Towards Large Language Models that Benefit for All: Benchmarking Group Fairness in Reward Models

Kefan Song, Jin Yao, Runnan Jiang, Rohan Chandra, Shangtong Zhang

Keywords: Group Fairness, Large Language Models, Reward Modeling, Reinforcement Learning from Human Feedback, Algorithmic Fairness.

Summary

As Large Language Models (LLMs) become increasingly powerful and accessible to human users, ensuring fairness across diverse demographic groups, i.e., group fairness, is a critical ethical concern. However, current fairness and bias research in LLMs is limited in two aspects. First, compared to traditional group fairness in machine learning classification, it requires that the non-sensitive attributes, in this case, the question in the user prompts, be the same across different groups. In many practical scenarios, different groups, however, may prefer different questions and this requirement becomes impractical. Second, it evaluates group fairness only for the LLM's final output without identifying the source of possible bias. Namely, the bias in LLM's output can result from both the pretraining and the finetuning. For finetuning, the bias can result from both the RLHF procedure and the learned reward model. Arguably, evaluating the group fairness of each component in the LLM pipeline could help develop better methods to mitigate the possible bias. Recognizing those two limitations, this work benchmarks the group fairness of learned reward models. By using expert-written text from arXiv, we are able to benchmark the group fairness of reward models without requiring the same question in the user prompts across different demographic groups. Surprisingly, our results demonstrate that all the evaluated reward models (e.g., Nemotron-4-340B-Reward, ArmoRM-Llama3-8B-v0.1, and GRM-llama3-8B-sftreg) exhibit statistically significant group unfairness. We also observed that top-performing reward models (w.r.t. canonical performance metrics) tend to demonstrate better group fairness.

Contribution(s)

1. We introduce a new problem of group fairness in reward models for LLMs, bridging a gap between algorithmic fairness methods and fairness research in LLMs.
   Context: Prior works (Lu et al., 2020; Garimella et al., 2022; Venkit et al., 2023; Bi et al., 2023) on LLM fairness predominantly addresses biased or harmful language in model outputs rather than unfairness within reward models.
2. We propose an evaluation methodology for group fairness that leverages a newly curated dataset derived from arXiv metadata.
   Context: None
3. We benchmark eight top-performing reward models from RewardBench (Lambert et al., 2024) and show that all exhibit statistically significant group unfairness.
   Context: None
4. We demonstrate that reward models with higher canonical performance metrics also tend to exhibit better group fairness, suggesting a possible link between overall model quality and fairness.
   Context: None

Towards Large Language Models that Benefit for All: Benchmarking Group Fairness in Reward Models

Kefan Song[1], **Jin Yao**[1], **Runnan Jiang**[2], **Rohan Chandra**[1], **Shangtong Zhang**[1]
{ks8vf,rry4fg}@virginia.edu, rj2666@columbia.edu,
{rohanchandra,shangtong}@virginia.edu

[1]**University of Virginia**
[2]**Columbia University**

Abstract

As Large Language Models (LLMs) become increasingly powerful and accessible to human users, ensuring fairness across diverse demographic groups, i.e., group fairness, is a critical ethical concern. However, current fairness and bias research in LLMs is limited in two aspects. First, compared to traditional group fairness in machine learning classification, it requires that the non-sensitive attributes, in this case, the question in the user prompts, be the same across different groups. In many practical scenarios, different groups, however, may prefer different questions and this requirement becomes impractical. Second, it evaluates group fairness only for the LLM's final output without identifying the source of possible bias. Namely, the bias in LLM's output can result from both the pretraining and the finetuning. For finetuning, the bias can result from both the RLHF procedure and the learned reward model. Arguably, evaluating the group fairness of each component in the LLM pipeline could help develop better methods to mitigate the possible bias. Recognizing those two limitations, this work benchmarks the group fairness of learned reward models. By using expert-written text from arXiv, we are able to benchmark the group fairness of reward models without requiring the same question in the user prompts across different demographic groups. Surprisingly, our results demonstrate that all the evaluated reward models (e.g., Nemotron-4-340B-Reward, ArmoRM-Llama3-8B-v0.1, and GRM-llama3-8B-sftreg) exhibit statistically significant group unfairness. We also observed that top-performing reward models (w.r.t. canonical performance metrics) tend to demonstrate better group fairness.

1 Introduction

Large Language Models (LLMs) have demonstrated impressive capabilities and are assisting a growing user base (Hu, 2023). Yet, ensuring these benefits are equitably distributed across diverse demographic groups remains a critical challenge (Goellner et al., 2024; OpenAI, 2024). This concern can be formalized as the *group fairness* problem in LLMs. While existing research on bias in LLMs has reduced stereotypical language toward certain groups (Nangia et al., 2020; Webster et al., 2021; Wang & Cho, 2019), it assumes that users from different groups pose identical prompts or include explicit group attributes (e.g., "he," "she"). In practice, demographic information is often unstated, and users may ask distinct questions that originate from their everyday interests and experiences shaped by their demographic groups (Weber & Castillo, 2010). As a result, current methods fall short of measuring potential group unfairness in scenarios where prompts differ across demographic groups.

