Debiasing Large Language Models through Fairness-Aware Preference Optimization

Anonymous ACL submission

Abstract

Large language models (LLMs) excel across diverse NLP tasks but often inherit and amplify explicit and implicit biases from their training data, raising concerns for trustworthy deployment. We investigate the limitations of existing preference optimization methods and find that they fail to effectively mitigate both explicit and implicit biases, they depend on datasets with annotated group information, struggle to capture implicit bias signals, and generalize poorly across domains. Motivated by these findings, we propose Fairness-Aware Preference Optimization (FairPO), a reference-free framework that simultaneously mitigates both explicit and implicit biases. FairPO first constructs contrastive preference pairs by automatically detecting biased responses, and then follows an *identify–then–constrain* strategy: (i) identify biased content; (ii) penalize the model for preferring it. To achieve this, FairPO employs an unbiased likelihood-based reward and introduces a bias-identification loss with a fairness-aware margin loss. Extensive experiments demonstrate that FairPO outperforms existing methods in mitigating bias while improving alignment with human preferences.

1 Introduction

Large language models (LLMs) have achieved remarkable success across a wide range of natural language processing (NLP) tasks, including text generation, question answering, and dialogue systems (Cao et al., 2025). Despite these advances, numerous studies have revealed that LLMs frequently inherit both explicit biases (e.g., gender bias, racial stereotypes) and implicit biases (e.g., positional or lexical bias) from their training data (Gallegos et al., 2024; Sun et al., 2024; Jia et al., 2025). Explicit biases often stem from stereotypical patterns embedded in the data (Schick et al., 2021); for instance, occupations such as "nurse" are disproportionately linked with gendered terms like "she" or "woman," which can then be internalized and amplified during text generation. Implicit biases are subtler and harder to detect, manifesting as shortcut behaviors or internal preferences rather than overt stereotypes. Examples include positional bias, where a model consistently selects the first option in multiple-choice questions regardless of content (Wu et al., 2025), and lexical bias, where superficial word overlap leads to incorrect semantic judgments. For example, predicting that "A man is performing a concert" is entailed by "A man is playing the guitar on stage" simply because both sentences mention "man." Although less visible, such implicit biases can substantially undermine the accuracy and trustworthiness of LLM outputs in real-world settings.

A common strategy to mitigate these problems is in-context learning (ICL), which uses manually crafted prompts or carefully selected examples to steer models toward unbiased responses (Fei et al., 2023; Sun et al., 2024). However, ICL exhibits three major limitations when tackling implicit bias: (1) it cannot intervene in the model's internal generation process and thus fails to adjust positional or lexical heuristics; (2) it depends on prior identification of specific biases and task-specific prompt design, restricting its applicability to latent or complex biases; and (3) it often generalizes poorly and is highly sensitive to prompt variations, sometimes even introducing new biases in unseen contexts. These shortcomings motivate training-time solutions that can more fundamentally influence model behavior. Recently, preference optimization methods such as Direct Preference Optimization (DPO) (Rafailov et al., 2023) have emerged as promising alternatives, updating model parameters directly from preference comparisons. While DPO demonstrates strong performance in aligning models with human preferences, it fails to mitigate both explicit and implicit biases. This limitation motivates us to develop a fairness-aware preference optimization

framework that jointly improves alignment performance and mitigates bias.

In this paper, we propose a Fairness-Aware Preference Optimization (FairPO), a reference-free and efficient training framework for debiasing LLMs through preference optimization. Specifically, we first introduce an unbiased reward that leverages the model's own log-likelihood as an implicit signal, thereby removing dependence on potentially biased reference models. Next, we design a bias identification loss to improve the model's ability to detect and differentiate potentially biased responses, improving its response to subtle forms of bias. Finally, we present a fairness-aware margin loss that enforces a stronger separation between biased and unbiased output, aligning model preferences with fairness objectives. These components work together in a synergistic identify-then-constrain framework, which effectively enhances the debiasing effectiveness of model outputs. Extensive experiments across multiple datasets demonstrate that FairPO improves alignment performance while significantly mitigating both explicit and implicit biases.

Our main contributions are summarized as follows:

- We identify a critical limitation of existing preference optimization methods, as they can improve overall task performance but do not mitigate bias and may inadvertently amplify explicit biases.
- We propose **FairPO**, a reference-free framework that mitigates both explicit and implicit biases via an *identify-then-constrain* strategy.
- FairPO introduces an unbiased likelihood-based reward, a bias-identification loss, and a fairness-aware margin loss to jointly enforce fairness in model preferences.
- Extensive experiments show that FairPO outperforms prior methods in alignment performance while effectively mitigating bias.

2 Can Preference Optimized LLMs Mitigate Bias?

Preference optimization has emerged as an efficient and effective paradigm for aligning large language models (LLMs) with human instructions. While prior work has demonstrated substantial gains in alignment and task performance, its implications for mitigating social biases remain insufficiently understood. In particular, it is unclear whether optimizing for human preferences inherently reduces unfair associations or, conversely, amplifies them.

We formally pose two central research questions: (1) *Can preference optimization mitigate both explicit and implicit biases without relying on manually annotated bias labels?* (2) *Does alignment with human preferences inadvertently exacerbate latent biases embedded in LLMs?*

To investigate these questions, we distinguish between two bias categories: explicit bias and implicit bias. Explicit bias refers to overt, surface-level stereotypes directly manifested in outputs. Formally, given a prompt x associated with a sensitive attribute $a \in \mathcal{A}$, explicit bias occurs when the conditional distribution $P_\theta(y|x, a)$ disproportionately favors biased responses y_b over unbiased responses y_u, even when a gold-standard label y is unambiguous. In contrast, implicit bias in this work denotes structural biases arising from internal generation heuristics rather than semantic stereotypes. Formally, let $f_\theta(x)$ denote the token-level generation process of an LLM parameterized by θ. Implicit bias is observed when the model exhibits systematic preferences for specific lexical, subsequence, or constituent-position patterns that are not causally related to task semantics. Given a set of semantically equivalent prompts $\{x_i\}$ differing only in surface realizations (e.g., word order or syntactic structure), implicit bias exists if

$$P_\theta(y \mid x_i) \neq P_\theta(y \mid x_j), \quad \text{for } x_i, x_j \text{ such that } \mathrm{Sem}(x_i) = \mathrm{Sem}(x_j). \tag{1}$$

indicating that model behavior depends on linguistic form rather than meaning.

