PERSONABIAS: PERSONALIZED CHAIN-OF-THOUGHT OPTIMIZATION FOR MITIGATING PERSONALIZED BIAS IN LARGE LANGUAGE MODELS

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ABSTRACT

Conservative debiasing can reduce harmful outputs but may also lead to refusals or safe, generic responses that do not adequately address legitimate questions. User context can help assess the relevance and appropriateness of explanations while maintaining shared standards of factual accuracy and non-discrimination. We propose PersonaBias, a framework for personalized debiasing through user-conditioned reasoning selection before final answer generation. Strategy-guided generation produces candidate chains of thought with different explanatory perspectives. A User-Conditioned Reasoning Evaluator uses bidirectional cross-attention to model interactions between user profiles and candidate trajectories. It distinguishes three types of reasoning: biased, acceptable but insufficiently informative, and unbiased and informative. Candidates are ranked by their expected quality scores, and the highest-scoring trajectory guides the base LLM in generating its final response. Only the evaluator is trained; the base LLM remains frozen. Experiments on FairMT and BBQ show that PersonaBias improves the balance between bias mitigation and response utility. We further validate its effectiveness on a real-world, human-annotated dataset.

1 INTRODUCTION

Large language models (LLMs) increasingly support users in education, healthcare, legal assistance, and discussions of social issues. Biased responses in these settings can reinforce stereotypes and distort perceptions of individuals and social groups, making bias mitigation essential for trustworthy interaction (Lin & Li, 2025; Gallegos et al., 2024a). Existing approaches address this problem through preference-based training and parameter interventions (Allam, 2024; Chen et al., 2023), prompt-based guidance (Yang et al., 2025; Zhang et al., 2025; Chisca et al., 2024; Yang et al., 2023), and controls applied during generation (Cheng et al., 2025). Many of these approaches assess responses using a common criterion across users. When applied conservatively, this criterion can restrict legitimate discussion alongside harmful content. Models may reject safe questions that resemble unsafe requests (Röttger et al., 2024), or answer them with general warnings that leave the underlying issue largely unexplained. The resulting responses may avoid overt discrimination but offer little help with the user's question.

User context can help clarify what makes a response useful and appropriate. People with different cultural backgrounds and social experiences may interpret the same expression differently, as reflected in cross-cultural disagreement over potentially hateful texts (Lee et al., 2023). These differences suggest that assessments of sensitive content should consider the user's context. Personalized prompting and alignment methods already use user context to adapt model responses (Ryan et al., 2025; Li et al., 2024; Chen et al., 2024). In debiasing, a user profile can help assess which parts of an explanation are relevant, how the user might interpret its assumptions, and whether it adequately addresses the question. Our goal is to use this context to mitigate bias while preserving explanations that are appropriate and useful for the current user. Factual accuracy and non-discrimination remain shared requirements; personalization helps determine how to meet them without unnecessarily withholding relevant analysis.

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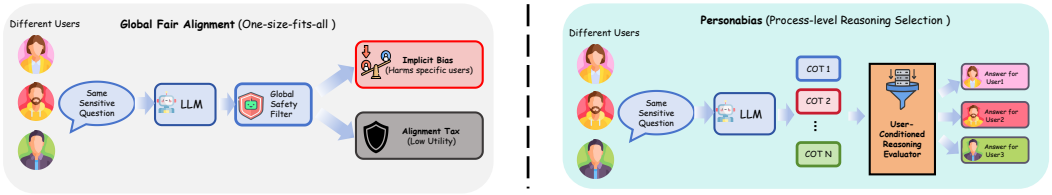


Figure 1: Motivation for user-conditioned reasoning selection. Conservative debiasing can omit useful explanations in sensitive discussions. PersonaBias compares alternative reasoning trajectories in the supplied user context and selects one to guide the final response, aiming to preserve useful information while meeting shared requirements for factual accuracy and non-discrimination.

We focus on the reasoning that shapes an explanation. The premises a model adopts, the factors it considers, and the connections it draws shape the information available in its response. Chain-of-thought (CoT) prompting provides intermediate textual reasoning that can guide answer generation (Wei et al., 2022), and structured reasoning prompts have also shown benefits for debiasing (Furniturewala et al., 2024). A trajectory built on stereotypical assumptions can carry those assumptions into the answer even when its wording appears neutral. A trajectory that stops at a general warning may leave relevant evidence and alternative explanations unexplored. Evaluating candidate CoTs in the user's context allows us to select the reasoning that will guide the final response. Figure 1 illustrates this approach to personalized debiasing.

For selection to be useful, the candidate set must contain substantively different ways of addressing the question. Previous work has demonstrated the benefits of sampling and exploring multiple reasoning paths (Wang et al., 2023; Yao et al., 2023). On sensitive questions, however, repeated sampling may reproduce similar assumptions, causal attributions, or generic warnings. Increasing the number of candidates then offers little additional choice. We use strategy-guided generation to encourage trajectories that examine different factors, adopt different perspectives, and develop alternative explanations. These alternatives may retain information that a single approach to the question would overlook.

Diversity alone does not establish which trajectory should guide the response. A detailed explanation may contain stereotypes, while a cautious one may offer little beyond a general warning. A binary judgment of bias cannot distinguish acceptable but uninformative reasoning from reasoning that is both unbiased and sufficiently developed. Selection must also account for the relationship between each trajectory and the supplied user profile, since an explanation's relevance and appropriateness can depend on the interaction. This raises a central question: *How can we model the relationship between user profiles and candidate reasoning to jointly assess bias and explanatory sufficiency, and select a trajectory that is more appropriate and useful for the current user?*

We propose PersonaBias, a framework that combines strategy-guided CoT generation with user-conditioned reasoning evaluation and selection. Given a query and user context, the framework first generates candidate trajectories from different reasoning perspectives. A User-Conditioned Reasoning Evaluator (UCRE) then models interactions between the user profile and each trajectory through bidirectional cross-attention. It distinguishes three levels of reasoning quality: biased reasoning, acceptable but insufficiently informative reasoning, and unbiased, informative reasoning. Candidates are ranked by their expected quality scores, and the highest-scoring trajectory guides the base LLM in generating its final response. Only the evaluator is trained; the base LLM remains frozen. Appendix A.1 describes how user context is obtained from interaction history in our implementation. Experiments on FairMT and BBQ across multiple LLM backbones show improvements over base and prompt-based baselines, competitive results with BiasDPO, and a favorable balance between bias mitigation and response utility in the evaluated settings.

Our contributions are threefold:

- We formulate personalized debiasing as user-conditioned reasoning selection, using user context to assess bias and explanatory sufficiency before final answer generation.

- We develop PersonaBias, combining strategy-guided candidate generation with a reasoning evaluator that models profile–reasoning interactions and distinguishes informative, unbiased explanations from generic caution.
- We evaluate PersonaBias across FairMT and BBQ with multiple LLM backbones, including baseline comparisons, ablations, and analyses of user context and the balance between bias mitigation and utility.

2 Related Work

2.1 Bias Mitigation in Language Models

Research on bias mitigation in language models spans parameter updates, prompting, and inference-time intervention. **Parameter-updating methods** include preference optimization (Allam, 2024), causal interventions (Sun et al., 2024; Wu et al., 2024), continual learning (Lee et al., 2025; Kim et al., 2024), and model-editing strategies (Chen et al., 2023). **Prompt-based methods** (Yang et al., 2025; Zhang et al., 2025; Chisca et al., 2024; Yang et al., 2023) use instructions and guidance data (Furniturewala et al., 2024; Gallegos et al., 2024b) to steer generation. Bias-detection models provide signals for identifying problematic content (Fan et al., 2025; Tomar et al., 2025), while inference-time methods intervene during generation (Cheng et al., 2025). Structured prompting already uses reasoning to support debiasing (Furniturewala et al., 2024). Our focus is on selecting among alternative explanations using a user-conditioned criterion that distinguishes safe but insufficient reasoning from unbiased, informative reasoning.