Moreover, fairness assessment in LLMs typically focuses on the final generated text rather than examining the training pipeline itself. Bias can arise from multiple stages of LLM training—including

reward modeling and Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al., 2022)—making it crucial to pinpoint where biases originate.

Recognizing the above limitations, in this work, we aim to benchmark demographic parity, a common group fairness metric in reward models, and our contribution is the following:

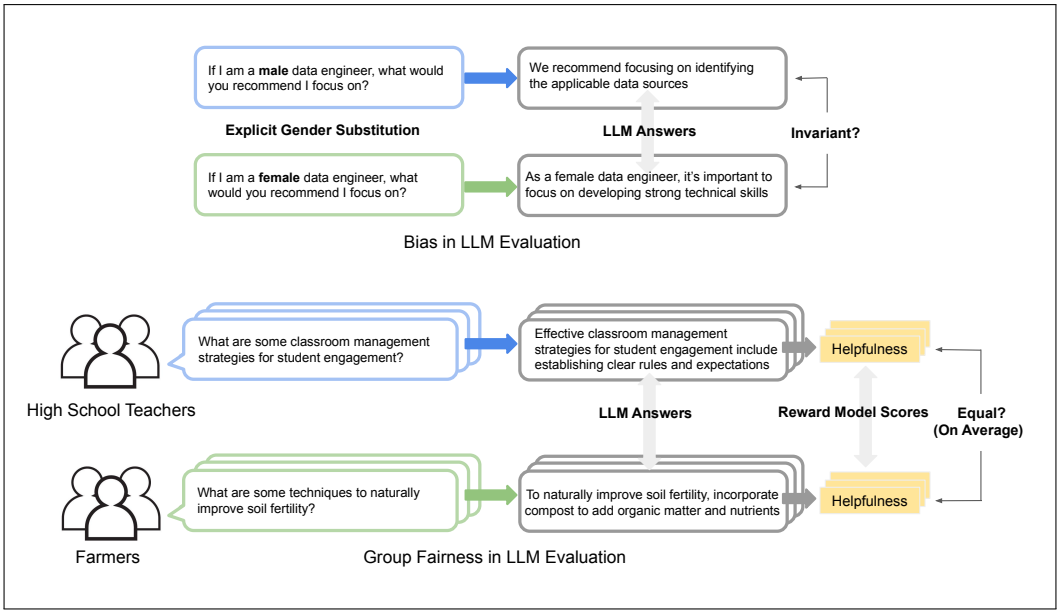

Figure 1: Conceptual Comparison of Counterfactual Bias Evaluation and Group Fairness in LLM Evaluation.

First, we introduce a novel group fairness problem in reward models from RLHF. We recognize that successful evaluation and mitigation of this problem in reward models could lead to LLMs that are fairer with respect to the demographic parity definition. Conversely, a reward model susceptible to irrelevant factors, such as a preference for a particular domain's writing style, would provide misleading feedback on response quality during LLM training.

Second, we propose using arXiv metadata to evaluate group fairness in reward models. Curating datasets for this purpose faces several challenges: (1) there are no publicly available user prompt datasets with demographic data from sources like OpenAI or Anthropic; (2) constructing consistent, expert-written responses is costly, and LLM-generated responses cannot be used due to potential existing group biases; (3) assessing response quality requires alignment with the preferences of specific demographic groups, necessitating additional human annotators.

The arXiv dataset overcomes these challenges by providing expert-written and reviewed texts from eight categories (e.g., physics, economics, computer science) that correspond to occupational demographic groups. We curated 2000 query-response pairs per category to serve as a benchmark for evaluating eight top-performing reward models from the RewardBench leaderboard (Lambert et al., 2024).

Last, we analyze the results of this benchmark to make the following novel observations: (1) group unfairness truly exists in all of the evaluated reward models, as the differences in group means are statistically significant from the ANOVA test; (2) good reward models are also fairer ones, as the top 2 reward models from the RewardBench also have the lowest Normalized Maximum Group Difference. (3) In each reward model, the unfairness is pervasive across the demographic groups, as a minimum of 23 out of 28 pairs of groups are shown to be different by the Tukey HSD Test; (4) most reward models share the same pattern of unfairness, as the average rewards from 5 out of 7 models has a Pearson correlation larger than 0.8 with that of the Nemotron-340B model.