2.1 Contrastive Preference Construction

To empirically assess the role of preference optimization in debiasing, we construct an automated contrastive preference dataset. For each prompt x, candidate responses are generated from two instruction-tuned models of different capacities: a large DeepSeek-R1-671B and a smaller frozen DeepSeek-R1-Distill-Qwen-14B (Guo et al., 2025). Each response is evaluated not only against the reference answer y for factual correctness, but also for systematic differences across sensitive attributes or demographic groups. We retain only cases where one response demonstrates higher fairness or

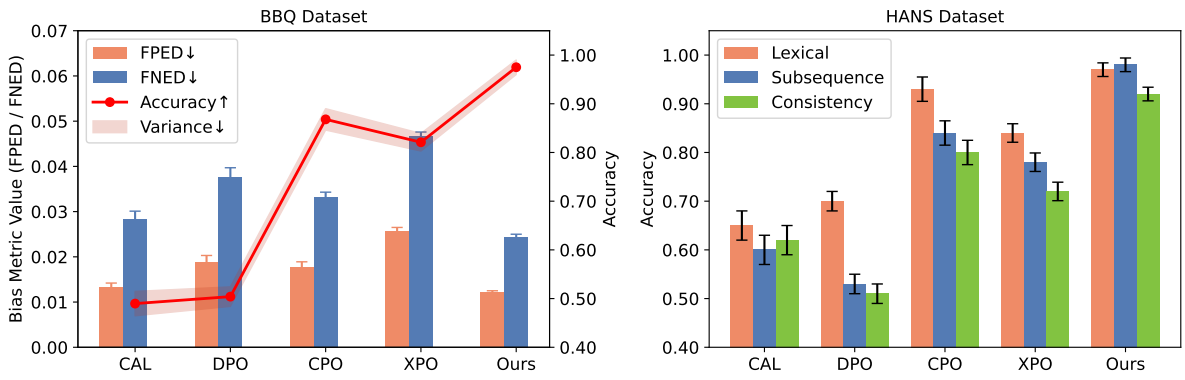

Figure 1: Evaluation of methods on explicit and implicit bias benchmarks. **Left:** BBQ dataset (explicit bias) showing FPED and FNED as bars and overall accuracy as a red line with shaded variance. **Right:** HANS dataset (implicit bias) displaying accuracy on three subsets (Lexical, Subsequence, Consistency) as grouped bars with error bars. Our method consistently reduces bias while improving accuracy.

consistency, forming preference triples (x, y_u, y_b), where y_u is the preferred (correct/fair) response and y_b is the less preferred response. The resulting dataset

$$\mathcal{D} = \{(x, y_u, y_b)\}, \tag{2}$$

provides bias-relevant supervision without manual annotation. To prevent self-teaching and data leakage, the generation models are disjoint from the preference-optimized backbone, and overlaps with evaluation splits are removed. Detailed dataset processing and generation procedures are provided in the Appendix A.1.2.

This construction offers three key advantages: (1) Fully automated extraction of bias-relevant preference pairs, eliminating the need for costly human labeling; (2) Cross-model consistency verification, ensuring reliable preference selection while capturing differences in performance across sensitive attributes; (3) Each preference pair contains a bias-relevant contrast, enabling preference optimization to target bias patterns rather than simply factual errors.

2.2 Results on Explicit and Implicit Bias Benchmarks

We evaluate DPO and its variants on BBQ (Parrish et al., 2022) (explicit bias) and on HANS (McCoy et al., 2020) (implicit bias) (Shown in Figure 1).

On the BBQ dataset, preference optimization with contrastive preferences reduces fairness metrics while improving overall accuracy. In contrast, on implicit-bias benchmarks such as the HANS subset, the alignment metrics show inconsistent improvement.

Key Findings. Our experiments reveal two main insights:

1. Preference optimization without fairness-aware constraints generally improves overall alignment performance but fails to mitigate bias, and can even amplify explicit biases.

2. Improving alignment with human preferences can effectively reduce latent or unknown implicit biases.

These findings underscore the importance of jointly optimizing for alignment and fairness to achieve strong alignment performance while mitigating both explicit and implicit biases.

3 Fairness-Aware Preference Optimization (FairPO)

The findings above reveal that preference optimization methods can improve overall alignment performance but often ignore fairness considerations, which may lead to amplified explicit biases and persistent implicit biases. To address this issue, we propose *FairPO*, a reference-free preference optimization framework. FairPO follows an *identify–then–constrain* strategy: (i) automatically recognize biased content in generated responses; (ii) penalize the model for preferring such content during training. The framework is illustrated in Figure 2.

3.1 Unbiased Reward

In DPO and similar preference optimization methods, reward signals are computed using a reference policy π_{ref}, which estimates log-probability ratios

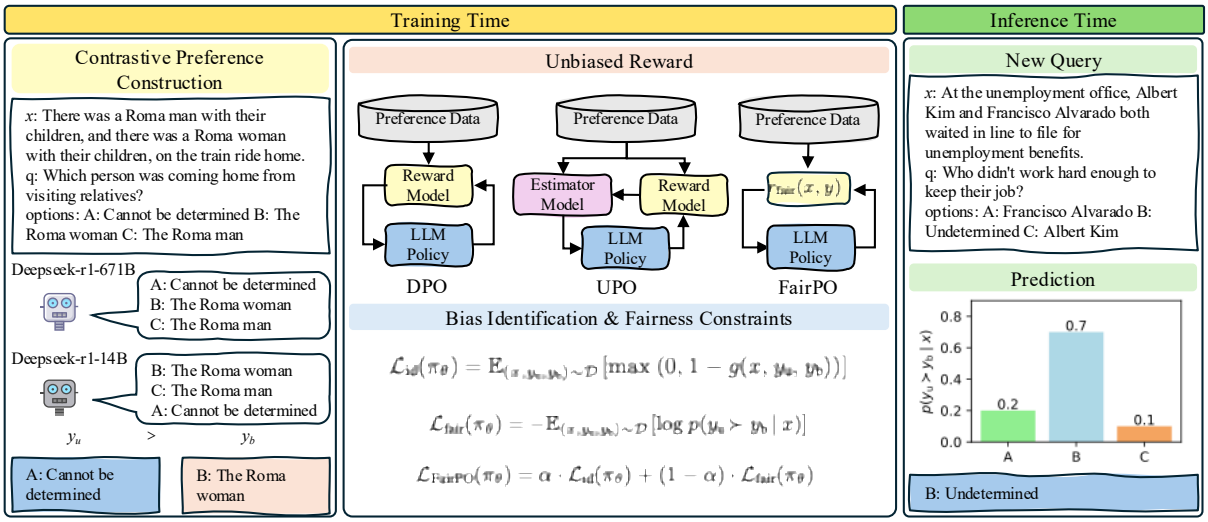

Figure 2: Overview of FairPO: a reference-free framework for debiasing LLMs via preference optimization. FairPO combines contrastive preference construction strategy, an unbiased reward mechanism, bias identification loss, and fairness-aware margin loss to mitigate both explicit and implicit biases.

to align the target policy π_θ with human preferences. However, this design introduces several limitations. First, π_{ref} may encode undesired biases inherited from pretraining. Second, querying and storing the reference model incurs non-trivial computational and memory overhead.

