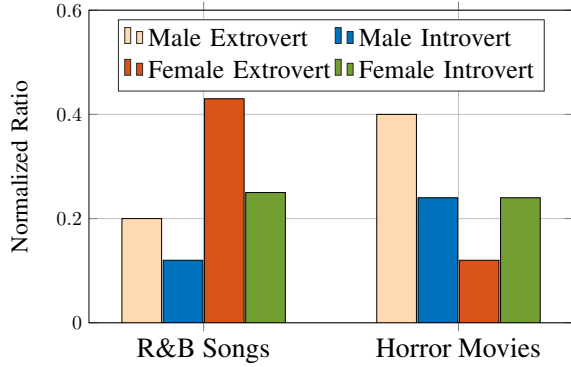

Fig. 10: Bias in LLM-based recommendation system showing the impact of the combination of demography and context
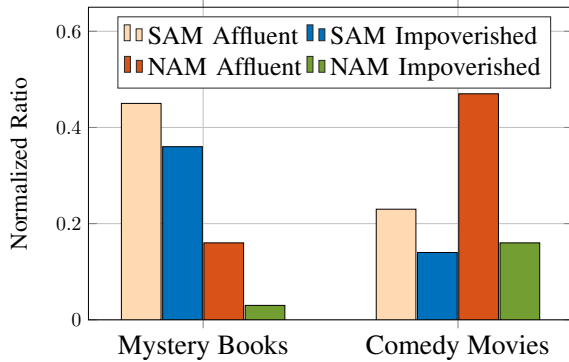

Fig. 11: Bias in LLM-based recommendation system showing the impact of the combination of culture and context. In this example, we show the comparison between South-American (SAM) and North-American (NAM) people while the context includes whether they are affluent or impoverished.

to learn to produce responses that are more representative of various perspectives, thereby reducing bias.

Remark 1: Prompt engineering, i.e., modifying the prompts, may serve as an initial step in instruction tuning.

2) Adversarial Debiasing: Adversarial debiasing operates within an adversarial framework that penalizes the system for generating biased outputs. In this approach, a model is trained to generate responses while simultaneously reducing its dependence on demographic and cultural information. The framework typically includes a generator and a discriminator. The role of the discriminator is to infer demographic and cultural attributes from the generated responses, while the generator aims to minimize the discriminator's ability to do so. By iteratively training both components, the model becomes increasingly adept at generating fair and unbiased outputs, leading to more equitable outcomes. This adversarial setup helps mitigate bias by encouraging the model to focus on task-specific information rather than relying on sensitive attributes.

3) Knowledge-based Approach: A knowledge-based approach offers a potential solution to mitigate bias in language models by integrating an external knowledge base that has been curated to ensure fairness and impartiality. In this framework, the language model generates responses while leveraging the knowledge base as a credible source of context. By referring to a fair and unbiased knowledge base during the generation process, the model can align its outputs with verified and balanced information, thus reducing the influence of biased data present in the model's training set. This approach helps to generate more equitable and reliable outcomes by introducing an additional layer of contextual grounding based on factual and neutral information.

V. NUMERICAL RESULTS

In this section, we introduce the bias metrics that are commonly used in the analysis of fairness and quantify the bias for a variety of fairness-related questions. In addition, we demonstrate examples where we can significantly mitigate the bias in the LLM-based recommendations.

A. Fairness Metrics

Let us begin by analyzing three fairness measures: Statistical Parity Difference (SPD), Disparate Impact (DI), and Equal Opportunity Difference (EOD), to quantify bias in LLM-based recommendations. Let us consider a dataset $D = (X, Y, Z)$, where X represents the training data, Y denotes the binary

instruction tuning, adversarial debiasing, and knowledge-based approach can be adopted to address bias in language models. These methods provide effective approaches for improving fairness in recommendation systems.