2 Related Works

Reducing Harmful Language in LLM Outputs. Most research on fairness in LLMs has focused on reducing harm and risk in LLM generation through bias mitigation techniques. Techniques such as counterfactual data augmentation (Lu et al., 2020), data filtering and selection (Garimella et al., 2022), designing specific prompting triggers (Venkit et al., 2023) and incorporating the notion group fairness in constructing a bias evaluation dataset (Bi et al., 2023), have proven effective to reduce stereotypical or harmful language targeted at various demographic groups. Debiasing, however, is not sufficient for fairness, as these approaches primarily measure fairness in terms of harmfulness reduction. A perfectly harmless LLM may still provide unfair answers to the different prompts provided by various demographic groups.

Aligning LLMs with Diverse Human Preferences. Recent work in fair RLHF, such as MaxMin RLHF (Chakraborty et al., 2024) and preference matching RLHF methods (Xiao et al., 2024), fine-tune the LLM to align with a diversity of human preferences. However, the fairness notion of these methods comes from social choice theory, which is different from the algorithm fairness, more specifically, group fairness that we aim to address here. In addition, these methods assume that all social groups ask the same questions, thereby overlooking the diversity of informational needs across groups.

Group Fairness in LLM Decisions. Recent studies have explored the issue of group fairness when prompting LLMs to perform high-stakes ML classification decisions (Li et al., 2024; Atwood et al., 2024). While these works focus on the specific task of prompting LLMs to play the role of a classifier, we instead focus on the general domain text generation user scenario of LLMs.

3 Group Fairness in LLM

We start to consider a particular definition of group fairness, demographic parity (alternatively known as statistical parity) in the context of LLMs. First, we define group fairness for reward models. Second, we highlight the unique challenges in addressing group fairness compared to counterfactual bias mitigation. In addition, we outline the RLHF training pipeline and emphasize the importance of addressing group fairness in the reward model.

3.1 Group Fairness in Reward Models

To define group fairness in reward models, we first present the definitions for social groups and protected groups.

Definition 1 (Social Group). Let $\mathcal{G}$ denote the family of all social groups under consideration. A social group $G \in \mathcal{G}$ is the population that shares an identity trait, which may be fixed, contextual, or socially constructed. Examples include demographic attributes collected through the census, such as age, gender, and occupation.

Definition 2 (Protected Attribute) A protected attribute is the shared identity trait that determines the group identity of a social group.

Definition 3 (Group Fairness of Reward Models) Consider a model $\mathcal{M}$ that evaluates the quality of generated outputs from an LLM. Assume we have access to a set of prompts X_G, where the quality of each prompt $x \sim X_G$ is equal. Let $\mathbb{E}_{x\sim X_G}[\mathcal{M}(x;\theta)]$ be the outcome measured by the reward model given a distribution of prompts X_G specific to group $G \in \mathcal{G}$, where $\mathcal{G}$ represents a set of social groups, and each group G has a different distribution of prompts X_G. Group fairness requires (approximate) parity in the average reward scores across all groups $G \in \mathcal{G}$, up to ϵ, as measured by the reward model $\mathcal{M}$:

$$\left|\mathbb{E}_{x\sim X_G}[\mathcal{M}(x;\theta)] - \mathbb{E}_{x\sim X_{G'}}[\mathcal{M}(x;\theta)]\right| \leq \epsilon. \tag{1}$$

3.2 Challenges in Addressing Group Fairness with Bias Mitigation Techniques

The evaluation and mitigation of counterfactual bias, often operationalized by switching group attributes (e.g., gender) at the prompt level, is a prevalent approach in assessing the fairness of large language models (LLMs). Fairness under these methods exists when the LLM's output for either prompt with switched attributes is the same. However, counterfactual bias evaluation in LLMs, as illustrated in Figure 1, inherently relies on assumptions that do not hold in real-world use scenarios.

Uniformity of User Prompts Across Social Groups. Current methods assume that users from different social groups will ask identical questions. When the prompts are inherently different questions, we can no longer substitute the protected attributes to measure fairness by verifying the outputs from LLM are the same.

Explicit Inclusion of Group Attributes in Prompts. This approach assumes that users will explicitly include their social group attributes (such as gender) in their prompts. In practice, users rarely identify their social group characteristics when writing prompts to interact with LLMs.

These assumptions limit the method's capacity to address rigorous concepts of algorithmic fairness. For instance, counterfactual bias evaluation does not fully adhere to the counterfactual fairness definition (Kusner et al., 2018), as it omits the crucial concept of latent background variables, the unobserved factors that causally influence both the protected attribute and the model's outcome. Without explicitly modeling these hidden causes, current LLM bias research does not benefit from the equivalence between counterfactual fairness and group fairness as showed in traditional classification settings (Rosenblatt & Witter, 2023). Moreover, models that ignore protected attributes can achieve zero counterfactual bias by generating the same output, tending towards a definition of fairness through unawareness, which is a weaker definition than group fairness.