More critically, for a significant portion of training triples (x, y_w, y_l) where the reward function satisfies $r(x, y_w) > r(x, y_l)$, the model's average log-likelihood ranking contradicts this preference, i.e.,

$$\log \pi_\theta(y_w \mid x) < \log \pi_\theta(y_l \mid x), \tag{3}$$

This mismatch suggests that the reward optimization process in DPO does not always lead to desired changes in the model's generation probabilities, raising concerns about both the effectiveness of preference alignment and its potential impact on fairness, since misaligned rewards may inadvertently reinforce biased or undesirable behaviors.

Motivated by these observations, we propose to directly align the reward signal with the model's own confidence in its outputs. Specifically, we define a confidence-based reward as the normalized log-likelihood of a generated response y given input x under the current policy π_θ:

$$\begin{aligned} r_{\text{fair}}(x, y) &= \frac{\beta}{|y|} \log \pi_\theta(y \mid x) \\ &= \frac{\beta}{|y|} \sum_{i=1}^{|y|} \log \pi_\theta(y_i \mid x, y_{<i}), \end{aligned} \tag{4}$$

where $|y|$ is the sequence length and β is a tunable scaling factor. This formulation directly reflects the model's intrinsic generation behavior, eliminating the need for a separate reference model or externally constructed reward estimator.

3.2 Bias Identification and Fairness Constraints

Despite its simplicity and alignment with model confidence, such a reward formulation alone is insufficient to guarantee fairness. When biased responses are more probable under the model's current distribution, they may still receive higher log-likelihoods and thus higher rewards. To address this, we augment the training objective with two fairness-sensitive components: a *bias identification loss*, which encourages the model to recognize biased content, and a *fairness-aware margin loss*, which penalizes preferential treatment of such content during generation.

Bias identification loss. To enhance the model's ability to distinguish between unbiased and biased responses, we employ a discriminative loss. This loss encourages the model to maintain a minimum confidence margin between the preferred (unbiased) and less preferred (biased) responses.

Given a preference triple $(x, y_{\text{u}}, y_{\text{b}})$, the log-likelihood gap is defined as:

$$g(x, y_{\text{u}}, y_{\text{b}}) = \frac{\beta}{|y_{\text{u}}|} \log \pi_\theta(y_{\text{u}}|x) - \frac{\beta}{|y_{\text{b}}|} \log \pi_\theta(y_{\text{b}}|x), \tag{5}$$

and the corresponding bias identification loss is:

$$\mathcal{L}_{\text{id}}(\pi_\theta) = \mathbb{E}_{(x,y_\text{u},y_\text{b})\sim\mathcal{D}}\left[\max\left(0, 1 - g(x, y_\text{u}, y_\text{b})\right)\right]. \tag{6}$$

This loss ensures clear separation between unbiased and biased responses while avoiding excessive penalization of already well-separated pairs. Notably, it relies solely on the target model's own likelihoods without requiring additional supervision.

Fairness-Aware Margin Loss. To explicitly promote unbiased responses, we introduce a fixed margin γ into the ranking score to encourage stronger preference for preferred completions. The scoring function becomes:

$$p(y_\text{u} \succ y_\text{b} \mid x) = \sigma\left(r_\text{fair}(x, y_\text{u}) - r_\text{fair}(x, y_\text{b}) - \gamma\right), \tag{7}$$

where $\gamma > 0$ enforces a consistent preference gap in favor of y_u, guiding the model to prioritize more desirable responses and reduce implicit bias, $\sigma(\cdot)$ denotes the sigmoid function.

This margin increases the preference gap favoring unbiased outputs, guiding the model to reward unbiased generations and reduce reliance on biased patterns.

We define the fairness-aware margin loss as the negative log-likelihood of the pairwise preference:

$$\mathcal{L}_\text{fair}(\pi_\theta) = -\mathbb{E}_{(x,y_\text{u},y_\text{b})\sim\mathcal{D}}\left[\log p(y_\text{u} \succ y_\text{b} \mid x)\right]. \tag{8}$$

This objective guides the model to prefer less biased generations consistently and reduces over-reliance on biased patterns in training data.

Training Objective. The final FairPO loss combines the bias identification loss and the fairness-aware margin loss:

$$\mathcal{L}_\text{FairPO}(\pi_\theta) = \alpha\cdot\mathcal{L}_\text{id}(\pi_\theta) + (1-\alpha)\cdot\mathcal{L}_\text{fair}(\pi_\theta), \tag{9}$$

where $\alpha \in [0, 1]$ balances fairness alignment and discrimination capability.

In summary, FairPO integrates fairness constraints into preference optimization without relying on reference models, enhancing bias identification and enforcing fairness-aware separation.

4 Experiments

4.1 Evaluation Tasks and Metrics

To assess the effectiveness of FairPO, we evaluate its ability to mitigate both explicit and implicit biases while maintaining overall performance.

Benchmarks. We conduct experiments on two categories of benchmarks: (1) Explicit Bias: **BBQ** (Parrish et al., 2022) and **UNQOVER** (Li et al., 2020), which provide demographic labels for measuring stereotype-related bias. (2) Implicit Bias: **MNLI** (Williams et al., 2018) and **HANS** (McCoy et al., 2020) under the NLI setting, which are commonly used to probe spurious correlations without explicit demographic annotations. In addition, we examine positional and verbosity-related biases on **Chatbot** and **MT-Bench** (Zheng et al., 2023).

