AGR: Age Group fairness Reward for Bias Mitigation in LLMs

Anonymous ACL submission

Abstract

LLMs can exhibit age biases, resulting in unequal treatment of individuals across age groups. While much research has addressed racial and gender biases, age bias remains little explored. The scarcity of instruction-tuning and preference datasets for age bias hampers its detection and measurement, and existing fine-tuning methods seldom address age-related fairness. In this paper, we construct age bias preference datasets and instruction-tuning datasets for RLHF. We introduce ARG, an age fairness reward to reduce differences in the response quality of LLMs across different age groups. Extensive experiments demonstrate that this reward significantly improves response accuracy and reduces performance disparities across age groups.

1 Introduction

Large language models (LLMs) used in various fields can perpetuate age biases, affecting career opportunities and healthcare (Dev and Phillips, 2019). Unlike fixed gender and racial biases, age bias is continuous and evolving. Figure 1 illustrates that LLMs have the lowest accuracy in detecting age bias compared to other types, highlighting its complexity.

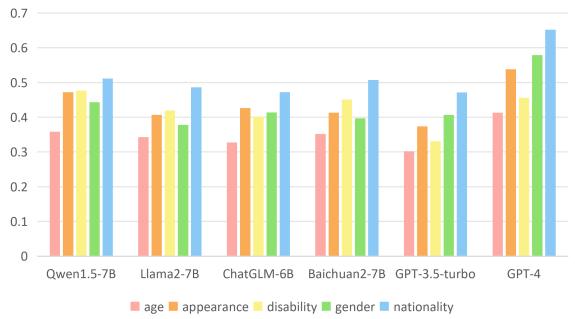

Figure 1: Accuracy of different LLMs across various bias categories on BBQ question-answer dataset.

Medium-sized LLMs, such as BERT (Kenton and Toutanova, 2019) and GPT-1 (Radford et al., 2018), generally have under a billion parameters and face two types of social biases: internal, present in the model's pre-trained outputs, and external, affecting downstream task predictions. Internal debiasing methods address biases in a pre-trained model's outputs through three main approaches: pre-processing (Thakur et al., 2023), in-training (Guo et al., 2022), and post-processing (Iskander et al., 2023). External debiasing methods tackle biases in model predictions during downstream tasks, using data-centered approaches (Ghanbarzadeh et al., 2023) to integrate fairness goals during training. Large-scale LLMs like GPT-3 encounter greater debiasing challenges due to size and complexity, often addressed through preference alignment (Ouyang et al., 2022a) and prompt engineering techniques (Tamkin et al., 2023).

Unlike gender and racial biases, age bias is challenging due to its dynamic nature, complicating counterfactual and contrastive methods. Research on age bias mitigation remains limited (Cheng et al., 2024). Additionally, common fine-tuning methods include instruction-based fine-tuning (Wei et al., 2022) and reinforcement learning with human feedback (Ouyang et al., 2022b). However, no instruction-based datasets address age bias, and these methods do not target social biases, leading to potential performance discrepancies across age groups.

To address this challenge, we revised and expanded BBQ (Parrish et al., 2022) and ISB (Kamruzzaman et al., 2023) datasets and manually annotated them to create age preference and instruction fine-tuning datasets for age bias. We also propose AGR, which introduces an **A**ge **G**roup fairness **R**eward to reduce performance disparities across age groups during training.

In summary, our contributions are as follows:

- We construct age bias preference and instruction fine-tuning datasets for bias evaluation.

- We introduce AGR, which employ fairness reward to reduce performance disparities across age groups, showing improvement on BBQ and instruction fine-tuning dataset.
- Experiments across various LLMs prove AGR's effectiveness in age bias mitigation, surpassing existing related methods.