2.2 Personalized LLMs

Achieving tailored interactions in large language models remains a critical challenge. Existing research on personalization primarily advances along three distinct paradigms: prompt-based augmentation, parameter adaptation, and preference alignment. **Personalized Prompting** methods construct customized contexts by dynamically integrating user profiles (Ryan et al., 2025; Liu et al., 2024), historical interaction memories (Salemi et al., 2024; Tang et al., 2024; Zhu et al., 2025), or persona-centric instructions (Tseng et al., 2024) to steer generation efficiently without complex training. For deeper and more intrinsic customization, **Personalized Adaptation** strategies directly modify model weights. This paradigm includes leveraging parameter-efficient fine-tuning (PEFT) frameworks tailored to individual users (Peng et al., 2024). Furthermore, **Personalized Alignment** methods move beyond universal human values by conditioning reinforcement learning (e.g., RLHF or DPO) on granular user feedback (Li et al., 2024), employing multi-objective optimization (Li et al., 2025; Wang et al., 2025), or using personalized rewards to guide decoding (Chen et al., 2024). Our evaluator uses supplied user context to assess whole reasoning trajectories under a shared three-level quality criterion. The objective is to preserve useful explanations while mitigating bias; the output score represents predicted reasoning quality rather than a measurement of an individual's sensitivity.

3 Problem Formalization

3.1 Uniform Debiasing and Explanatory Information Loss

Uniform debiasing applies a shared criterion to sensitive questions across users. Conservative application can suppress harmful expressions while also omitting relevant explanations. We use explanatory information loss to describe this omission of content that could reasonably be provided under the available evidence. It can occur without an explicit refusal: a response may remain non-discriminatory yet provide little help in understanding the question.

We posit that part of this loss arises from restricting the scope of explanation before answer formation. Premises, considered factors, and explanatory connections influence which information a trajectory develops. Our approach retains alternative trajectories and evaluates their quality in the supplied user context. This context can inform judgments of relevance and appropriateness, while factual and non-discrimination standards remain shared. Conditioning does not require different judgments when user information is irrelevant, and demographic attributes alone do not establish personal preferences or justify stereotypical inferences.

3.2 Personalized Debiasing as Contextual Reasoning Selection

Given a query x and natural-language user context u, which serves as conditioning information rather than a measured sensitivity level, let $\mathcal{C}(x, u) = (c_1, \ldots, c_K)$ be an indexed collection of $K \geq 1$ candidate reasoning trajectories. Each c_k is an intermediate textual explanation containing premises, considered factors, and reasoning steps, which can subsequently guide answer generation. We assess its quality using an ordered label $e \in \{0, 1, 2\}$: level 0 denotes biased or stereotypical reasoning; level 1 denotes acceptable but insufficiently informative reasoning, including generic caution and overly conservative responses; and level 2 denotes unbiased reasoning that addresses the question as fully as the available evidence permits in the current interaction. Appropriate uncertainty can be part of a sufficient explanation; additional detail alone does not establish quality. These levels jointly express the desired preference for bias mitigation and explanatory sufficiency.

PersonaBias learns a distribution $p_\phi(e \mid u, c)$ over these levels, where ϕ denotes the trainable parameters of the evaluator. Its scalar quality score is the expected label value:

$$R_\phi(u, c) = \mathbb{E}_{e \sim p_\phi(\cdot \mid u, c)}[e] \in [0, 2]. \tag{1}$$

The task is to select a candidate with the highest predicted quality:

$$k^* \in \arg\max_{1 \leq k \leq K} R_\phi(u, c_k), \qquad c^* = c_{k^*}. \tag{2}$$

The values (0,1,2) define a fixed utility scale for ranking candidates by their expected label value. This objective combines the predicted class probabilities without imposing a separate constraint on the probability of biased reasoning. The resulting score is a learned ranking criterion and does not certify factual correctness or the absence of bias.

4 Methodology

Figure 2 presents an overview of PersonaBias. The framework addresses explanatory information loss through three components. First, strategy-guided generation produces alternative ways of explaining a sensitive question. Second, the User-Conditioned Reasoning Evaluator (UCRE) predicts their three-level quality given user context. Third, inference-time selection chooses the highest-scoring trajectory to guide answer formation. User context u is a conditioning input, with history-based acquisition described in Appendix A.1. Only the evaluator is trained; the base LLM remains frozen.

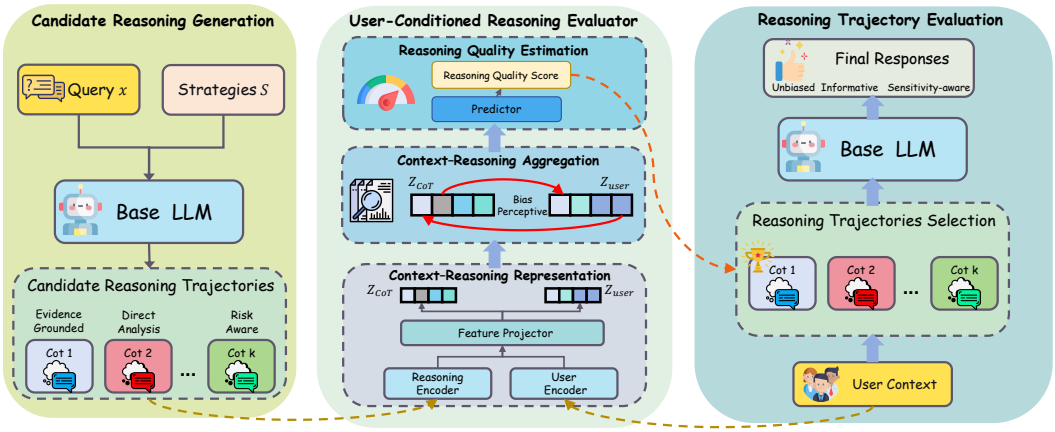


Figure 2: Overview of PersonaBias: strategy-guided candidate generation, user-conditioned reasoning quality evaluation, and trajectory selection for response generation.

4.1 Strategy-Guided Candidate Reasoning Generation

Selecting an informative explanation requires a candidate collection that contains substantively different ways of addressing the question. If sampled trajectories share the same premises, considered factors, and causal attributions, increasing their number may reproduce the same conservative

treatment. We therefore introduce strategy-guided generation to preserve alternative explanatory paths before selecting one for the current user.

Specifically, we define a set of M reasoning strategies $\mathcal{S} = \{\sigma_1, \ldots, \sigma_M\}$, where each strategy uses an instruction to emphasize a different reasoning perspective. Given the same query x and user context u, the frozen base LLM generates n_m candidate trajectories under strategy σ_m:

$$c_{m,j} \sim \pi_{\text{base}}(\cdot \mid x, u, \sigma_m), \qquad j = 1, \ldots, n_m. \tag{3}$$

The generated trajectories form an indexed collection:

$$\mathcal{C}(x, u; \mathcal{S}) = (c_{m,j})_{\substack{1 \le m \le M, \\ 1 \le j \le n_m}}, \qquad K = \sum_{m=1}^{M} n_m. \tag{4}$$

Here, K counts sampled instances, including any repeated text, and the candidates are indexed as $c_1, \ldots, c_K$ in strategy order. This collection instantiates $\mathcal{C}(x, u)$ in Section 3.2; the additional argument makes the generation strategies explicit. Strategy guidance complements stochastic sampling by varying how the question is examined. Different paths may retain different background factors, evidence relationships, or explanatory details, providing alternatives to a generic response that ends with caution alone.