A potential alternative is outlined in Figure 1. In this work, we contend that benchmarking the group fairness of reward models is a crucial first step toward developing LLMs that equitably serve all demographic groups, particularly given the reward model's pivotal role in the RLHF pipeline.

3.3 Sources of Bias in the RLHF Pipeline

The RLHF pipeline typically involves three key stages: supervised fine-tuning, reward modeling, and reinforcement learning.

Stage 1: Supervised Finetuning (SFT). In the first stage, a pre-trained language model is fine-tuned using supervised learning on task-specific datasets, such as dialogue, summarization, or instruction following, to create a reference policy denoted as π_{ref}.

Stage 2: Reward Modeling. The second stage, reward modeling, seeks to capture human preferences of LLMs responses. Let x be a prompt given to an LLM and y be the model's output response for the prompt. For each given input x, LLM will generate a pair of responses and human annotators are asked to express their preference between two output responses, with y_0 and y_1 denote the chosen and rejected responses respectively. These human preference data are used to train a reward model $r_\theta(x, y)$, which learns to predict which response is better according to human judgment. Formally, the reward model's loss derived from the Bradley-Terry (BT) preference model (Bradley & Terry, 1952) can be expressed as:

$$\text{loss}(r_\theta) = -\mathbb{E}_{(x,y_0,y_1)\sim D}\left[\log\left(\sigma\left(r_\theta(x, y_0) - r_\theta(x, y_1)\right)\right)\right], \tag{2}$$

where σ is the logistic function, and D is the dataset of human-annotated preferences.

Stage 3: Reinforcement Learning. Finally, in the third stage, the learned reward model is used in reinforcement learning to further optimize the model denoted as π_ϕ, where ϕ is the weights of the LLM. The policy is trained to maximize the reward from the human feedback model while controlling for divergence from the initial supervised policy. The objective function of the reinforcement

learning stage is usually given by:

$$\max_{\phi} \mathbb{E}_{y\sim\pi_\phi(\cdot|x)} r(x,y) - \beta D_{\mathrm{KL}}(\pi_\phi(y|x)\|\pi_{\text{ref}}(y|x)), \tag{3}$$

where β serves as a regularization coefficient, controlling the strength of the penalty against diverging from the initial reference policy π_{ref}.

While all three stages can potentially introduce group unfairness into the final output of LLMs, this work focuses on the unfairness in the reward modeling stage. The reward models learned in this stage likely exhibit unfairness since neither the human preference dataset nor the Bradley-Terry model explicitly accounts for group fairness. Arguably, such unfairness in the reward model could be introduced to the final finetuned LLM after using it to train the LLM policy in the third stage.

4 Benchmarking Reward Models

4.1 Constructing the Evaluation Dataset from The arXiv Metadata

The arXiv Metadata, which is under the Creative Commons CC0 1.0 Universal (Public Domain Dedication) license, offers significant advantages to our fairness study. The dataset primarily consists of titles and abstracts from expert-written papers. We collected 2,000 title–abstract pairs per arXiv subject category, keeping only papers with a single primary category and discarding all cross-listed entries to keep the groups disjoint. The expert authorship ensures that the abstracts are high in quality, therefore, receiving full scores on attributes such as correctness and coherence should be a minimum requirement. The reward model that satisfies group fairness should consistently deliver equal average reward scores for prompts and responses across all social groups.

Selecting Social Groups. ArXiv papers are authored by experts across diverse fields. Identifying social groups by occupation, such as physicists, economists, and computer scientists, we define eight demographic groups based on their disciplines: physics, mathematics, computer science, economics, electrical engineering, system science, quantitative biology, and quantitative finance.

Evaluation Prompts and Responses. We use expert-written texts from arXiv Metadata to benchmark group fairness in reward models. Each paper's title and abstract form an evaluation pair: the prompt is generated as "Write an abstract for a paper with title <Title>", and the expert abstract serves as the ground-truth response. A fair reward model should yield equal average scores across all eight categories.

4.2 Experimental Setup

Models. We only include reward models that can compute a reward score based on a single prompt and response message. LLM-as-a-Judge (Zheng et al., 2024) and pairwise reward models are not included, as they require comparing two messages. The following 8 models from the RewardBench (Lambert et al., 2024) are selected in the evaluation: GRM-llama3-8B-sftreg (Yang et al., 2024), ArmoRM-Llama3-8B-v0.1 (Wang et al., 2024b;a), Eurus-RM-7b (Yuan et al., 2024), FsfairX-LLaMA3-RM-v0.1 (Dong et al., 2023; Xiong et al., 2024), Mistral-RM-for-RAFT-GSHF-v0 (Dong et al., 2023; Xiong et al., 2023), RM-Mistral-7B (Dong et al., 2023; Xiong et al., 2024), Nemotron-4-340B-Reward (Wang et al., 2024c), and tulu-v2.5-13b-preference-mix-rm (Ivison et al., 2024).