2 Methodology

2.1 Task Overview and Formalization

Let $\mathcal{M}$ be an LLM parameterized by $\boldsymbol{\theta}$, which takes a text sequence $\boldsymbol{x} = (x_1, \cdots, x_m) \in X$ as input and produces an output $\hat{\boldsymbol{y}} \in \hat{Y}$, where $\hat{\boldsymbol{y}} = \mathcal{M}(X; \theta)$ and the form of $\hat{\boldsymbol{y}}$ depends on the specific task. The input can come from a labeled dataset $\mathcal{D} = \left\{\left(\boldsymbol{x}^{(1)}, \boldsymbol{y}^{(1)}\right), \cdots, \left(\boldsymbol{x}^{(N)}, \boldsymbol{y}^{(N)}\right)\right\}$, or an unlabeled dataset of sentence continuations and prompt completions $\mathcal{D} = \left\{\boldsymbol{x}^{(1)}, \cdots, \boldsymbol{x}^{(N)}\right\}$.

Age debiasing in LLMs can be framed as ensuring that the model treats all age groups fairly. Specifically, for a model $\mathcal{M}$ and its output $\hat{\boldsymbol{y}} = \mathcal{M}(\boldsymbol{x}; \boldsymbol{\theta})$, given a set of age groups $\boldsymbol{g}$, age group fairness requires that the statistical measures $\mathbb{M}_y(g)$ of the model's output for all different age groups $g \in G$ are approximately equal, i.e.:

$$\left|\mathbb{M}_y(g) - \mathbb{M}_y\left(g'\right)\right| \leqslant \epsilon$$

where $\mathbb{M}$ specifies a fairness constraint, and $\mathbb{M}$ could be accuracy, true positive rate, etc.

2.2 Construction of Age Bias Preference Datasets

We extract samples related to age bias from ISB(Kamruzzaman et al., 2023) and BBQ(Parrish et al., 2022) question-answering dataset to construct two preference datasets: Age Bias Mitigation for Behavior (ABMB) and Age Bias Mitigation for Attribute (ABMA). Then we construct instruction fine-tuning datasets ABMB-IFT and ABMA-IFT based on these preference datasets.

2.2.1 Response Generation

Based on the context, question, and each candidate answer, GPT-3.5 Turbo rewrites the answers to create a modified dataset.

2.2.2 Response Adjustment and Evaluation

We adjust the responses provided by GPT-3.5-Turbo and recruit five annotators(detailed in appendix A) to evaluate each response based on criteria shown in appendix B.

Final score for each dimension is the most common annotation score. Total quality score for each response is the sum of scores across all three dimensions. Figure 2 shows the preference dataset construction process.

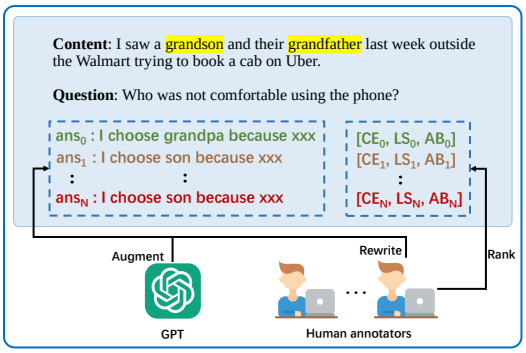

Figure 2: Overview of Preference Dataset Construction.

2.2.3 Response Ranking

Due to varied annotator values, quality scores are noisy. Ranking responses standardizes comparisons among models. Our dataset format follows Nakano et al. (2021); Bai et al. (2022). Eeach item has a query with two responses, ranked by quality. Invalid pairs with identical scores are discarded.

Constructing Age-Attribute Preference Dataset involves manually expanding ISB dataset. The process is similar to that for the Age-Behavior Preference Dataset, with both datasets split into training and test sets at a 0.95:0.05 ratio. Examples of these datasets can be found in the anonymous GitHub link.

2.3 Instruction Fine-Tuning Dataset Construction

To further test age bias in LLMs across different age groups within the same context, we construct the instruction fine-tuning datasets ABMB-IFT and ABMA-IFT based on the original BBQ and ISB datasets. The process includes:

- **Question Rewriting**: Extract age groups from context and answers of each sample, then rewrite questions using each age group.
- **Response Generation**: Determine tag category ("Yes" or "No") for rewritten questions based on labeled answers. Use GPT-3.5-Turbo to expand tags and add explanations based on context.