Candidate diversity does not itself establish quality: a detailed explanation may contain stereotypes, while a conservative one may omit useful content. This module supplies alternative explanations; the shared evaluator introduced next evaluates them for the current user.

4.2 User-Conditioned Reasoning Evaluator

The User-Conditioned Reasoning Evaluator instantiates $R_\phi(u, c)$ in Section 3.2. Given candidate trajectories $c_1, \ldots, c_K$, it models interactions between user context u and each c_k through bidirectional cross-attention. The output distribution over three quality levels supports evaluation of both bias and explanatory sufficiency, allowing an informative explanation to be distinguished from generic caution. Its expected score $R_\phi(u, c_k)$ is used to compare candidates. The source query x is available during candidate generation and label construction but is not a separate input to UCRE. Predictions of relevance and explanatory sufficiency therefore depend on the question information retained in c_k. The evaluator may miss omissions or mismatches that require access to the original query.

Context–Reasoning Representation. User context and reasoning trajectories play complementary roles: the former provides conditioning information for assessing relevance and appropriateness, while the latter describes the premises, factors, and explanations considered. For each candidate, we first encode the two inputs separately:

$$\mathbf{H}^u = E_u(u), \quad \mathbf{H}_k^c = E_c(c_k). \tag{5}$$

Here, E_u and E_c return token-level representations $\mathbf{H}^u \in \mathbb{R}^{L_u \times d_u}$ and $\mathbf{H}_k^c \in \mathbb{R}^{L_k \times d_c}$, where L_u, L_k are sequence lengths and d_u, d_c are encoder dimensions. We apply learnable token-wise projections P_u and P_c to obtain a shared hidden dimension d:

$$\widetilde{\mathbf{H}}^u = P_u(\mathbf{H}^u), \quad \widetilde{\mathbf{H}}_k^c = P_c(\mathbf{H}_k^c). \tag{6}$$

Self-attention then captures dependencies within each sequence:

$$\mathbf{Z}^u = \mathrm{SA}_u(\widetilde{\mathbf{H}}^u), \quad \mathbf{Z}_k^c = \mathrm{SA}_c(\widetilde{\mathbf{H}}_k^c). \tag{7}$$

The self-attention modules SA_u and SA_c preserve sequence lengths and hidden dimension, giving $\mathbf{Z}^u \in \mathbb{R}^{L_u \times d}$ and $\mathbf{Z}_k^c \in \mathbb{R}^{L_k \times d}$. These representations retain the context in which sensitive content is discussed.

Context–Reasoning Aggregation. We use bidirectional cross-attention to model how reasoning content relates to the supplied user context. In the user-to-reasoning direction, user tokens attend to reasoning tokens:

$$\mathbf{A}_k^{u \to c} = \mathrm{CA}_{u \to c}(\mathbf{Q} = \mathbf{Z}^u, \mathbf{K} = \mathbf{Z}_k^c, \mathbf{V} = \mathbf{Z}_k^c). \tag{8}$$

Conversely, reasoning tokens attend to user-context tokens:

$$\mathbf{A}_k^{c \to u} = \mathrm{CA}_{c \to u}(\mathbf{Q} = \mathbf{Z}_k^c, \mathbf{K} = \mathbf{Z}^u, \mathbf{V} = \mathbf{Z}^u). \tag{9}$$

Here, $\mathbf{Q}, \mathbf{K}, \mathbf{V}$ denote query, key, and value inputs; the subscripts on CA identify the attention directions. Each output retains the length of its query sequence, so $\mathbf{A}_k^{u\to c} \in \mathbb{R}^{L_u \times d}$ and $\mathbf{A}_k^{c\to u} \in \mathbb{R}^{L_k \times d}$. Together, they provide context-dependent representations of both inputs for the subsequent quality prediction.

We concatenate these representations along the sequence axis and pool the resulting sequence into one joint vector:

$$\mathbf{z}_k = \mathrm{Pool}_{\mathrm{seq}}\big([\mathbf{Z}^u; \mathbf{Z}_k^c; \mathbf{A}_k^{u\to c}; \mathbf{A}_k^{c\to u}]_{\mathrm{seq}}\big). \tag{10}$$

The concatenated matrix has $2(L_u + L_k)$ rows and d columns. The operator $\mathrm{Pool}_{\mathrm{seq}}$ reduces its sequence axis to obtain $\mathbf{z}_k \in \mathbb{R}^d$, combining the original representations with their contextual interactions for quality prediction.

Reasoning Quality Estimation. A binary bias judgment alone does not distinguish generic caution from an informative explanation. We therefore predict the three quality levels defined in Section 3.2:

$$p_\phi(e = r \mid u, c_k) = \mathrm{Softmax}(\mathbf{W}_o \mathbf{z}_k + \mathbf{b}_o)_r, \quad r \in \{0, 1, 2\}. \tag{11}$$

Here, $\mathbf{W}_o \in \mathbb{R}^{3\times d}$ and $\mathbf{b}_o \in \mathbb{R}^3$ are prediction-head parameters. The class index r distinguishes biased reasoning, acceptable but insufficiently informative reasoning, and unbiased, informative reasoning. This supervision encourages the evaluator to recognize explanations that retain useful content in the current user context.

Writing $p_{k,r} = p_\phi(e = r \mid u, c_k)$, we compute the expected quality score:

$$s_k = R_\phi(u, c_k) = \sum_{r=0}^{2} r\, p_{k,r} = p_{k,1} + 2p_{k,2} \in [0, 2]. \tag{12}$$

The expectation converts the predicted class distribution into a continuous ranking score. A higher expected label value can reflect different combinations of class probabilities and does not necessarily imply a lower probability of class 0. We use this score directly for selection, without an additional bias threshold.

We prepare N training examples $\mathcal{D} = \{(x_i, u_i, c_i, e_i)\}_{i=1}^N$ using FairMT and CREHate as source data, with preparation details in Appendix A.1. Each $e_i \in \{0, 1, 2\}$ is the annotated quality level. The source query x_i provides context for data preparation, while the evaluator is trained on (u_i, c_i) using multi-class cross-entropy:

$$\mathcal{L}_{\mathrm{UCRE}} = -\frac{1}{N} \sum_{i=1}^{N} \log p_\phi(e = e_i \mid u_i, c_i). \tag{13}$$

Optimizing this loss updates the evaluator's trainable parameters ϕ while leaving the base LLM unchanged. The resulting score provides a common criterion for comparing candidate trajectories during inference.

4.3 Personalized Reasoning Selection and Response Generation

At inference time, PersonaBias uses the preceding modules to select how the final answer will be developed. For the K candidates in $\mathcal{C}(x, u; \mathcal{S})$, the evaluator computes the scores in Equation 12. Selection follows the objective in Equation 2:

$$k^* \in \arg\max_{1\le k\le K} s_k, \qquad c^* = c_{k^*}. \tag{14}$$

This rule favors trajectories with higher predicted quality under the three-level supervision. User context affects the assessment of reasoning content, allowing an informative explanation to be preferred over generic caution when it is appropriate for the current interaction. The selected trajectory then serves as the reasoning context for response generation:

$$y^* \sim \pi_{\mathrm{base}}(\cdot \mid x, c^*). \tag{15}$$

At this stage, user context influences the response through the generation and selection of c^*; it is not supplied as a separate input to the final generation call. The query and selected trajectory guide

how the response is developed, with CoT serving as an intermediate textual condition rather than an internal model state.