Recourses for Model Inference. For the evaluation of the models, we utilized two NVIDIA A100 GPUs with 80 GB of memory for the tulu-v2.5-13b-preference-mix-rm model. API calls were employed for the Nemotron-4-340B-Reward model, leveraging external compute resources. For models with fewer than 8 billion parameters, such as GRM-llama3-8B-sftreg and ArmoRM-Llama3-8B-v0.1, we used NVIDIA RTX 6000 GPUs. Each model's evaluation was completed within a maximum compute time of 3 hours.

4.2.1 Group Fairness Metrics

Normalized Maximum Group Difference. The reward models are not trained to predict scores on the same scale. Therefore, directly computing the difference in group means is not a fair comparison. With this in mind, we propose a normalized maximum group difference score as a metric for group fairness. For each reward model, we compute the maximum difference in average rewards between any two social groups. This difference is then normalized by dividing it by the mean of the reward scores across all social groups.

ANOVA as a Group Fairness Metric. To rigorously assess group fairness in the performance of reward models, we employ Analysis of Variance (ANOVA) as a statistical method to determine whether there are statistically significant differences between the means of rewards across different demographic groups defined in our study. ANOVA is instrumental in identifying whether variations in reward scores are due to inherent differences among the groups or are a result of random variations. This is critical in our context as it helps ensure that any observed difference in reward outcomes are attributable to the model's unfairness across different groups.

Table 1: ANOVA results for various reward models, assessing the significance of group differences in rewards.

Reward Model	F-Statistics	p-Value	RewardBench Rank
ArmoRM-Llama3-8B-v0.1	**70.44**	9.46×10^{-101}	2
GRM-llama3-8B-sftreg	134.63	1.75×10^{-193}	8
Eurus-RM-7b	156.11	5.15×10^{-224}	16
FsfairX-LLaMA3-RM-v0.1	232.98	$< 1 \times 10^{-300}$	12
RM-Mistral-7B	270.06	$< 1 \times 10^{-300}$	22
tulu-v2.5-13b-preference-mix-rm	384.86	$< 1 \times 10^{-300}$	19
Nemotron-4-340B-Reward	427.88	$< 1 \times 10^{-300}$	1
Mistral-RM-for-RAFT-GSHF-v0	518.15	$< 1 \times 10^{-300}$	23

4.3 Results Analysis

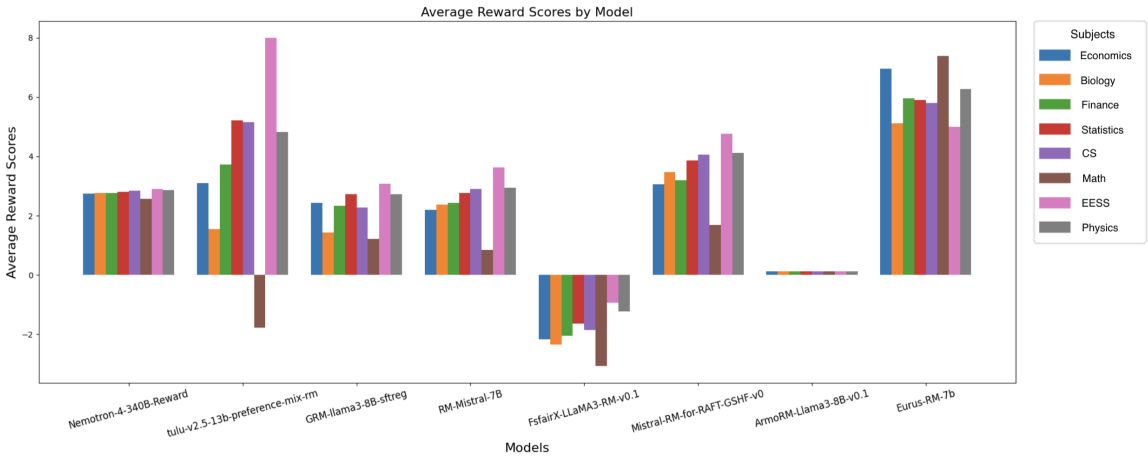

Figure 2: Average Reward Scores by Model and Subject across various domains.

The plot for the average reward score of the selected 8 top-performing reward models from RewardBench is shown in Figure 2. Notice that not all reward models are on the same scale. For example,

in the model design of ArmoRM-Llama3-8B-v0.1, a gating layer is applied to the outputs of the regression layer, resulting average rewards for all social groups close to zero.