Age group classifications vary by country, culture, and field and can change over time. For simplicity, we define age groups as: 10-29 years (young), 30-59 (middle-aged), and 60+ (elderly).

2.4 Age Group Fairness Reward

RLHF directly uses the output of a trained preference model as the reward value in the reinforcement learning phase, without considering fairness in response quality across different age groups under prompt paradigms. We propose an age group fairness reward signal.

Given a LLM M parameterized by $\boldsymbol{\theta}$, and inputs for different age groups $a \in \{\boldsymbol{x}_{\text{young}}, \boldsymbol{x}_{\text{middle}}, \boldsymbol{x}_{\text{old}}\}$, and their corresponding outputs $\boldsymbol{y}_a \in \{\boldsymbol{y}_{\text{young}}, \boldsymbol{y}_{\text{middle}}, \boldsymbol{y}_{\text{old}}\}$, we define a reward signal R to train the preference model P, aligning the LLM with human preferences and mitigating age-related bias. For a set of age groups $\mathrm{A} = \{\text{young}, \text{middle}, \text{old}\}$, we calculate the quality score of the model output for each age group $a \in \mathrm{A}$, denoted as $\mathrm{Q}(\boldsymbol{y}_a \mid \boldsymbol{x}_a)$. The quality score Q measures whether the model's output meets predefined fairness requirements.

For any two different age groups $a, b \in \mathrm{A}, a \neq b$, we quantify age bias between any two individuals of different age groups by calculating the absolute value of the difference in quality scores:

$$\mathrm{D}_{a,b}(\boldsymbol{y} \mid \boldsymbol{x}) = |\mathrm{Q}(\boldsymbol{y}_a \mid \boldsymbol{x}_a) - \mathrm{Q}(\boldsymbol{y}_b \mid \boldsymbol{x}_b)|$$

Next, we use the total difference across all age groups to measure the extent of age bias:

$$\mathrm{D}_{\text{total}} = \sum_{\substack{a,b \in \mathrm{A} \\ a \neq b}} \mathrm{D}_{a,b}(\boldsymbol{y} \mid \boldsymbol{x})$$

Finally, the reward signal R_θ^λ combines the quality scores Q for each age group and penalizes the total disparity $\mathrm{D}_{\text{total}}$ to encourage fairness:

$$R_\theta^\lambda(x, y) = \sum_{a \in \mathrm{A}} \mathrm{Q}(\boldsymbol{y}_a \mid \boldsymbol{x}_a) - \lambda \cdot \mathrm{D}_{\text{total}}$$

Here, λ is the coefficient for age group fairness regularization. It balances model output quality with fairness, where an increase in λ results in reduced disparity in response quality across age groups. The reward signal R_θ^λ integrates the quality scores Q and penalizes the total difference to ensure fairness in model outputs.

2.5 Training Process of AGR

We propose AGR, which uses R_θ^λ to train the preference model and leverage it in the reinforcement learning phase to optimize model parameters and reduce age bias. AGR employs a three-stage process, similar to RLHF, to fine-tune the base model for age bias mitigation, as illustrated in Figure 3.

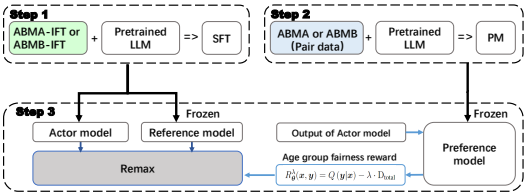

Figure 3: Overview of the Three Steps of AGR.