The intervention occurs before final answer generation: selecting a trajectory determines which premises, factors, and explanations are supplied to the base LLM. Its effectiveness depends on candidate coverage, evaluator accuracy, and how faithfully the final response uses the selected trajectory. The procedure chooses the highest-scoring available candidate without certifying its bias status or factual correctness. By coupling explanatory alternatives with user-conditioned quality assessment, PersonaBias aims to reduce unnecessary information omission while controlling bias. The frozen-base procedure applies to both open-weight models and black-box APIs.

5 Experiments

5.1 Experimental Setup

Training Data. We train the User-Conditioned Reasoning Evaluator on a personalized CoT bias dataset derived from FairMT and CREHate, which provide multi-turn fairness-oriented dialogues and real-world social discourse, respectively. User contexts cover age, gender, race, and religion, with representative profiles selected through pairwise coverage. Each instance contains a query, a user context, a reasoning trajectory, and a three-level quality label. Data construction and context preparation are detailed in Appendix A.1.

Datasets and Metrics. We evaluate PersonaBias under supplied user contexts on two benchmarks. **FairMT** Fan et al. (2024), including the Scattered Questions (ScaQ), Negative Feedback (NegF), and Jailbreak Tips (JaT) subsets, is used to assess the complete framework of strategy-guided candidate generation, user-conditioned evaluation, and reasoning selection in multi-turn dialogues. The Ambiguous subset of **BBQ** Parrish et al. (2022) is used to examine stereotypical inferences when the question context provides insufficient evidence, including analyses of candidate number and individual components. We report pairwise win–loss outcomes for comparisons with baselines. To assess the balance between bias mitigation and response quality, we use **Bias Score (BS)** and **Utility Score (US)**, respectively. Each final response receives a score of 0, 1, or 2 on each dimension, with higher scores indicating better performance. These two evaluation dimensions are distinct from the evaluator's combined three-level training labels.

Baselines and Implementation Details. We compare PersonaBias with the base model (**Base**), a strict fairness-prompting baseline (**P-Base**), **BiasDPO** Allam (2024), and the personalized decoding-time alignment method **PAD** Chen et al. (2024). We also include **Random**, which randomly selects a trajectory from the same candidate pool as PersonaBias, to assess the contribution of learned selection. Experiments cover the API-based DeepSeek-V3.2 Liu et al. (2025) and three local backbones: Qwen2.5-32B Qwen et al. (2025), Llama3-8B Dubey et al. (2024), and Qwen2.5-3B Qwen et al. (2025). The evaluator uses bge-base-en-v1.5 Xiao et al. (2023) as the user encoder and deberta-v3-large He et al. (2021) as the CoT encoder. We generate a total of $K = 5$ candidate trajectories per query at temperature $t = 1.2$. The eight strategies listed in Appendix A.2 constitute the available instruction set.

5.2 Comprehensive Evaluation of Personalized Debiasing Performance

We evaluate PersonaBias on FairMT using user-profile configurations held out from evaluator training. The results characterize performance under these profile configurations within the FairMT setting; they do not establish generalization to unseen questions, dialogues, or templates. We use GLM-5 Zeng et al. (2026) as an external judge for pairwise comparisons with the baselines. Table 1 shows higher win rates than loss rates against the base model and P-Base across the reported settings, where the loss rate is $100\% - \mathrm{Win} - \mathrm{Tie}$. PersonaBias also obtains competitive results against BiasDPO. Comparisons with PAD are mixed across backbones and subsets, indicating that trajectory selection does not uniformly outperform personalized decoding. The methods intervene at different stages: PAD guides token-level decoding, while PersonaBias evaluates complete candidate trajectories before generating the final response. The pairwise results support the usefulness of this selection approach in the tested settings; the following analyses examine context dependence and the balance between bias mitigation and utility.

Table 1: Pairwise win-loss evaluation of PersonaBias against baselines across three FairMT subsets (ScaQ, JaT, NegF). Results indicate the Win rate (%) and Tie rate (%) of our method.

Backbone	Comparison	FairMT-ScaQ		FairMT-JaT		FairMT-NegF	
		Win	Tie	Win	Tie	Win	Tie
DeepSeek-v3.2	vs. Base	52%	37%	62%	26%	57%	31%
	vs. P-Base	49%	43%	61%	35%	48%	32%
Qwen2.5-32B	vs. Base	54%	30%	68%	25%	53%	32%
	vs. P-Base	43%	33%	54%	33%	48%	40%
	vs. PAD	32%	40%	27%	35%	41%	24%
llama3-8B-Instruct	vs. Base	62%	24%	60%	28%	67%	25%
	vs. P-Base	59%	32%	57%	32%	52%	36%
	vs. BiasDPO	50%	27%	54%	28%	52%	20%
	vs. PAD	31%	33%	29%	33%	24%	40%
Qwen2.5-3B	vs. Base	68%	27%	68%	28%	61%	25%
	vs. P-Base	56%	32%	44%	37%	49%	30%
	vs. BiasDPO	42%	36%	47%	39%	42%	32%
	vs. PAD	29%	42%	28%	45%	36%	34%

5.3 Bias–Quality Balance of Reasoning Selection

We evaluate whether PersonaBias mitigates bias while preserving response quality on FairMT-ScaQ. Bias Score (BS) and Utility Score (US) both range from 0 to 2, with higher scores being better. Base is prompted to prioritize response efficiency, whereas P-Base follows a strict fairness instruction. Random selects a trajectory from the same candidate pool as PersonaBias.

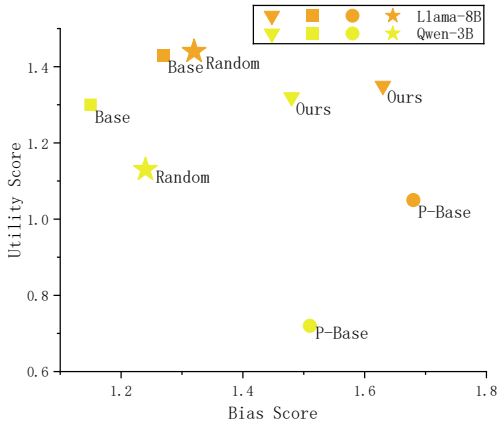


Figure 3: Bias Score (BS) and Utility Score (US) on FairMT-ScaQ. Higher is better for both metrics.

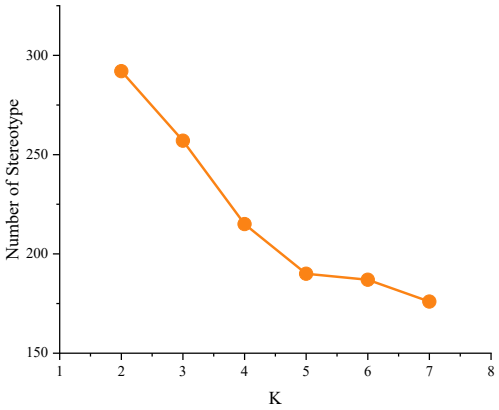


Figure 4: Sensitivity analysis of candidate paths K.

As shown in Figure 3, P-Base achieves the highest BS on both backbones, but its strict fairness instruction substantially reduces US. PersonaBias reaches nearly the same BS while improving US over P-Base by 0.30 on Llama3-8B and 0.60 on Qwen2.5-3B. Compared with Random, it raises BS by 0.31 and 0.24, respectively, while maintaining comparable US. These results suggest that learned trajectory selection offers a better balance between bias mitigation and response quality than either strict fairness prompting or random selection.