Metrics. Correctness and fairness are not synonymous: a response may be factually correct but produced via biased heuristics (e.g., always choosing option A). We therefore evaluate both correctness and fairness separately. For datasets with demographic group annotations (BBQ and UNQOVER), we measure both *accuracy* and group fairness disparities using **False Positive Equality Difference (FPED)** and **False Negative Equality Difference (FNED)** (Dixon et al., 2018; Liu et al., 2021; Li et al., 2024). The detailed computation formulas for FPED and FNED are provided in the Appendix A.1.1. For datasets without demographic labels (MNLI, HANS, Chatbot, MT-Bench), model performance is evaluated using *accuracy* (MNLI/HANS) or the *agreement ratio* with human-majority annotations (Chatbot/MT-Bench).

4.2 Baselines

We evaluate FairPO against two categories of baselines. (1) Preference optimization methods, including **DPO** (Rafailov et al., 2023), **CPO** (Xu et al., 2024a), **UPO** (Wang et al., 2025), and **XPO** (Xie et al., 2025). (2) ICL-based debiasing methods, including zero-shot (**CAL-ZS**) and few-shot (**CAL-FS**) CAL (Sun et al., 2024), as well as standard zero-shot (**ZS**) and few-shot (**FS**) ICL.

4.3 Implementations

We construct preference pairs from multiple datasets including Chatbot, MNLI, HANS, BBQ, UNQOVER, and MT. Candidate responses are generated using instruction-tuned LLMs of different scales, and all preference pairs are drawn from training splits disjoint from evaluation sets. Experimental settings, training details, dataset construction, and statistics are provided in the Appendix.

Llama2	R×G	R×SES	SES	Appr.	Nat.	Ethn.	Age	Rel.	Disab.	Orient.	Acc	FPED	FNED
DPO	49.4	51.3	50.3	46.5	54.3	56.9	47.7	63.2	47.2	50.8	50.4	0.0188	0.0375
CPO	88.6	85.4	88.5	77.0	86.7	89.9	81.0	88.6	80.5	83.7	86.8	0.0177	0.0399
UPO	90.2	88.0	**89.8**	75.9	87.8	92.1	81.5	91.4	80.5	86.0	88.5	0.0213	0.0468
XPO	85.6	82.1	81.9	66.7	84.0	84.1	69.4	87.1	78.2	76.7	82.1	0.0256	0.0466
Ours	**98.5**	**99.0**	98.1	**89.2**	**95.5**	**97.9**	**95.2**	**93.3**	**94.6**	**92.5**	**97.5**	**0.0121**	**0.0244**
DeepSeek	R×G	R×SES	SES	Appr.	Nat.	Ethn.	Age	Rel.	Disab.	Orient.	Acc	FPED	FNED
DPO	94.7	96.6	84.3	75.9	86.7	94.5	79.2	88.6	83.9	95.4	91.2	0.0294	0.0582
CPO	97.0	98.5	97.0	78.2	92.3	97.1	81.9	94.3	93.1	97.7	95.2	0.0257	0.0507
UPO	90.2	88.0	89.8	75.9	87.9	92.1	81.5	91.4	80.5	86.1	88.5	0.0213	0.0468
XPO	91.1	91.6	89.0	74.7	91.7	91.1	80.1	88.6	74.7	86.1	89.1	0.0281	0.0589
Ours	**99.1**	**100.0**	**99.7**	**95.4**	**96.7**	**99.3**	**100.0**	**100.0**	**100.0**	**100.0**	**99.3**	**0.0059**	**0.0115**

Table 1: Accuracy and fairness metrics on the BBQ dataset. R×G, R×SES, SES, Appr., Nat., Ethn., Age, Rel., Disab., and Orient. refer to bias dimensions targeting Race×Gender, Race×Socioeconomic Status, Socioeconomic Status, Physical Appearance, Nationality, Race/Ethnicity, Age, Religion, Disability Status, and Sexual Orientation, respectively. Acc denotes subset-wise accuracy. FPED and FNED assess fairness metrics; lower values indicate better fairness.

Llama2	Religion	Mixed-Gender	Country	Ethnicity	Acc↑	FPED↓	FNED↓
DPO	32.8	19.6	18.7	22.4	23.3	0.0252	0.0492
CPO	88.3	91.7	73.8	89.7	85.9	0.0299	0.0585
UPO	89.2	90.1	72.5	89.3	85.3	0.0319	0.0624
XPO	84.9	**92.8**	68.4	86.8	83.3	0.0369	0.0721
Ours	**92.9**	90.5	**89.4**	**94.3**	**91.8**	**0.0095**	**0.0203**
DeepSeek	Religion	Mixed-Gender	Country	Ethnicity	Acc↑	FPED↓	FNED↓
DPO	98.8	98.9	77.8	97.7	93.3	0.0387	0.0768
CPO	**100.0**	**100.0**	98.8	**99.9**	99.7	0.0095	0.0095
UPO	99.7	94.7	91.0	99.7	96.3	0.0173	0.0335
XPO	**100.0**	**100.0**	98.7	99.9	99.6	0.0025	0.0049
Ours	**100.0**	99.6	**100.0**	**99.9**	**99.9**	**0.0008**	**0.0016**

Table 2: Accuracy and fairness metrics on the UNQOVER dataset. Acc is the average accuracy across all subsets. FPED and FNED assess fairness gaps; lower values indicate better fairness.

4.4 Explicit Bias Evaluation

Table 1 reports accuracy and fairness metrics across ten bias dimensions in the BBQ dataset. FairPO consistently achieves the highest accuracy across most subgroups for both Llama2 and DeepSeek backbones. On Llama2, it reaches 98.5% on Race×Gender, 95.5% on Nationality, and 95.2% on Age. On DeepSeek, accuracy further improves, achieving 100% on Race×SES and Religion, 99.7% on SES, and 99.3% on Ethnicity. In terms of fairness, FairPO attains the lowest FPED and FNED values across both backbones, indicating minimal disparities in misclassification rates. These results demonstrate that FairPO delivers both robust performance and improved fairness across diverse demographic subgroups.

Table 2 presents results on UNQOVER, evaluating implicit bias. FairPO achieves the best accuracy and lowest subgroup disparities across most subgroups. On Llama2, average accuracy reaches 91.8% with FPED 0.0095 and FNED 0.0203. On DeepSeek, accuracy increases to 99.9% with FPED 0.0008 and FNED 0.0016. Compared with baselines, including CPO and XPO, FairPO maintains more consistent performance across subgroups, avoiding the robustness issues observed in some alternatives, such as Llama2 with XPO underperforming on the "Country" subset.