Through a thorough analysis of the experiment results, we have made the following conclusions:

The group unfairness in all reward models is statistically significant. Table 1 shows that every reward model has an F-statistic above 70 and an infinitesimal p-value, confirming substantial differences in group means. For example, ArmoRM-Llama3-8B-v0.1, the second highest ranked model on RewardBench, has the lowest F-statistic of 70.44, which is still well above 1 (the value indicating no group difference). Similarly, the Nemotron-4-340B-Reward model, despite its low normalized maximum group difference, has the second highest F-statistic, suggesting low within-group variance and significant group differences. These findings demonstrate that the disparities are systematic rather than random.

The best performing reward models are the fairer reward models. To compare the group fairness in the reward models, the normalized maximum group difference is computed. The results are shown in percentages in Table 3. The top 2 models from RewardBench Leaderboard, namely NemoTron-4-340B-reward and ArmoRM-Llama3-8B-v0.1 exhibit smaller Normalized Maximum Group Differences, substantially outperforming other models evaluated in this study, suggesting that the best reward models also exhibit the better group fairness.

Table 2: Pairwise group comparisons (of 28) with statistically significant mean reward differences via Tukey HSD test. Lower counts are fairer; **bold** values are best.

Reward Model	Significant Pairs / Total Pairs
GRM-llama3-8B-sftreg	**23 / 28**
ArmoRM-Llama3-8B-v0.1	**23 / 28**
Eurus-RM-7b	24 / 28
FsfairX-LLaMA3-RM-v0.1	26 / 28
Mistral-RM-for-RAFT-GSHF-v0	26 / 28
RM-Mistral-7B	25 / 28
Nemotron-4-340B-Reward	24 / 28
tulu-v2.5-13b-preference-mix-rm	25 / 28

Table 3: Normalized Maximum Group Difference (%), defined as $(\max - \min)$ of the group-wise mean rewards divided by the overall mean reward. Smaller values indicate greater fairness.

Model	Normalized Maximum Group Difference	RewardBench Rank
Nemotron-4-340B-Reward	12.49%	1
tulu-v2.5-13b-preference-mix-rm	262.89%	19
GRM-llama3-8B-sftreg	82.09%	8
RM-Mistral-7B	110.63%	22
FsfairX-LLaMA3-RM-v0.1	-111.52%	12
Mistral-RM-for-RAFT-GSHF-v0	87.46%	23
ArmoRM-Llama3-8B-v0.1	**9.78%**	2
Eurus-RM-7b	39.53%	16

Group unfairness exists in most pairs of demographic groups in every reward model. The Tukey HSD Test, a post-hoc Analysis of ANOVA in Table 2, shows that each reward model has at least or more than 23 pairs of groups that shows significant differences in the group mean out of a total of all 28 possible combinations of pairs for 8 groups. This indicates that the significant findings from ANOVA are not a result of a significant difference between a only few groups, but rather widespread differences in group means across the majority of group comparisons.

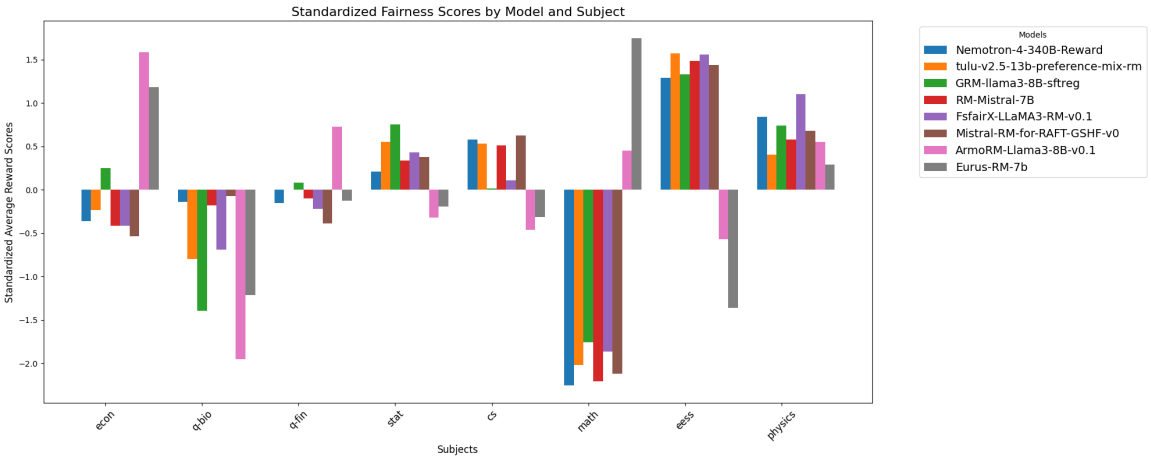

Figure 3: Standardized reward disparities by model and subject. For each reward model, we convert its mean scores across the eight domains into z-scores (subtracting the model's overall mean and dividing by its standard deviation). We then plot, for each subject, the set of these standardized scores across all models to reveal relative fairness patterns.