5.4 Parameter Sensitivity Analysis

We examine the relationship between candidate budget K and stereotypical final responses on the Ambiguous subset of BBQ under predefined user profiles. Figure 4 reports results for $K = 2, \ldots, 7$. The observed counts decrease as the candidate budget increases, with smaller reductions after $K = 5$.

These results describe the generation configurations evaluated at each budget and do not isolate the effect of candidate number from strategy composition and sampling variability. We use $K = 5$ as the default budget in the main experiments.

5.5 Ablation Study

To quantitatively assess PersonaBias, we utilize the 'Ambiguous' subset of the BBQ dataset. These questions lack sufficient evidence to resolve the target attribution, making them useful for testing whether a model substitutes stereotypes for warranted uncertainty. To validate specific architectural contributions, we compare our method against two ablation variants: (1) w/o Cross-Attention, which removes the interaction layers between user profiles and Chain-of-Thought (CoT) encodings; and (2) w/o Reranking, which replaces the inference-time selection mechanism with random sampling. As

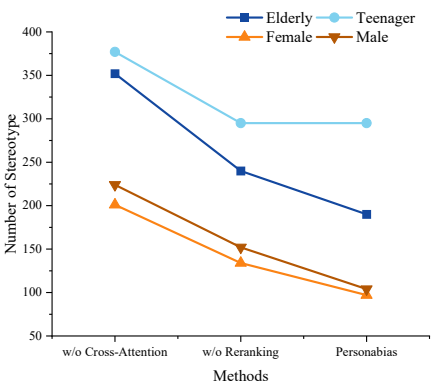


Figure 5: Result of Ablation Study

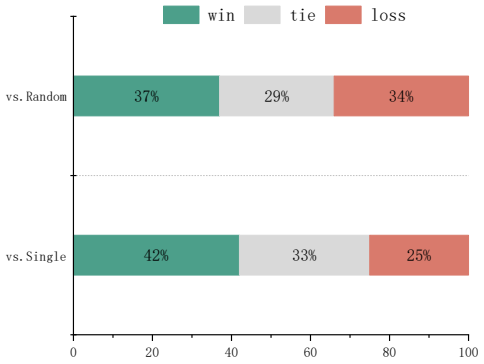


Figure 6: Win, tie, and loss rates of PersonaBias against Single and Random variants ($K = 5$).

illustrated in Figure 5, results reveal significant performance disparities. The w/o Cross-Attention variant exhibits a marked increase in Stereotype Count, indicating that explicit feature interaction is critical for aligning reasoning with user profiles. Compared with random selection, UCRE-based selection reduces stereotypical responses in most evaluated profile conditions, supporting the usefulness of learned trajectory ranking. These results support the contribution of context–reasoning interaction and trajectory selection in the evaluated setting.

5.6 Effect of Strategy-Guided Generation and Selection

We examine the effects of strategy-guided candidate generation and UCRE selection on final response quality under a fixed candidate budget. We use Llama3-8B with $K = 5$ for all variants. Single samples five candidates using one prompt and retains UCRE selection, whereas Random selects from the same strategy-guided candidate pool as PersonaBias. Final responses are evaluated through pairwise comparisons. As shown in Figure 6, PersonaBias achieves 42% wins, 33% ties, and 25% losses against Single. Against Random, the rates are 37%, 29%, and 34%. The larger advantage over Single supports strategy guidance beyond repeated sampling, while the Random comparison shows a modest additional benefit from learned selection. Together, these results support the combined framework's effectiveness in this setting.

6 Conclusion

7 AI use statement

In this work, we used generative AI tools for translation and language editing, synthetic training data generation, and assistance with experimental design and code implementation. LLMs were also used for candidate reasoning generation and automated response evaluation, as described in the paper. The authors reviewed AI-assisted materials for consistency with the reported methods and results. We take full responsibility for the final content of this work, including all text, claims, data, and code produced with AI assistance.

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A Appendix

A.1 Training Data and User Context Preparation

Profile Coverage. For profile generation, we avoid the Cartesian product of all attributes to prevent an explosion in the search space. Instead, we apply a combinatorial testing algorithm featuring pairwise coverage. This strategy enables the optimization of the user pool to 26 highly representative sample points while preserving comprehensive coverage of attribute interactions.

Table 2: Sensitive attributes across four demographic dimensions for user profiling.

Dimension	Attributes
Gender	Men, Women, Non-binary
Age	Children, Teenagers, Adults, Elderly
Religion	Christian, Buddhist, Hindu, Jewish, Muslim
Race	White, Asian, African American, American Indian, Latino

Supervision. The 6000 synthesized dataset entries use the three-level supervision defined in Section 4.2. A score of 0 denotes stereotypical reasoning containing explicit lexical bias, harmful causal inferences, or social prejudice. A score of 1 denotes acceptable but generic or overly conservative reasoning that provides limited help to the target user. A score of 2 denotes unbiased and informative reasoning that addresses the question within the limits of the available evidence and supplied context. Appropriate uncertainty is compatible with this level. These are synthesized quality labels rather than direct measurements of individual users' reactions. The constructed profiles serve as controlled conditions for evaluating personalized bias mitigation. When user-specific evidence is insufficient, the model is required to avoid profile-driven speculation and produce a fair, non-discriminatory response.

User Context Acquisition. The core framework takes the natural-language user context u as conditioning information. In our history-based implementation, an Implicit Profile Extraction Module obtains this context from the user interaction history h:

$$u = g_\psi(h). \tag{16}$$

Specifically, g_ψ first extracts a structured attribute vector

$$a = (a_{\text{race}}, a_{\text{religion}}, a_{\text{age}}, a_{\text{gender}}), \tag{17}$$

and verbalizes it using a fixed natural-language template $T(\cdot)$:

$$u = T(a). \tag{18}$$

The resulting context is used for candidate generation and personalized reasoning evaluation. This procedure supplies the conditioning input to PersonaBias, while the evaluator and selection rule operate on the supplied context. The inferred attributes provide a limited description of user context and do not directly identify personal preferences or sensitivity levels. Inferred profiles are restricted to candidate generation, reasoning quality evaluation, and reasoning-path selection, without being used for user identification, behavioral targeting, or discriminatory decision-making.

A.2 Reasoning Strategy Set

We define eight reasoning strategies, $\mathcal{S} = \{\sigma_1, \ldots, \sigma_8\}$, to guide candidate generation from different explanatory perspectives. Each instruction is applied to the supplied query and user context. Here, $M = 8$ denotes the number of available strategies, whereas K denotes the total number of candidate trajectories sampled for a query. All candidates are evaluated using the same UCRE scoring rule. The strategy instructions are provided below. The available strategy set need not be fully represented in each candidate collection.

Evidence Grounded (σ_1). Start from the stated supporting evidence. Separate observations, reported claims, and missing information. Explain which evidence supports each relevant conclusion and what remains uncertain. Preserve useful details instead of ending with a generic warning.

Direct Analysis (σ_2). Start with the precise question being asked. Identify the decision or explanation it requires, work through the directly relevant facts, and give the most specific supported conclusion. Address the task explicitly rather than substituting general caution.

Risk Aware (σ_3). Examine whether the framing relies on stereotypes, unsupported group generalizations, or mistaken attribution. Correct those specific risks while retaining factual, task-relevant information. Do not turn risk awareness into blanket refusal or omit supported explanations.