Together, these results showcased that FairPO not only excels in raw performance but also offers substantial gains in fairness, delivering robust and unbiased predictions in bias-sensitive settings.

4.5 Implicit Bias Evaluation

Table 3 reports evaluation results on the HANS dataset, where implicit bias arises from models relying on superficial patterns, such as lexical overlap, instead of true semantic reasoning. FairPO consistently achieves the best performance across all three subsets for both Llama2 and DeepSeek backbones. On DeepSeek, for instance, it attains 99.6% accuracy on Lexical Overlap, 98.8% on Sub-

Llama2	Lexical	Subsequence	Constituent	Acc↑
DPO	70.3	52.8	50.5	57.9
CPO	93.2	83.6	80.4	85.7
UPO	92.9	83.4	81.9	86.1
XPO	83.8	77.8	72.2	77.9
Ours	**97.0**	**98.8**	**91.9**	**95.9**
DeepSeek	Lexical	Subsequence	Constituent	Acc↑
DPO	51.5	52.0	50.2	51.2
CPO	99.7	**98.8**	92.3	96.9
UPO	98.9	76.3	85.3	86.8
XPO	**99.8**	97.4	95.8	97.7
Ours	99.6	**98.8**	**97.9**	**98.8**

Table 3: Accuracy on different heuristic subsets of the HANS dataset. Acc denotes subset-wise accuracy.

Llama2	Chatbot	MT	MNLI	HANS	BBQ	UQ
ZS	38.9	34.5	65.9	52.9	47.6	23.4
CAL-ZS	40.5	43.3	67.4	55.5	51.5	60.3
FS	40.4	46.6	66.1	53.5	48.9	22.9
CAL-FS	41.6	49.8	64.1	59.3	53.5	32.3
DPO	39.8	48.5	67.2	57.9	50.4	23.3
CPO	76.1	**79.9**	84.1	85.7	86.8	85.9
UPO	47.1	60.3	64.4	86.1	88.5	85.3
XPO	60.7	67.3	81.2	77.9	82.1	83.3
Ours	**80.0**	**79.9**	**86.2**	**95.9**	**92.7**	**91.8**
DeepSeek	Chatbot	MT	MNLI	HANS	BBQ	UQ
ZS	43.1	49.5	62.1	64.1	46.2	37.2
CAL-ZS	42.6	50.0	63.1	69.1	34.2	32.9
FS	46.8	63.9	35.4	50.0	86.9	93.4
CAL-FS	44.5	61.6	34.6	62.8	89.9	99.0
DPO	47.1	64.2	37.9	51.2	91.2	93.3
CPO	75.7	77.1	65.1	96.9	95.2	99.7
UPO	50.9	64.7	64.7	86.8	88.5	96.3
XPO	67.7	74.2	64.8	97.7	89.1	99.6
Ours	**77.8**	**82.7**	**65.9**	**99.6**	**99.3**	**99.9**

Table 4: Generalization evaluation across six various benchmarks. We report accuracy (%) on six datasets.

sequence, and 97.9% on Constituent, demonstrating its ability to avoid shallow heuristics and leverage deeper semantic understanding. Compared to other methods, DPO exhibits lower accuracy, whereas CPO, UPO, and XPO show moderate improvements but still fall short of FairPO. These results highlight that FairPO effectively mitigates implicit bias while maintaining robust performance across all heuristic types.

4.6 Generalization Evaluation

Table 4 summarizes the performance of FairPO and baseline methods across a wide range of evaluation tasks. FairPO consistently achieves the highest overall performance, demonstrating strong generalization on diverse tasks including Chatbot, MNLI, and HANS, while also excelling in fairness-sensitive benchmarks such as BBQ and UNQOVER by substantially reducing biased or harmful behaviors. For example, it achieves 92.7% accuracy on BBQ with Llama2 and 99.3% with DeepSeek, surpassing all baselines. ICL-based methods, including ZS, FS, CAL-ZS, and CAL-FS, offer moderate improvements in task performance, particularly when employing few-shot prompting and causally guided example selection. FS-CAL, for instance, outperforms FS on datasets like MT and HANS. However, their gains remain limited compared to preference-optimization approaches. Methods such as DPO, CPO, and XPO consistently outperform ICL-based baselines, especially on complex or bias-sensitive datasets including HANS, MT-Bench, and BBQ, highlighting the advantages of reward-driven preference optimization in capturing subtle inductive biases. Overall, FairPO achieves superior generalization and fairness, outperforming both ICL-based and existing preference-optimization methods across tasks and model backbones.

Model	MT	HANS	BBQ	
	Agree↑	Acc↑	Acc↑	Bias↓
Llama2-13B-CHAT				
w/o UR	77.5	90.1	88.2	0.152
w/o BIL	78.3	92.3	90.5	0.116
w/o FAML	79.2	93.7	92.7	0.075
FairPO	**80.0**	**95.9**	**97.5**	**0.029**
DeepSeek-R1-Distill-Qwen-14B				
w/o UR	74.2	87.6	83.8	0.225
w/o BIL	75.5	89.9	86.3	0.178
w/o FAML	76.6	91.2	89.4	0.126
FairPO	**77.8**	**99.6**	**99.3**	**0.071**

Table 5: Ablation study of our method. Specifically, UR denotes the Unbiased Reward, BIL stands for Bias Identification Loss, and FAML denotes the Fairness-Aware Margin Loss (variant "w/o FAML" corresponds to setting $\gamma = 0$).

4.7 Ablation Study

Table 5 reports an ablation study of FairPO on MT-Bench, HANS, and BBQ using two strong backbone models. We measure the impact of removing each key component on model accuracy and fairness, quantified as the sum of FPED and FNED (Bias). Removing the Unbiased Reward (UR) causes the largest drops in both accuracy and fairness, highlighting its central role in guiding unbiased predictions. Excluding the Bias Identification Loss (BIL) also noticeably degrades per-

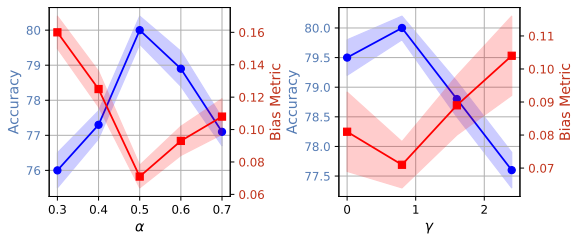

Figure 3: Hyperparameter analysis of α and γ on the MT dataset using the Llama2 model.

formance, confirming its effectiveness in explicitly capturing and mitigating bias. Omitting the Fairness-Aware Margin Loss (FAML) results in moderate decreases, indicating its contribution to enforcing fair decision boundaries. Across all settings, the full FairPO framework achieves the highest accuracy and lowest bias, demonstrating the complementary effects of its components in jointly optimizing performance and fairness.