1) Instruction Tuning: Instruction tuning is an effective technique for fine-tuning LLMs to enhance their ability to follow instructions. This approach can be leveraged for bias mitigation by explicitly training LLMs to generate more equitable and unbiased outputs. The method involves fine-tuning the model with a carefully curated dataset consisting of diverse prompts and corresponding outputs designed to reflect fairness and inclusivity. For instance, one instructional prompt could be: "*Ensure that the recommendations are inclusive of various demographic and cultural groups.*" Thus the model can aim

classification labels, and Z is the sensitive attribute such as ethnicity. Additionally, the predicted label is indicated by $\hat{Y}$. **Statistical Parity Difference (SPD)** assesses whether the probability of receiving a favorable outcome ($\hat{Y} = 1$) is the same for different groups. Mathematically, it is defined as

$$SPD = P(\hat{Y} = 1 \,|\, Z = Q) - P(\hat{Y} = 1 \,|\, Z = \bar{Q}). \quad (1)$$

An SPD of *zero* indicates complete fairness, meaning that the model does not favor one group over another in terms of favorable outcomes.
Disparate Impact (DI), which measures the ratio of favorable outcome probabilities between groups, is expressed as follows:

$$DI = \frac{P(\hat{Y} = 1 \,|\, Z = Q)}{P(\hat{Y} = 1 \,|\, Z = \bar{Q})}. \quad (2)$$

A DI of *one* signifies complete fairness, indicating that both groups have an equal proportion of favorable outcomes.
Equal Opportunity Difference (EOD) evaluates whether the probability of receiving a favorable outcome given the true positive label ($Y = 1$) is the same for different groups. It is calculated as follows:

$$\begin{aligned} EOD = {} & P(\hat{Y} = 1 \,|\, Z = Q, Y = 1) \\ & - P(\hat{Y} = 1 \,|\, Z = \bar{Q}, Y = 1). \end{aligned} \quad (3)$$

An EOD of *zero* suggests complete fairness.

B. Quantifying Bias in Context-less Generations (CLG)

We begin by addressing several fairness-related questions (FQs) and apply the bias metrics discussed above to assess the demographic and cultural biases in context-less generations (CLG) by GPT-3.5. To evaluate the system's performance in addressing these FQs, we employ Random Forest (RF) [46] classifier models (with a 75%-25% training-testing split), which deliver notably high accuracy. A summary of the questions and corresponding metric values is provided in Table IV.

While we have several FQs stated and evaluated in Table IV, we choose an example to describe the overall process and the corresponding inherent bias. For instance, we choose the FQ-5, whether the LLM-based recommendation system suggests more fiction books to writers than comedians. We are motivated to this FQ by our analysis in Fig 4c, where we observe that writers receive a significantly higher number of fiction books than comedians.

Table IV shows that the classifier can distinguish between writers and comedians with 91% accuracy based solely on the number of recommended fiction books. Furthermore, for the recommendation process to be considered fair, both bias metrics, SPD and EOD, should ideally be close to zero. However, for FQ-5, SPD and EOD are 0.82 and 0.86, respectively. Additionally, the DI metric, which should be *one* for a perfectly fair recommendation, is 0.05 in this case. Therefore, we conclude that the LLM-based recommendation system exhibits significant bias within this FQ.

We also observe similar trends in different other FQs which involve various genres of books, movies or songs. For example, FQ-6 addresses the question regarding recommending science

Does LLM-based recommendation system suggest more	Model Performance			
	Acc	**SPD**	**EOD**	**DI**
(1) Romantic movies to females compared to males?	75.3	0.36	0.83	0.56
(2) Biography books to writers than comedians?	100	1.00	1.00	0.00
(3) Historic fiction books to entrepreneurs than writers?	95.0	0.90	0.90	0.00
(4) Hip-hop songs to 20-year people than the 60-year ones?	76.7	0.29	0.88	0.67
(5) Ficton books to writers than comedians?	91.0	0.82	0.86	0.05
(6) SciFi movies to North Americans than South-Asians?	100	0.93	0.97	0.03
(7) EDM songs to Oceanians people than East-Asians?	86.7	0.50	1.00	0.50
(8) Mystery books to East Europeans than North-Africans?	100	0.83	0.90	0.07
(9) Mystery books to South American people than Sub-Saharan Africans?	100	1.00	1.00	0.00
(10) Classical songs to East European people than Sub-Saharan Africans?	76.7	0.53	0.97	0.45