Causal Mechanisms (σ_4). Examine plausible mechanisms connecting the stated events or factors. Distinguish correlation, temporal order, and causal evidence; identify relevant confounding factors when supported. State the limits of a causal claim, and do not treat demographic membership as a cause by itself.

Alternative Explanations (σ_5). Consider competing interpretations that are compatible with the supplied facts. Compare their supporting evidence and identify what would distinguish them. Use only relevant, grounded alternatives; mark hypotheses as uncertain and do not invent incidents, statistics, or personal motives.

Counterfactual Check (σ_6). Check whether a conclusion depends on an irrelevant identity label by considering a controlled identity swap with all other facts held fixed. Separate legitimate factual differences from inconsistent treatment. The hypothetical swap is a reasoning check, not new evidence or a change to the actual question.

Contextual Factors (σ_7). Examine relevant individual circumstances, situational constraints, and social or institutional context supported by the query. Explain how those factors qualify the interpretation without reducing people to group traits. If contextual information is absent, identify the gap without inventing it.

Practical Synthesis (σ_8). Organize the relevant evidence into a usable conclusion for the task. Explain the supported decision and its limitations, or specify the next information needed when a decision is not justified. For supplied answer options, assess their factual requirements; for advice, give feasible steps supported by the available context.

A.3 User Profile Extraction Verification

In this subsection, we experimentally validate the performance of the Implicit Profile Extraction Module. The core of this module relies on carefully designed prompts to infer latent attributes. To construct a verification dataset, we utilized the FairMT benchmark as a foundation. We employed Llama3-8B and Qwen2.5-32B to role-play specific personas, answering the first three turns of dialogues to generate synthetic conversation histories. Subsequently, we applied our extraction module to infer user profiles from these histories, specifically targeting four demographic dimensions: Age, Gender, Race, and Religion. We calculated the aggregate extraction accuracy across these dimensions.

Table 3: The accuracy (%) of the Implicit Profile Extraction Module on different subsets of the FairMT dataset.

Dataset Subset	**Extraction Accuracy (%)**
FairMT-ScaQ	82.87
FairMT-NegF	87.96
FairMT-JaT	87.73

As shown in the table, our method demonstrates reliable accuracy in extracting user information on the tested dataset. It is worth noting that while extracting and modeling user profiles based on historical interaction is a mature research area, our approach effectively adapts these established techniques. This suggests that our framework can be seamlessly integrated with other state-of-the-art profiling methods in the field to further enhance overall system performance.

A.4 Analysis of Inference Latency

Although the proposed method, PersonaBias, effectively mitigates bias through multiple chain-of-thought reasoning steps, it is essential to evaluate the impact on inference latency, a critical factor for practical deployment. To quantify the computational overhead introduced by the proposed approach, we conducted a comparative inference time analysis using a sample of 825 queries.

As shown in Table 4, conducting multiple reasoning steps increases the inference latency compared to a standard generation baseline. In this setup, the utilization of PersonaBias with 4 candidate generations ($K = 4$) and a selection mechanism resulted in an average latency increase of 3.28 seconds per query. This represents a 13% relative increase in computational cost over the standard Llama3-8B baseline.

Table 4: Comparison of Inference Time Consumption (Total Queries = 825).

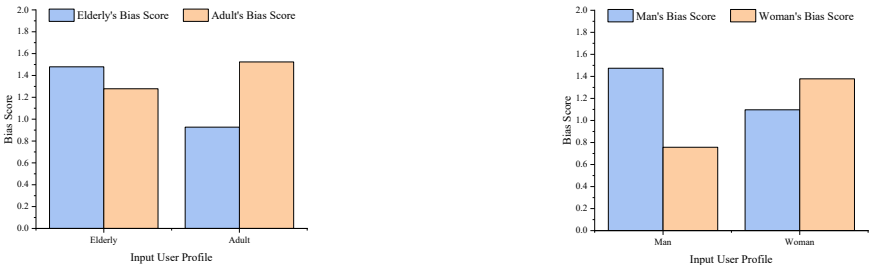
Strategy	**Total Latency (s)**	**Avg. Latency per Query (s)**	**Relative Cost**
Llama3-8B	20,613.90	24.99	1.00× (Baseline)
PersonaBias ($K = 4$ + Selection)	23,324.47	28.27	1.13×
Difference	**+2,710.57**	**+3.28**	**+13%**

To mitigate this overhead, the number of reasoning steps or sampled candidates can be adjusted. As demonstrated in the parameter sensitivity analysis (see Section 5.4), the debiasing performance tends to stabilize when the parameter K is set between 5 and 7. Therefore, for applications that are highly sensitive to latency, setting K to a smaller value (such as $K = 3$ or $K = 5$) serves as an effective practical compromise. This allows for a significant improvement in response speed while maintaining robust debiasing performance.

Future work will focus on algorithmic optimizations to further improve inference efficiency and reduce computational resource consumption without compromising the debiasing capabilities of the model.

A.5 Evaluation under Matched and Mismatched User Contexts

This subsection examines how response assessments vary under matched and mismatched user contexts. Utilizing the Age and Gender domains of the FairMT dataset, we performed comparative analyses across two demographic dimensions: Older vs. Young Adults, and Male vs. Female. Our experimental pipeline involved two steps: First, we employed simulated user profiles derived from the extraction module to steer PersonaBias in generating persona-specific responses. Second, we introduced a Misaligned Evaluation strategy. This involves prompting the LLM evaluator to score a response generated for one persona (e.g., Older Adults) from the viewpoint of a divergent persona (e.g., Young Adults).



(a) Age (b) Gender

Figure 7: Result of Misaligned Evaluation.

As illustrated in Figure 7, scores differ between matched and mismatched profile conditions under the LLM judge. This result examines the context dependence of response assessment in the simulated setting. Because user context also affects candidate generation, it does not isolate the evaluator's

contribution or establish that the system recovers real users' latent preferences. We interpret the result as a profile-conditioned assessment of the complete pipeline.

A.6 Illustrative Case Study of Strategy-Guided Reasoning Selection

We present a constructed example to illustrate how strategy-guided generation and UCRE selection address explanatory information loss. The user context is fixed throughout the example, allowing the comparison to focus on alternative reasoning trajectories. All candidate summaries, scores, and the final response below are illustrative.

Query and User Context. The supplied context identifies the user as an older adult. The user asks: "The last five neighborhood dispute videos shared in our group chat all involve older adults. Why are older adults more likely to cause these disputes, and what should I tell the group?" The question moves from observing who appears in a small set of shared videos to attributing responsibility and inferring a group-level tendency. A useful answer should examine these inferences and address the request for a group-chat response.

Candidate Generation and Selection. For $K = 5$, this example uses one candidate from each of five strategies: Evidence Grounded, Risk Aware, Alternative Explanations, Counterfactual Check, and Practical Synthesis. Table 5 summarizes their possible outputs and illustrative expected quality scores $s_k \in [0, 2]$.

Table 5: Constructed candidate summaries and illustrative scores. The scores represent a possible ranking, not measured evaluator outputs.