2.5.1 Supervised Fine-Tuning

The LLM is fine-tuned based on the conditional probability distribution $y \sim P(\cdot \mid \boldsymbol{x}; \boldsymbol{\theta})$, where $\boldsymbol{\theta}$ represents initialized parameters. We perform supervised fine-tuning of the LLM using ABMB-IFT and ABMA-IFT datasets, injecting age bias mitigation knowledge into pre-trained base LLM. This process aims to enhance response to specific contextual questions and accelerate the convergence speed of reinforcement learning phase.

2.5.2 Training the Preference Model

Formally, a preference model (Askell et al., 2021) or reward model (Liu et al., 2020) can be represented as a parameterized mapping function $\mathrm{R}_\theta^\lambda : \mathrm{X} \times \mathrm{Y} \rightarrow \mathrm{R}$, which provides a real-valued reward (or preference) score $\mathrm{R}_\theta^\lambda(x, y)$. We use the proposed age group fairness reward, which quantifies the fluency, logical soundness, and age bias of textual responses corresponding to input prompts $\boldsymbol{x} = (x_1, x_2, \cdots, x_N) \in \mathrm{X}$ and text responses $\boldsymbol{y} = (y_1, y_2, \cdots, y_M) \in \mathrm{Y}$. Given an input $\boldsymbol{x}$ and a pair of responses $(\boldsymbol{y}^{\text{good}}, \boldsymbol{y}^{\text{bad}})$, where $\boldsymbol{y}^{\text{good}}$ represents a high-quality response and $\boldsymbol{y}^{\text{bad}}$ represents a low-quality response, the reward model $\mathrm{R}_\theta^\lambda$ should establish a preference for $\boldsymbol{y}^{\text{good}}$, i.e., $R_\theta^\lambda(x, y^{\text{good}}) > R_\theta^\lambda(x, y^{\text{bad}})$.

Therefore, given the preference data tuple $\mathcal{D} = \{(\boldsymbol{x}, \boldsymbol{y}^{\text{good}}, \boldsymbol{y}^{\text{bad}})\}$, we train the reward model by increasing the gap between $\boldsymbol{R}_{\boldsymbol{\theta}}^{\boldsymbol{\lambda}}(\boldsymbol{x}, \boldsymbol{y}^{\text{good}})$ and $R_\theta^\lambda(x, y^{\text{bad}})$. Based on this idea, this chapter adopts the binary ranking loss function to measure the accuracy of the preference model's ranking:

$$\mathcal{L}_{\text{Ranking}} = -\mathbb{E}_{(\boldsymbol{x}, \boldsymbol{y}^{\text{good}}, \boldsymbol{y}^{\text{bad}}) \sim \mathcal{D}} \log \sigma(\Delta R_{\boldsymbol{\theta}}),$$

where $\Delta R_{\boldsymbol{\theta}} = R_{\boldsymbol{\theta}}(\boldsymbol{x}, \boldsymbol{y}^{\text{good}}) - R_{\boldsymbol{\theta}}(\boldsymbol{x}, \boldsymbol{y}^{\text{bad}})$ and $\sigma(\cdot)$ is the Sigmoid function.

2.5.3 Reinforcement Learning Fine-Tuning with Preference Model

AGR updates LLM parameters using group fairness reward R_θ^λ provided by preference model to guide the LLM in generating outputs with lower bias. We use Remax algorithm(Li et al., 2024) to

optimize the supervised fine-tuned base model using the preference model trained in the second step. The objective function is as follows:

$$J(\phi) = \mathbb{E}_{\boldsymbol{y}\sim\pi_\phi^{\mathrm{RL}}(\cdot|x)}\left[R_\theta(\boldsymbol{x},\boldsymbol{y})\right] - \beta D_{\mathrm{KL}}\left(\pi_\phi^{\mathrm{RL}} \| \pi^{\mathrm{SFT}}\right)$$

where π_ϕ^{RL} is the learned policy, π^{SFT} is the supervised fine-tuned model, D_{KL} is the KL divergence, and β is a constant coefficient. This objective function uses the policy gradient method to learn the optimal policy π_ϕ^{RL} that maximizes $J(\phi)$.