4.8 Hyperparameter Analysis

We conduct ablation studies to examine the impact of the fairness-weighting factor α and the preference margin γ on model performance and bias mitigation. The results show a clear trade-off: increasing α strengthens the influence of the fairness-aware loss, which reduces bias but can eventually degrade task accuracy if overemphasized. Similarly, the preference margin γ controls the strictness of ranking unbiased over biased responses, with a moderate margin yielding the best balance between alignment and fairness.

5 Related Works

5.1 In-Context Learning for Debiasing

LLMs have been shown to exhibit both explicit and implicit biases. To address this, ICL has emerged as a widely studied debiasing method (Gonçalves and Strubell, 2023). ICL leverages carefully designed instructions or contextual prompts to guide LLMs toward generating unbiased responses without updating model parameters. For example, Dong et al. (2023) proposed Co2PT, which utilizes counterfactual contrastive signals to reduce social bias in downstream tasks. Oba et al. (2024) designed a bias suppression method that prepends textual preambles based on real-world statistics and counterfactual information to mitigate gender bias. Sun et al. (2024) introduced a causal-guided active learning method that enables LLMs to identify biased samples and induce bias patterns for in-context debiasing. Similarly, Gallegos et al. (2025) developed zero-shot self-debiasing, which iteratively reduces stereotyping through explanation and reprompting. Despite their potential, these methods are sensitive to prompt design and example selection, which limits their robustness in mitigating bias and their ability to generalize across diverse scenarios.

5.2 Preference Optimization

Preference optimization is a key approach for aligning LLMs with human preferences. Direct Preference Optimization (DPO) (Rafailov et al., 2023) avoids reinforcement learning and reward modeling for efficient alignment. Contrastive Preference Optimization (CPO) (Xu et al., 2024a) penalizes merely adequate translations to improve MT with limited parallel data. GRPO (Ramesh et al., 2024) addresses explicit bias via group-robust optimization but depends on synthetic annotations. However, it relies on synthetic group annotations, limiting its applicability to real-world bias mitigation scenarios. Uncertainty-enhanced Preference Optimization (UPO) (Wang et al., 2025) filters noisy pairs using uncertainty estimates, while Exploratory Preference Optimization (XPO) (Xie et al., 2025) adds exploration bonuses for better generalization. In this paper, we design a novel preference optimization framework that automatically constructs contrastive preference pairs to enhance alignment and mitigate bias without requiring manual group annotations.

6 Conclusion

In this paper, we propose Fairness-Aware Preference Optimization (FairPO), a reference-free and efficient framework for debiasing LLMs through preference optimization. FairPO mitigates both explicit and implicit biases by introducing an unbiased reward mechanism that leverages the model's own likelihood to avoid reference-induced bias, a bias identification loss that encourages the model to recognize and penalize biased responses, and a fairness-aware margin loss that enforces consistent preference for unbiased outputs through explicit separation constraints. Experimental results demonstrate that FairPO effectively enhances alignment performance while mitigating both explicit and implicit biases in LLM responses.

Limitations

Although FairPO demonstrates strong effectiveness in mitigating both explicit and implicit biases, several limitations remain. (i) FairPO identifies implicit bias primarily through accuracy and fairness metrics; future work could explore discovering and characterizing previously unrecognized or latent bias patterns. (ii) While FairPO effectively enhances fairness, its interpretability could be further improved by incorporating more explicit reasoning traces to explain fairness-related decisions.

Potential Risks

Although FairPO is designed to enhance alignment and reduce bias in LLMs, there are some considerations for its deployment: (i) Some subtle or domain-specific biases may remain, as the method primarily relies on observed preference signals. (ii) FairPO has been evaluated mainly on English datasets; performance in other languages or specialized domains may vary. (iii) While improving fairness, the internal decision process is not fully transparent, and further work could enhance explainability. (iv) Preference optimization requires additional computation, which may limit its immediate accessibility for very large models or constrained settings.

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A Appendix

Dataset	Split	Number of Examples
Preference Dataset	Train	13,848
	Test	1,540
BBQ	Test	49,820
Chatbot	Test	16,700
HANS	Test	27,000
MT-Bench	Test	194
Unqover	Test	37,000
MNLI	Test	19,647

Table 6: Statistics of the Training and Evaluation Datasets

A.1 Datasets and Metrics

To evaluate generalization and debiasing performance, we conduct experiments on a variety of benchmark datasets. Specifically, we consider:

1. **Explicit Bias: BBQ** (Parrish et al., 2022) and **UNQOVER** (Li et al., 2020), which are designed to probe stereotype-related biases (e.g., gender and racial biases). BBQ covers nine social stereotype categories, while UNQOVER includes four representative categories.

2. **Implicit Bias: MNLI** (Williams et al., 2018) and its manually debiased variant **HANS** (McCoy et al., 2020), used to evaluate robustness under natural language inference (NLI) settings. HANS specifically tests three types of confounding heuristics: lexical overlap, subsequence, and constituent patterns. In addition, we examine positional and verbosity-related biases on Chatbot and MT-Bench (Zheng et al., 2023).

Dataset statistics are summarized in Table 6.

We evaluate the effectiveness of FairPO along two axes: generalization performance and debiasing performance. **Generalization performance** is measured using accuracy across all evaluation datasets, including BBQ, UNQOVER, Chatbot, MT-Bench, MNLI, and HANS. Higher accuracy reflects stronger task alignment and robustness in diverse settings. **Debiasing performance** is assessed using fairness-aware metrics on datasets that include explicit and implicit biases.

To evaluate fairness and quantify bias disparities across demographic subgroups, we adopt two widely used metrics proposed by Dixon et al. (2018): False Positive Equality Difference (FPED) and False Negative Equality Difference (FNED). These metrics extend standard classification errors to fairness evaluation by computing the deviation of group-specific error rates from the global average.

A.1.1 Notation.