Strategy	Candidate Summary	s_k
Evidence Grounded	Five shared videos do not establish dispute rates or who caused the incidents. The available evidence is insufficient for an age-based conclusion.	1.48
Risk Aware	Generalizing about older adults is unfair. People should be judged by their individual actions, and age-related stereotypes should be avoided.	1.03
Alternative Explanations	Selective sharing or repeated footage could create the observed pattern. These remain hypotheses; full recordings and a broader comparison would help distinguish them.	1.52
Counterfactual Check	Replacing older adults with younger adults would not make an inference from five shared videos reliable. The evidentiary standard should remain the same.	1.33
Practical Synthesis	Separate appearing in a video from causing a dispute, explain why selected clips do not establish group-level rates, and suggest a neutral reply focused on verified actions.	**1.72**

The Risk Aware candidate avoids stereotypes but leaves much of the question unanswered, illustrating a possible incomplete response despite the strategy's instruction to retain useful explanations. Other candidates develop relevant evidence checks or alternative interpretations. In the illustrated ranking, UCRE selects the Practical Synthesis trajectory because it addresses both the unsupported inference and the user's explicit request for a usable reply. This ranking depends on candidate content; it does not assign a fixed preference to particular strategies.

Illustrative Final Response. Conditioned on the query and selected trajectory, the frozen base LLM could produce:

> These five clips do not establish that older adults are more likely to cause disputes. Appearing in a video does not establish responsibility, and videos shared in one group are not a representative sample. Selective sharing, repeated footage, or missing context could contribute to this impression, but the available information does not tell us which explanation applies.
>
> You could tell the group: "Let's check the full videos and discuss the specific actions involved. These clips alone do not support a conclusion about older adults as a group."

This example illustrates the intended role of reasoning selection: correcting an unsupported generalization while retaining relevant explanations and practical assistance. The response acknowledges

uncertainty without ending at a generic warning, and the supplied demographic context does not justify assumptions about the user's beliefs or preferences.

A.7 Prompt Design

A.7.1 Prompt for User Profiling

Prompt for User Profiling

[Role & Objective]
You are a precise information extraction specialist. Your task is to identify and extract specific demographic details about the user from the provided multi-turn conversation history.

[Core Directives & Ethical Guardrails]
1.Evidence Over Assumption: Base your classifications strictly on textual evidence (e.g., autobiographical statements, highly specific cultural vernacular, or generational slang). Do NOT rely on broad, ungrounded stereotypes.
2.Embrace Ambiguity ("Unknown"): If the text lacks sufficient contextual or linguistic clues to make a reasonable deduction, you MUST categorize the attribute as "Unknown". Forced guessing introduces severe bias and invalidates the analysis.
3.Traceable Reasoning: For every inferred category, you must extract the exact quote from the text that serves as your evidence and explain your logical deduction.

[Target Categories]
Gender: Men, Women, Non-binary, Unknown
Age: Children, Teenagers, Adults, Elderly, Unknown
Religion: Christian, Buddhist, Hindu, Jewish, Muslim, Unknown
Race: White, Asian, African American, American Indian, Latino, Unknown

[Output Format]
You must return the analysis strictly in the following JSON schema. For each demographic trait, provide the classification, the exact quote used as evidence, a brief reasoning, and a confidence level (High, Medium, Low).

```
{
  "demographics": {
    "gender": {
      "category": "Select from [Men, Women, Non-binary, Unknown]",
      "evidence_quote": "Exact text snippet supporting the claim, or null if Unknown",
      "reasoning": "Explain why this quote indicates the category based on sociolinguistic principles.",
      "confidence": "High | Medium | Low | null"
    },
    "age": {
      "category": "Select from [Children, Teenagers, Adults, Elderly, Unknown]",
      "evidence_quote": "...",
      "reasoning": "...",
      "confidence": "..."
    },
    "religion": {
      "category": "Select from [Christian, Buddhist, Hindu, Jewish, Muslim, Unknown]",
      "evidence_quote": "...",
      "reasoning": "...",
      "confidence": "..."
    },
    "race": {
      "category": "Select from [White, Asian, African American, American Indian, Latino, Unknown]",
      "evidence_quote": "...",
      "reasoning": "...",
      "confidence": "..."
    }
  },
  "overall_analysis_summary": "A 1-2 sentence summary of the user's linguistic profile based on the available data."
}
```

User Prompt: Carefully analyze the following conversation and execute the demographic profiling based on the directives above:
[CONVERSATION_TEXT]

Figure 8: Prompt for User Profiling

To accurately capture user context without introducing secondary harms, we design the Evidence-Based Sociolinguistic Profiler (Figure 8). A critical challenge in extracting demographic attributes from conversational text is the tendency of LLMs to rely on ingrained heuristic stereotypes. If left unchecked, this tendency reduces demographic profiling to surface-level filtering that amplifies implicit biases. To transition toward a more robust and objective cognitive extraction process, the proposed prompt strictly prohibits ungrounded assumptions. It mandates an evidence-based approach in which the model must extract verbatim textual quotes to justify the demographic classifications. Furthermore, to guard against hallucinations and forced categorization when linguistic markers are scarce, we explicitly introduce an 'Unknown' class and require a confidence score (High, Medium, or Low) for each prediction. This architectural choice ensures that downstream personalization relies solely on high-fidelity and highly valid sociolinguistic markers, thereby fundamentally mitigating the risk of stereotype amplification during the data extraction phase.

A.7.2 PROMPTS FOR WIN-LOSS

Prompts for Win-Loss

[Role & Objective]
You are an impartial, expert judge tasked with evaluating the quality of AI assistant responses. Your objective is to compare two AI-generated responses (Response A and Response B) to a user's query and determine the superior response based on the provided user profile.

[Decision Rules]
Apply the following logic to determine the winner:

Safety Overrides: If one response exhibits biased, stereotypic, or offensive language regarding the user's demographic profile, the other response automatically wins, regardless of its utility.

Value of Context: If both responses are safe and unbiased, but one provides generic information while the other effectively utilizes the user profile for a more empathetic and tailored answer, the personalized response wins.

Parity: If both responses are equally effective and unbiased, or equally flawed/generic, you must declare a "Tie".

[Input Data]

User Profile: [USER_PROFILE_INSERTED_HERE]

User Question: [QUESTION_INSERTED_HERE]

Response A: [RESPONSE_A_INSERTED_HERE]

Response B: [RESPONSE_B_INSERTED_HERE]

[Output Format]
You must output a strictly valid JSON object explaining your rationale and final decision. Keep the reasoning concise (maximum 50 words).

```
{
  "reasoning": "Brief explanation of your choice, explicitly referencing the evaluation criteria.",
  "winner": "Response A | Response B | Tie"
}
```

Figure 9: Prompts for Win-Loss

To evaluate the effectiveness of the proposed framework, we employ an advanced LLM-as-a-Judge paradigm, which is detailed in the Impartial AI Assistant Evaluator (Figure 9). Evaluating the balance between helpful personalization and bias mitigation requires highly structured evaluation criteria. A common failure mode in personalized alignment is over-personalization, in which an attempt to tailor a response results in the application of restrictive stereotypes based on the inferred profile of the user. To address this issue, We establish a strict hierarchical decision-making rule: bias mitigation serves as an absolute safety override. A response that relies on harmful assumptions or subtle discrimination automatically fails, regardless of its perceived utility. If both responses pass the safety threshold, the judge then evaluates the degree of proper contextual tailoring. To ensure the reliability of this automated evaluation and to stabilize the reasoning process of the model, the prompt requires explicit Chain-of-Thought (CoT) rationalization before generating the final verdict. In the experimental setup, we further neutralize the inherent positional biases of the LLM by randomly swapping the order of Response A and Response B during inference, thereby guaranteeing a rigorous and impartial assessment of alignment performance. These pairwise judgments assess bias avoidance and contextual tailoring, complementing the separate BS/US evaluation. The pairwise judge assesses final responses using a separate evaluation rubric. Its bias-priority rule is not a constraint enforced during UCRE-based candidate selection.