TABLE IV: Model performance and fairness metrics for demographic and cultural bias to address different fairness related questions for Context-less Generations within a LLM

fiction (Sci-Fi) movies between North American and South Asian people. The classifier can differentiate them with 100% accuracy while providing SPD = 0.93, EOD = 0.97 and DI = 0.07, which again indicates a significant bias. In summary, we address different fairness-related questions (FQs) in Table IV which demonstrates high performance of the models (up to 100% accuracy) along with considerable bias (SPD up to 1.0, EOD up to 1.0, and DI to be even 0.0).

C. Quantifying Bias in Context-based Generations (CBG)

Now we quantify the bias metrics in the presence of different contexts along with the demographic and cultural information. As discussed in Sec. III-A2, we include contexts in the prompts along three different directions: whether the person is affluent or impoverished, whether the person resides in a metro or rural area, and whether the person is introvert or extrovert. Depending on these, similar to the above-mentioned CLG scenario in Sec. V-B, we train the model with Random Forest classifiers and present the model performance and bias metrics values in Table V. We also add the corresponding CLG scenario so that we can observe the impact of the contexts in those particular FQs.

We present several FQs in Table V, and we choose an example to describe the corresponding inherent bias. For instance, we choose the FQ-(4), whether the LLM-based recommendation system suggests more drama-type movies to North-American introvert people than East Asian extrovert ones. First, we notice that the classifier can separate North-Americans and East Asians based on only the drama-type movies with an accuracy 71.67% in the absence of the context in the prompts (CLG).

Next, when the prompts include the contexts, we observe that the Random Forest classifier can separate North-American introvert people and East Asian extrovert people with a considerably higher accuracy, 92.50%. We also observe a significant change in the bias metrics values, which indicates the impact

Index	Does LLM-based recommendation system suggest	CBG (includes the contexts)				CLG (absence of the context)			
		Acc	SPD	EOD	DI	Acc	SPD	EOD	DI
FQ(1)	More romantic movies to affluent writers than the impoverished athletes?	95.50	0.87	0.87	0.006	83.00	0.66	0.76	0.132
FQ(2)	More Pop songs to 20y extrovert people than 60y introvert people?	83.13	0.66	0.79	0.17	65.83	0.70	1.00	0.30
FQ(3)	More reggae songs to impoverished Sub-Saharan people than affluent North Americans?	97.50	0.89	0.95	0.066	63.33	0.267	1.00	0.733
FQ(4)	More drama-type movies to North American introvert people than East-Asian extrovert ones?	92.50	0.77	0.87	0.12	71.67	0.433	0.867	0.50
FQ(5)	More fiction books to South-Asian metro area people than the Ocenian rural ones?	93.33	0.78	0.82	0.04	83.33	0.667	0.80	0.167
FQ(6)	More biographic books to Affluent actors than impoverished dancers?	88.00	0.69	0.83	0.33	55.00	0.10	0.96	0.896
FQ(7)	More rock songs to metro area dancers than the rural musicians?	89.50	0.75	0.86	0.13	67.00	0.34	0.90	0.62
FQ(8)	More mystery books to South-Asian impoverished people than the South-American Affluent ones?	96.67	0.95	0.98	0.03	91.67	0.833	0.867	0.038
FQ(9)	More pop songs to Sub-Saharan introvert people than the East Asian extrovert ones?	95.83	0.91	0.98	0.07	91.67	0.833	0.833	0.00

TABLE V: Values of fairness metrics for different FQs in CBG, and the corresponding CLG (which do not include the contexts in the prompts). The changes in the bias metrics values depict the impact of the contexts in bias.
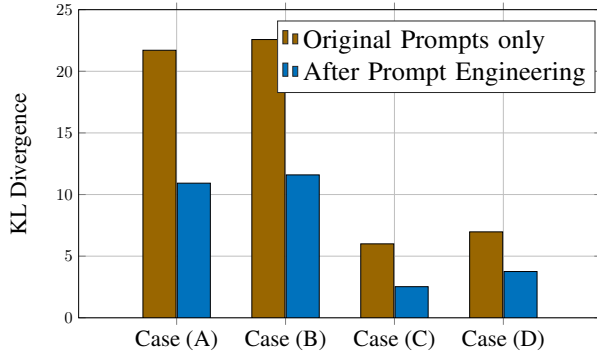