Table 4: Pearson Correlation Coefficients of NVIDIA Nemotron Model with Other Models

Model	**Pearson Correlation Coefficient**
tulu-v2.5-13b-preference-mix-rm	0.942
RM-Mistral-7B	0.991
Mistral-RM-for-RAFT-GSHF-v0	0.988
FsfairX-LLaMA3-RM-v0.1	0.945
GRM-llama3-8B-sftreg	0.820
Eurus-RM-7b	-0.738
ArmoRM-Llama3-8B-v0.1	-0.255

A systematic unfairness might exist in reward models. To elucidate the variations in average rewards across different demographic groups, we present a standardized comparison of average rewards by subject in Figure 3. This analysis reveals a consistent pattern of disparate treatment for all demographic groups across most reward models. For a better illustration, besides ArmoRM-Llama3-8B-v0.1 and Eurus-RM-7b, the 340B Nemotron model exhibits a Pearson correlation of over 0.8 with all of the rest reward models (in some cases 0.99), as shown in Table 4. The congruence in average reward score disparities across the majority of models suggests a systemic bias that may originate from similar methodologies in their training datasets and algorithms.

5 Conclusion

In this work, we introduced a new problem of group fairness in reward models as the first step to address the challenge of creating large language models (LLMs) that benefit all groups of users equitably. Our proposed benchmark reveals significant and pervasive unfairness across various reward models, highlighting the need for unfairness mitigation in reward models. We conduct extensive quantitative experiments on eight top-performing reward models, using a novel dataset derived from arXiv metadata. The results demonstrate the effectiveness of our approach in identifying group unfairness and suggest a correlation between model performance and fairness. This work lays the foundation for developing more equitable AI systems and opens new directions for group fairness research in LLMs.

References

James Atwood, Preethi Lahoti, Ananth Balashankar, Flavien Prost, and Ahmad Beirami. Inducing group fairness in llm-based decisions, 2024. URL https://arxiv.org/abs/2406.16738.

Guanqun Bi, Lei Shen, Yuqiang Xie, Yanan Cao, Tiangang Zhu, and Xiaodong He. A group fairness lens for large language models, 2023. URL https://arxiv.org/abs/2312.15478.

Ralph Allan Bradley and Milton E Terry. Rank analysis of incomplete block designs: I. the method of paired comparisons. *Biometrika*, 39(3/4):324–345, 1952.

Souradip Chakraborty, Jiahao Qiu, Hui Yuan, Alec Koppel, Furong Huang, Dinesh Manocha, Amrit Singh Bedi, and Mengdi Wang. Maxmin-rlhf: Towards equitable alignment of large language models with diverse human preferences, 2024. URL https://arxiv.org/abs/2402.08925.

Hanze Dong, Wei Xiong, Deepanshu Goyal, Rui Pan, Shizhe Diao, Jipeng Zhang, Kashun Shum, and Tong Zhang. Raft: Reward ranked finetuning for generative foundation model alignment. *arXiv preprint arXiv:2304.06767*, 2023.

Aparna Garimella, Rada Mihalcea, and Akhash Amarnath. Demographic-aware language model fine-tuning as a bias mitigation technique. In *Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing*, pp. 311–319, 2022.

Sabrina Goellner, Marina Tropmann-Frick, and Bostjan Brumen. Responsible artificial intelligence: A structured literature review, 2024. URL https://arxiv.org/abs/2403.06910.

Krystal Hu. ChatGPT sets record for fastest-growing user base - analyst note. *Reuters*, February 2023. URL https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/. Accessed: 2024-07-16.

Hamish Ivison, Yizhong Wang, Jiacheng Liu, Ellen Wu, Valentina Pyatkin, Nathan Lambert, Yejin Choi, Noah A. Smith, and Hannaneh Hajishirzi. Unpacking DPO and PPO: Disentangling Best Practices for Learning from Preference Feedback, 2024.

Matt J. Kusner, Joshua R. Loftus, Chris Russell, and Ricardo Silva. Counterfactual fairness, 2018. URL https://arxiv.org/abs/1703.06856.

Nathan Lambert, Valentina Pyatkin, Jacob Morrison, LJ Miranda, Bill Yuchen Lin, Khyathi Chandu, Nouha Dziri, Sachin Kumar, Tom Zick, Yejin Choi, Noah A. Smith, and Hannaneh Hajishirzi. Rewardbench: Evaluating reward models for language modeling, 2024. URL https://arxiv.org/abs/2403.13787.