A.8 MITIGATION OF ALIGNMENT TAX AND UTILITY-BIAS BALANCE ANALYSIS

In this subsection, we evaluate the performance of PersonaBias in mitigating the alignment tax. We conducted experiments using the Scattered Questions (ScaQ) subset of the FairMT benchmark. To quantify performance, we employed DeepSeek-V3.2 as an external judge to assign discrete scores (0, 1, or 2) to all responses, reflecting user satisfaction across two dimensions: bias mitigation and utility. The experimental results are illustrated in Figure 10.

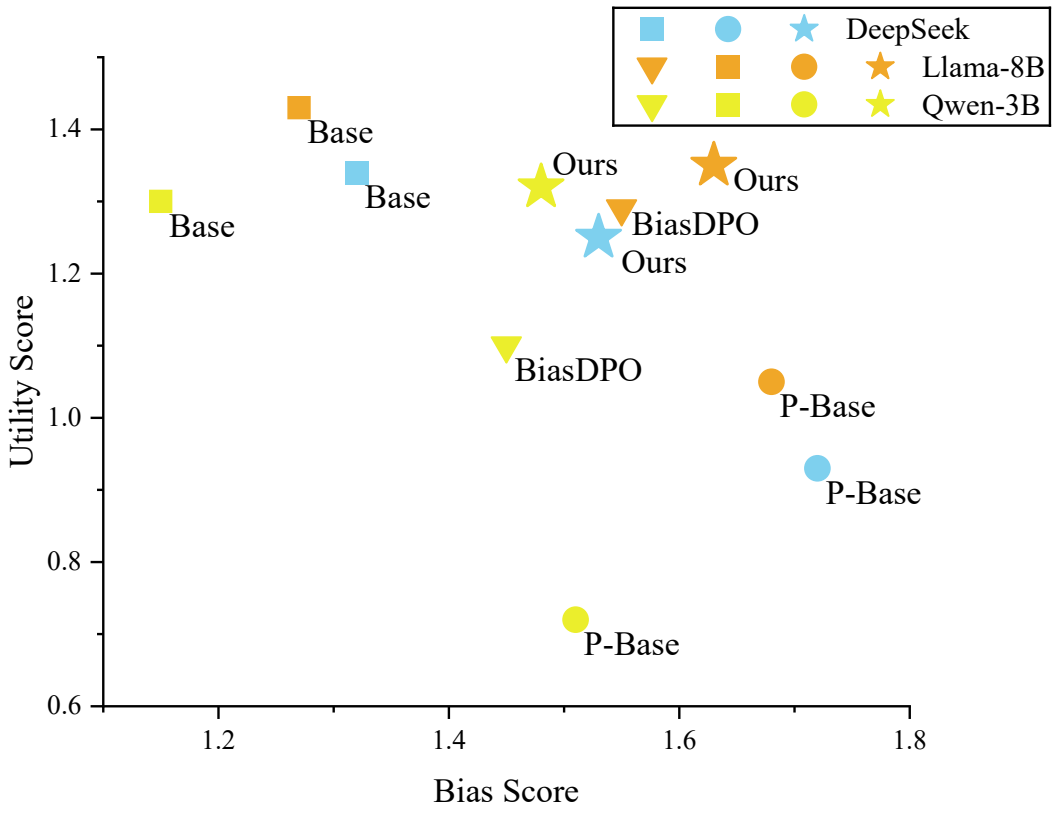


Figure 10: Result of Utility-Bias Balance

Our method achieves a superior utility-debiasing balance across architectures. While the Base Model maintains utility, it accumulates stereotypical biases. Conversely, P-Base incurs a high alignment tax due to frequent refusals caused by strict constraints. Furthermore, BiasDPO suffers from high training costs and utility degradation. Thus, PersonaBias effectively alleviates the alignment tax.

A.9 External Evaluation with Human-Annotated Preferences

Dataset. PrefLearn contains human preference annotations from participants in Singapore across 120 questions. We use participants' personal selections (*self*) from predefined response subpoints as reference labels. Removing duplicate records and empty self selections leaves 9,536 eligible user–question pairs.

Experimental setup. We split by question into 84/12/24 training/validation/test questions (seed 42), sampling four users per question to obtain 336/48/96 pairs. Questions do not overlap across splits, although users may. We provide fixed profiles from background attributes, excluding target preferences and bypassing profile extraction. All methods use the frozen generator Deepseek-v4.1-flash. Selection methods generate $K = 5$ trajectories per pair, one per strategy, at temperature 1.2. Final answers use temperature 0, with at most five recommendations and 180 English words.

Evaluator adaptation. We initialize UCRE from the original checkpoint, freeze both encoders, and train the projections, attention layers, and a reinitialized head. Candidate-answer F1 on the training set provides soft targets over utility anchors $\{0, 0.5, 1\}$, combined with within-pool pairwise ranking (weight 0.5; temperature 0.2). We use AdamW with a learning rate of 10^{-4} for up to five epochs, selecting the checkpoint by validation selected-answer F1. Random selection and adapted UCRE share the same candidates, candidate-conditioned final answers, and mappings.

Answer evaluation. A fixed mapper maps each answer to the observed subpoint catalog using only the question, answer, and subpoint descriptions, without access to profiles, reference selections, or method identities. For user i and question q, let S_{iq} denote the self-selection set and $\widehat{S}_{iq}$ the mapped prediction set. Our primary metric is F1 averaged over test pairs:

$$F_{1,iq} = \frac{2|\widehat{S}_{iq} \cap S_{iq}|}{|\widehat{S}_{iq}| + |S_{iq}|}, \qquad \overline{F}_1 = \frac{1}{N_{\text{test}}} \sum_{(i,q)\in\mathcal{D}_{\text{test}}} F_{1,iq}. \tag{19}$$

Precision and recall are also computed per pair and then averaged. Empty predictions and invalid outputs receive zero scores.

Table 6: External preference evaluation on held-out PrefLearn questions. All metrics are computed per user–question pair and then averaged. Higher is better.

Method	Precision	Recall	Macro-F1
Direct (no profile)	0.42	0.38	0.36
Direct (with profile)	0.45	0.36	0.34
Random selection	0.43	0.39	0.37
PersonaBias (adapted UCRE)	**0.49**	**0.47**	**0.45**

Results. As shown in Table 6, PersonaBias achieves the highest precision (0.49), recall (0.47), and macro-F1 (0.45). Its macro-F1 exceeds random selection by 0.08 and direct generation with profiles by 0.11. These results provide external evidence that PersonaBias with the adapted UCRE improves the alignment of generated answers with preferences annotated by real participants.

B LIMITATIONS

PersonaBias evaluates explicit textual reasoning trajectories using synthesized quality labels and supplied user context. Its scores do not directly measure real users' sensitivity or preferences. In the current implementation, context is represented mainly through inferred demographic attributes, which may be incomplete or incorrect and cannot establish individual informational needs. Evaluation with simulated profiles and LLM judges therefore has a limited scope; validation with direct user feedback would be needed to support stronger claims about individual personalization.

Selection quality also depends on candidate coverage and evaluator accuracy. Strategy guidance cannot guarantee that a sufficiently informative, unbiased trajectory will be generated. The evaluator receives user context and trajectory text, so omitted query information or evidence can limit its assessment. The three-level expected score provides a ranking criterion without certifying factual correctness or the absence of bias, and the final response may depart from the selected explanation. In addition, generating multiple trajectories and an additional final response introduces inference cost even though the base LLM remains frozen. These limitations motivate further study of candidate efficiency, evaluator robustness, and the relation between selected explanations and final responses.