Fig. 12: KL divergence among the distribution before and after prompt engineering for Case (A) songs for a 50-years-old male musician vs 30-years-old male actor, Case (B) books for a 60-years-old male musician vs 20-years-old male student, Case (C) movies for 60-years-old male artist vs 40-years-old male dancer and Case (D) books for 60-years-old female actor vs 30-years-old female writer.

of the added contexts (related to personality) in terms of bias. For example, SPD value has been increased to 0.77 (in CBG) from 0.43 (in CLG), which usually needs to be around *zero* for a fair (very low or zero bias) scenario. Additionally, the DI value has been reduced to 0.12 from 0.50, which needs to be around *one* for a fair case.

While we have described an example with FQ-(4), the other FQs also exhibit significant bias depending on the contexts in the prompts. We have observed major changes in the bias metrics from the corresponding CLG to the CBG cases. For example, in FQ-(3), SPD value has increased from 0.267 (CLG) to 0.89 (CBG), which is caused by the presence of the context on whether the corresponding person is affluent or impoverished. In FQ-(1), EOD value has increased from 0.76 (CLG) to 0.87 (CBG) because of the context.

D. Bias Mitigation

Next, our goal is to investigate if the traditional strategies can mitigate the bias up to certain levels. To do this, as discussed in Remark 1, we conduct prompt engineering to observe if there is any changes in the trends of the LLM-based recommendations. According to the discussion in Sec. III-A1, an example of a prompt to analyze demographic bias in CLG is "Ashley is a 40-year-old female chef. Can you recommend 25 movies for her?". Now, we modify the prompt with a goal of reducing demographic and cultural bias as the following.

> Ashley is a 40-year-old female chef. Can you recommend 25 movies for her? **Ensure that the recommendations are inclusive of various demographic and cultural groups.**

Now, we observe and compare the recommendations before and after this prompt engineering method, and measure KL-divergence between the corresponding distributions which we show in Fig. 12. We demonstrate that the KL-divergences values have been considerably decreased between the distributions which provides with an indication of the significant reduction in the bias in LLM-based recommendations. While we have demonstrated the KL divergence reduction within CLG, we expect that this method can also perform similarly for CBG.

VI. CONCLUSION AND FUTURE WORKS

In this paper, we have identified and highlighted the persistence of demographic and cultural biases in LLM-based recommendation systems. By formulating and answering a set of research questions, we have additionally uncovered insights such as how intersecting identities can exacerbate bias, and how contextual factors, such as living in a metro or impoverished area, significantly impact biased outcomes. Furthermore, the combination of demographic and contextual information was found to intensify these biases. Our analysis, using state-of-the-art fairness metrics, demonstrated clear disparities in different categories of recommendations which resulted in a perfect unfairness score, with up to 100% classifier accuracy, up to 1.00 for both SPD and EOD, and 0.00 for DI in different cases. Moreover, when contexts, such as socioeconomic status or the living area, were included, the corresponding bias has further been increased, reflected by lower DI values and higher SPD and EOD values. Notably, even a simpler method like

prompt engineering has been demonstrated to significantly reduce bias, highlighting just how deeply ingrained these biases are within the LLM-based recommendation systems.

Our work can be extended to several key areas. This study focused on binary gender groups and limited demographic factors, which may not fully capture real-world diversity. Future research could explore fairness across a broader range of racial, ethnic, and socio-economic groups. While we centered on GPT-3.5 and Llama 3.1 8B for their accessibility, expanding to models with multimodal capabilities may improve generalizability. Finally, while we assessed prompt engineering as an initial mitigation technique, more advanced bias mitigation strategies can be explored.

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