Yunqi Li, Lanjing Zhang, and Yongfeng Zhang. Fairness of chatgpt, 2024. URL https://arxiv.org/abs/2305.18569.

Kaiji Lu, Piotr Mardziel, Fangjing Wu, Preetam Amancharla, and Anupam Datta. Gender bias in neural natural language processing. In *Logic, Language, and Security: Essays Dedicated to Andre Scedrov on the Occasion of His 65th Birthday*, pp. 189–202. 2020.

Nikita Nangia, Clara Vania, Rasika Bhalerao, and Samuel R. Bowman. Crows-pairs: A challenge dataset for measuring social biases in masked language models, 2020. URL https://arxiv.org/abs/2010.00133.

OpenAI. Openai charter. https://openai.com/charter/, 2024. Accessed: 2024-07-15.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in neural information processing systems*, 35: 27730–27744, 2022.

Lucas Rosenblatt and R. Teal Witter. Counterfactual fairness is basically demographic parity. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 37, pp. 14461–14469. AAAI, 2023. DOI: 10.1609/aaai.v37i12.26691. URL https://ojs.aaai.org/index.php/AAAI/article/view/26691.

Pranav Narayanan Venkit, Sanjana Gautam, Ruchi Panchanadikar, Ting-Hao Huang, and Shomir Wilson. Nationality bias in text generation. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, pp. 116–122, Dubrovnik, Croatia, 2023. Association for Computational Linguistics. URL https://aclanthology.org/2023.eacl-main.9.

Alex Wang and Kyunghyun Cho. Bert has a mouth, and it must speak: Bert as a markov random field language model, 2019. URL https://arxiv.org/abs/1902.04094.

Haoxiang Wang, Yong Lin, Wei Xiong, Rui Yang, Shizhe Diao, Shuang Qiu, Han Zhao, and Tong Zhang. Arithmetic control of llms for diverse user preferences: Directional preference alignment with multi-objective rewards. In *ACL*, 2024a.

Haoxiang Wang, Wei Xiong, Tengyang Xie, Han Zhao, and Tong Zhang. Interpretable preferences via multi-objective reward modeling and mixture-of-experts. *arXiv preprint arXiv:2406.12845*, 2024b.

Zhilin Wang, Yi Dong, Olivier Delalleau, Jiaqi Zeng, Gerald Shen, Daniel Egert, Jimmy J. Zhang, Makesh Narsimhan Sreedhar, and Oleksii Kuchaiev. Helpsteer2: Open-source dataset for training top-performing reward models, 2024c.

Ingmar Weber and Carlos Castillo. The demographics of web search. In *Proceedings of the 33rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 523–530. ACM, 2010. DOI: 10.1145/1835449.1835537.

Kellie Webster, Xuezhi Wang, Ian Tenney, Alex Beutel, Emily Pitler, Ellie Pavlick, Jilin Chen, Ed Chi, and Slav Petrov. Measuring and reducing gendered correlations in pre-trained models, 2021. URL https://arxiv.org/abs/2010.06032.

Jiancong Xiao, Ziniu Li, Xingyu Xie, Emily Getzen, Cong Fang, Qi Long, and Weijie J. Su. On the algorithmic bias of aligning large language models with rlhf: Preference collapse and matching regularization, 2024. URL https://arxiv.org/abs/2405.16455.

Wei Xiong, Hanze Dong, Chenlu Ye, Han Zhong, Nan Jiang, and Tong Zhang. Gibbs sampling from human feedback: A provable kl-constrained framework for rlhf. *arXiv preprint arXiv:2312.11456*, 2023.

Wei Xiong, Hanze Dong, Chenlu Ye, Ziqi Wang, Han Zhong, Heng Ji, Nan Jiang, and Tong Zhang. Iterative preference learning from human feedback: Bridging theory and practice for rlhf under kl-constraint, 2024.

Rui Yang, Ruomeng Ding, Yong Lin, Huan Zhang, and Tong Zhang. Regularizing hidden states enables learning generalizable reward model for llms. *arXiv preprint arXiv:2406.10216*, 2024.

Lifan Yuan, Ganqu Cui, Hanbin Wang, Ning Ding, Xingyao Wang, Jia Deng, Boji Shan, Huimin Chen, Ruobing Xie, Yankai Lin, Zhenghao Liu, Bowen Zhou, Hao Peng, Zhiyuan Liu, and Maosong Sun. Advancing llm reasoning generalists with preference trees, 2024.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, et al. Judging llm-as-a-judge with mt-bench and chatbot arena. *Advances in Neural Information Processing Systems*, 36, 2024.