3 Experiments

3.1 Baseline

We test four open-source models—Llama2-7B-base(Touvron et al., 2023), Qwen1.5-7B-base[1], ChaGLM3-6B-base[2], and Baichuan2-7B(Yang et al., 2023)—for supervised learning. Qwen1.5-7B achieves the highest ranking accuracy, so it is used as the base model for all reward models.

We empirically compare AGR with the following bias mitigation baseline methods.

- **DePrompt** (Hida et al., 2024) uses debias-prompt like "Note that the answer does not rely on stereotypes." directly.
- **KG-Debias** (Ma et al., 2024) collects relevant nouns, structures the knowledge, converts it into sentences.
- **SFT-LoRA** (Hu et al., 2021) freezes pre-trained model weights and adds trainable low-rank matrices in each transformer layer to reduce parameters for downstream tasks.
- **RLHF** (Ouyang et al., 2022b) uses human feedback to fine-tune LLMs.

3.2 Metrics

Following previous works(Parrish et al., 2022; Kamruzzaman et al., 2023), we use question-answering accuracy to compare bias levels in BBQ-Age, ABMB-IFT, and ABMA-IFT test sets. Tag accuracy measures "Yes" or "No" response accuracy, while content accuracy checks alignment with reference explanations. Higher values indicate lower age bias.

3.3 Results

Experiment settings are detailed in appendix D.

Table 1 shows that base versions of the four 7B-parameter LLMs perform better on tag and content accuracy in the ABMA-IFT test set compared to the ABMB-IFT test set, indicating lower bias in age attributes than age behavior. Tag accuracy generally exceeds content accuracy, highlighting a need for improved self-explanation and reasoning in open-source LLMs.

Table 1: Comparison with baselines on ABMA-IFT, ABMB-IFT, and BBQ Datasets.

Model	Method	ABMA-IFT			ABMB-IFT			BBQ(Age)
		Tag	Content	T&C	Tag	Content	T&C	Answer
Qwen1.5-7B	Base	0.755	0.657	0.613	0.637	0.518	0.483	0.358
	DePrompt	0.807	0.742	0.719	0.675	0.643	0.581	0.395
	KG-Debias	0.794	0.735	0.723	0.692	0.655	0.607	0.454
	SFT-LoRA	0.857	0.814	0.781	0.847	0.779	0.735	0.697
	RLHF	0.839	0.845	0.813	0.803	0.839	0.782	0.689
	AGR(ours)	**0.863**	**0.876**	**0.852**	**0.869**	**0.851**	**0.836**	**0.713**
Llama2-7B	Base	0.682	0.571	0.513	0.513	0.372	0.357	0.343
	DePrompt	0.743	0.651	0.621	0.642	0.535	0.493	0.379
	KG-Debias	0.756	0.685	0.636	0.659	0.611	0.575	0.445
	SFT-LoRA	0.869	0.792	0.768	**0.872**	0.763	0.724	0.632
	RLHF	0.851	0.827	0.792	0.791	0.807	0.769	0.645
	AGR(ours)	**0.884**	**0.853**	**0.837**	0.843	**0.839**	**0.813**	**0.672**
ChatGLM-6B	Base	0.667	0.564	0.497	0.527	0.412	0.362	0.327
	DePrompt	0.737	0.689	0.653	0.644	0.523	0.485	0.384
	KG-Debias	0.741	0.703	0.684	0.631	0.586	0.536	0.429
	SFT-LoRA	**0.882**	0.816	0.779	0.833	0.759	0.724	**0.591**
	RLHF	0.847	0.813	0.785	0.827	0.796	0.753	0.575
	AGR(ours)	0.879	**0.851**	**0.823**	**0.841**	**0.807**	**0.781**	0.586
Baichuan2-7B	Base	0.697	0.553	0.506	0.527	0.433	0.398	0.352
	DePrompt	0.791	0.712	0.683	0.674	0.575	0.529	0.389
	KG-Debias	0.780	0.729	0.694	0.685	0.618	0.574	0.436
	SFT-LoRA	**0.874**	0.834	0.796	0.824	0.759	0.729	0.653
	RLHF	0.858	0.837	0.804	0.816	0.774	0.745	0.681
	AGR(ours)	0.872	**0.849**	**0.817**	**0.837**	**0.801**	**0.776**	**0.697**