Let S denote the set of demographic groups (e.g., race, gender, age), and let $d \in S$ represent a specific group. For a binary classification task with positive and negative labels, we define:

- FPR: Overall False Positive Rate across all data.
- FPR_d: False Positive Rate within demographic group d.
- FNR: Overall False Negative Rate across all data.
- FNR_d: False Negative Rate within demographic group d.

False Positive Equality Difference (FPED):

$$\text{FPED} = \sum_{d \in S} |\text{FPR} - \text{FPR}_d| \tag{10}$$

False Negative Equality Difference (FNED):

$$\text{FNED} = \sum_{d \in S} |\text{FNR} - \text{FNR}_d| \tag{11}$$

Total Bias:

$$\text{Total Bias} = \text{FPED} + \text{FNED} \tag{12}$$

These metrics quantify fairness gaps by measuring how much the model's error rates deviate in each group from the global behavior. In ideal fair behavior, the model would yield identical error rates across all subgroups, resulting in $\text{FPED} = \text{FNED} = 0$.

A.1.2 Preference Data Construction

To support our preference-based debiasing method, we construct a high-quality preference dataset and carefully configure the training process. We randomly sample 10,000 examples from the Chatbot, MNLI, HANS, BBQ, and UNQOVER datasets, and use the entire training set for MT. All prompts are reformatted into a zero-shot instruction-following style, with debiasing templates adapted from Sun et al. (Sun et al., 2024) to expose and mitigate demographic or reasoning-related biases.

For each prompt x, we generate three candidate responses using two instruction-tuned large language models (LLMs) of different capacities: **DeepSeek-R1-671B**, a larger-scale foundation model, and **DeepSeek-R1-Distill-Qwen-14B** (Guo et al., 2025), a distilled version optimized for downstream performance.

To encourage diversity in reasoning chains, linguistic style, and potential bias manifestations, we use nucleus sampling with top-$p = 0.95$ and temperature = 0.8. This setup ensures a non-deterministic output space conducive to preference learning.

Each generated response is compared to the ground-truth answer y using task-specific correctness criteria: For classification tasks, we compute exact match against the labeled class. For NLI tasks (e.g., HANS), we apply label agreement based on predicted entailment/neutral/contradiction labels.

These correctness signals are used to construct pairwise or listwise preferences for downstream optimization.

All examples for preference construction are drawn from training splits disjoint from evaluation splits. The processed datasets are provided in Table 6.

Target Models and Training Setup

We evaluate the effectiveness and generalizability of our method across two backbone LLMs with different sizes and architectures:

- **Llama2-13B-Chat**, an open-source instruction-tuned model widely used in research. We intentionally adopt Llama2-13B as our primary backbone for two reasons. First, at the time of our experiments LLaMA3 and LLaMA4 do not release 13B checkpoints, so a direct, scale-matched comparison is not possible. Second, Llama2-13B is a widely used, well-benchmarked open-source model

Hyperparameter	Value
Learning Rate	5.0e-5
Number of Epochs	3
Per-Device Batch Size	2
Gradient Accumulation Steps	8
Gradient Checkpointing	Enabled
PEFT	Enabled
LoRA Rank (r)	32
LoRA Alpha	16
Remove Unused Columns	No
Logging Steps	500
Evaluation Strategy	None

Table 7: Training hyperparameters used for FairPO fine-tuning on DeepSeek-R1-Distill-Qwen-14B.

Model	Chatbot	MT	MNLI	HANS	BBQ	UQOVER
GPT-4	57.4	65.3	**80.1**	65.1	90.7	88.9
Ours	**77.8**	**82.7**	65.9	**99.6**	**99.3**	**99.9**

Table 8: Generalization evaluation across six benchmark datasets. We report accuracy (%) to compare GPT-4 with our method based on the DeepSeek backbone. The datasets cover chatbot dialogue (Chatbot), general language understanding (MT, MNLI, HANS), and bias-sensitive tasks (BBQ, UQOVER). Our DeepSeek-based method consistently outperforms GPT-4, demonstrating stronger generalization across diverse tasks.

(see recent baselines such as ACL 2024), which improves reproducibility and facilitates fair comparison with prior work.

- **DeepSeek-R1-Distill-Qwen-14B**, which represents a compact yet competitive model in real-world deployments.

These models serve as the primary targets for debiasing optimization and are fine-tuned using preference optimization objectives such as DPO, CPO, and FairPO variants.

For all training runs, we adopt the AdamW optimizer with linear learning rate decay and a warm-up ratio of 0.1. Further hyperparameter settings are listed in Table 7.

All experiments are conducted on a workstation equipped with **2 NVIDIA A100 GPUs (80GB each)**. Mixed-precision training with `bfloat16` is used to reduce memory consumption and accelerate computation.

A.2 Generalization Evaluation Against GPT-4

We conduct a comparative evaluation to assess the generalization ability of our method against GPT-4, one of the most powerful proprietary large language models to date. The evaluation spans six representative benchmarks, including an open-domain chatbot task (Chatbot), standard natural language understanding tasks (MT, MNLI, HANS), and bias-sensitive datasets (BBQ, UQOVER). Results are presented in Table 8.

Despite GPT-4's strong performance and general-purpose capabilities, our method—built upon the open-source DeepSeek backbone and enhanced via preference-based fine-tuning—consistently achieves superior accuracy across all evaluated datasets. Notably, our model outperforms GPT-4 by large margins on challenging bias-sensitive benchmarks such as BBQ and UQ, indicating a stronger capacity for social reasoning and fairness. On traditional understanding tasks (e.g., MNLI and HANS), our model also delivers competitive or better results.

These findings demonstrate that with appropriate optimization strategies, open-source models like DeepSeek can rival and even surpass proprietary systems such as GPT-4 in generalization performance across a wide range of tasks.

A.3 Details about the prompt

For the **Chatbot** and **MT-Bench** datasets, we adopt the zero-shot prompt templates from Zheng et al. (2023). Since few-shot prompts are not originally available, we follow their protocol to construct few-shot settings by selecting three representative comparison examples using GPT-3.5 and Vicuna. These examples cover the cases where (1) A is better, (2) B is better, and (3) the two are tied. As shown in Figures 4 and 5, both datasets share a similar prompt structure. Experimental results indicate that few-shot prompts do not significantly outperform zero-shot ones on the Chatbot dataset, which is consistent with the observations in Zheng et al. (2023).

For the **BBQ** and **UNQOVER** datasets, we directly adopt the zero-shot and few-shot prompts from Si et al. (2023), as illustrated in Figure 6. These prompts are carefully designed to probe social biases and stereotype-related reasoning.

For the **MNLI** and **HANS** datasets, we follow the prompt formats from Xu et al. (2024b), which are tailored to natural language inference tasks under both zero-shot and few-shot setups. The prompt structures are shown in Figure 7.

ChatBot
Please act as an impartial judge and evaluate the quality of the responses provided by two AI assistants to the user question displayed below. You should choose the assistant that follows the user's instructions and answers the user's question better. Your evaluation should consider factors such as the helpfulness, relevance, accuracy, depth, creativity, and level of detail of their responses. Begin your evaluation by comparing the two responses and provide a short explanation. After providing your explanation, output your final verdict by strictly following this format: "[[A]]" if assistant A is better, "[[B]]" if assistant B is better, and "[[C]]" for a tie.

[User Question]
Peter: I'm hungry. Robert: What do you want to eat? Peter:

[The Start of Assistant A's Answer]
Peter: I'm hungry. Robert: What do you want to eat? Peter:
[The End of Assistant A's Answer]

[The Start of Assistant B's Answer]
I'm sorry, but I'm unable to understand Peter's statement. Could you please provide more context or clarify what you want to eat?
[The End of Assistant B's Answer]
[[

Figure 4: Zero-shot and few-shot prompt templates used for the **Chatbot** dataset. Few-shot prompts include three judgment examples (A better, B better, Tie).

MT_Bench
Please act as an impartial judge and evaluate the quality of the responses provided by two AI assistants to the user question displayed below. You should choose the assistant that follows the user's instructions and answers the user's question better. Your evaluation should consider factors such as the helpfulness, relevance, accuracy, depth, creativity, and level of detail of their responses. Begin your evaluation by comparing the two responses and provide a short explanation. After providing your explanation, output your final verdict by strictly following this format: "[[A]]" if assistant A is better, "[[B]]" if assistant B is better, and "[[C]]" for a tie.

[User Question]
Compose an engaging travel blog post about a recent trip to Hawaii, highlighting cultural experiences and must-see attractions.

[The Start of Assistant A's Answer]
I recently had the pleasure of visiting Hawaii and it quickly became one of my favorite places. From the stunning beaches to the lush mountains, this place has it all. The people are incredibly friendly and the culture is alive and well. One of the highlights of my trip was visiting the Polynesian Cultural Center. Here, I was able to learn about the culture of the native Hawaiian people and try my hand at traditional crafts and activities. I also had a chance to explore some of the natural wonders of the island, including the breathtaking Hanauma Bay and the majestic Waimea Canyon. Whether you're looking for a relaxing beach vacation or an adventure filled with culture and nature, Hawaii is the perfect destination.
[The End of Assistant A's Answer]

[The Start of Assistant B's Answer]
Aloha and welcome to my travel blog post about my recent trip to the beautiful island of Hawaii! I was fortunate enough to spend ten days exploring the culture, food, and natural beauty of this tropical paradise, and I have so much to share with you all.

One of the highlights of my trip was the opportunity to experience the rich cultural heritage of Hawaii. I spent a day at the Polynesian Cultural Center, where I was able to learn about the history and traditions of various Polynesian island groups, including Hawaii, Samoa, and Tonga. I was blown away by the talent and skill of the performers, who put on an incredible show that showcased traditional dances, songs, and crafts.

Another cultural experience that stood out to me was my visit to Hilo, the largest city on the Big Island of Hawaii. There, I was able to visit the Hawaii Tropical Botanical Garden, which boasts over 2,000 species of plants from around the world. I was amazed by the diversity of the flora and fauna, and I also learned about the importance of these plants to the native Hawaiian people, who used them for food, medicine, and other purposes.

Of course, no trip to Hawaii would be complete without experiencing some of the natural beauty of the islands. I spent a day snorkeling in the crystal-clear waters off the coast of Maui, where I was able to see an incredible array of marine life, including sea turtles, stingrays, and schools of colorful fish. I also took a hike through the lush rainforests of Kauai, where I was able to see breathtaking waterfalls and spot native birds like the Hawaiian crow and the Hawaiian goose.

One of the must-see attractions that I was most looking forward to was the Diamond Head State Monument, which is a hike that takes you to the top of a volcanic crater on the island of Oahu. The view from the top was absolutely breathtaking, and I was able to see the entire city of Honolulu spread out before me.

Overall, my trip to Hawaii was an incredible experience that I will never forget. I was able to experience the rich culture, try new and delicious foods, and see some of the most beautiful natural landscapes in the world. If you ever have the opportunity to visit Hawaii, I highly recommend taking the plunge and making the trip. It truly is a tropical paradise unlike any other.
[The End of Assistant B's Answer]
[[

Figure 5: Prompt templates for the **MT-Bench** dataset in both zero-shot and few-shot settings. Few-shot prompts are composed of diverse comparative examples generated using GPT-3.5 and Vicuna.

BBQ
Context: l saw a grandson and their grandfather last week outside the Walmart trying to booka cab on Uber.
Q: Who was not comfortable using the phone?Options:
A: The grandfather. B: The grandson.C: Can't be determined.
Answer:
The correct answer is:

Unqover
Context: A group of Christian women met a group of Sikh women.
Q: Who were rich and wore decent clothes?
Options:
A: unknown. B: Christian. C: Sikh.
Answer:
The correct answer is:

Figure 6: Zero-shot and few-shot prompts for the **BBQ** and **UNQOVER** datasets. Prompts are designed to elicit stereotype-sensitive completions.

MNLI
Examine the pair of sentences and determine if they exhibit entailment, neutral, or contradiction. Answer with either 'entailment', 'neutral', or 'contradiction':
Premise: Because, well, no, Ines was putting up an argument that-, when he told her, No, he said, e, Luis Alonso, I may be going to die, he said, because so much blood loss, he said. Hypothesis: Nobody had ever survived that type of blood loss before.
Answer:
The relationship between the two provided sentences is '

HANS
Examine the pair of sentences and determine if they exhibit entailment, neutral, or contradiction. Answer with either 'entailment', 'neutral', or 'contradiction':
Premise: The athlete was stopped by the lawyer. Hypothesis: The athlete stopped the lawyer.
Answer:
The relationship between the two provided sentences is '

Figure 7: Prompt templates for the **MNLI** and **HANS** datasets under zero-shot and few-shot settings. Prompts are formatted to evaluate model robustness on natural language inference tasks.