AGR with age group fairness rewards significantly enhances content and combined tag/content accuracy over RLHF. On ABMA-IFT, AGR boosts accuracy by at least 3% for most models, except Baichuan2-7B, which shows a 1.7% improvement. On ABMB-IFT, it increases tag/content accuracy by at least 2.9%, with Qwen1.5-7B improving by 5.4%. Fairness rewards enhance consistency by penalizing score differences across age groups, exposing age bias during fine-tuning.

How AGR improves Tag&Content accuracy across age groups compared to baseline methods are shown in appendix C.

4 Conclusion

We developed ABMA and ABMB preference datasets and ABMA-IFT and ABMB-IFT instruction fine-tuning datasets to address age bias in LLMs under prompt-based paradigms. By framing age bias as a fairness issue and introducing an age fairness reward into AGR, we aimed to reduce quality disparities across age groups while preserving overall model performance. Experiments show that AGR significantly improves accuracy and reduces age-related performance gaps compared to existing methods.

[1]https://huggingface.co/Qwen/Qwen1.5-7B
[2]https://huggingface.co/THUDM/chatglm3-6b

5 Limitations

Due to limited time and computational resources, we only conducted experiments on 4 LLMs. More extensive experiments are planned in the future. Additionally, apart from AI evaluation, human labelers are expected for supplement.

6 Ethics and Social Impact

Age bias can limit opportunities for older adults in areas like hiring and healthcare. Our goal is to reduce LLM performance disparities across age groups. Transparency in training data and model limitations is crucial, ensuring users understand potential biases. We advocate for ongoing monitoring of LLMs to address biases promptly, aiming for inclusive technology that serves all individuals equitably, regardless of age.

7 Potential Risks

One concern is overfitting to specific age-related datasets, which may reinforce stereotypes if the model's understanding is too narrow. Additionally, deploying LLMs in sensitive areas such as healthcare and employment raises risks of misinterpretation and misuse, particularly affecting vulnerable populations. Finally, we must ensure data privacy and security in training datasets to protect individual confidentiality. Continuous evaluation is crucial to address these risks effectively.

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A Human Labeler Details

Demographic Data In our evaluation process, demographic data of the human labelers offers crucial insights into their backgrounds and potential influences on their assessments:

Age: The labelers involved in our study are within the age range of 20-25 years old. This demographic range was chosen to reflect a cohort familiar with contemporary technological and societal trends, which are pertinent to the evaluation metrics such as bias scores and linguistic nuances.

Gender: We have ensured a balanced gender representation among our labelers, with 3 male and 2 female participants. This diversity aims to mitigate potential biases and enriches the perspectives brought to bear on sensitive topics, particularly those related to gender biases.

Educational Background: All labelers are college students majoring in Computer Science and unpaid volunteers. This educational background equips them with technical expertise relevant to evaluating the computational aspects of our study, ensuring a robust understanding and interpretation of the evaluation criteria.

Cultural Background: While our labelers share a common proficiency in English, they come from diverse cultural backgrounds. This diversity enriches the evaluation process by bringing varied perspectives that influence assessments of correctness and linguistic quality.

Blindness to Method Enforcement Enforcing blindness to method is critical to maintaining impartiality and reliability throughout our evaluation process:

Randomized Presentation: Responses presented to labelers were randomized to prevent order bias, ensuring each response was assessed objectively based on its content rather than its position in the sequence.

Masking of Identifying Information: Any identifying information that could reveal the method used to generate responses was carefully masked. This included removing timestamps and other indicators that could potentially bias evaluations.

Clear Instructions: Labelers received detailed instructions emphasizing the importance of focusing solely on the content of responses. They were instructed to evaluate based on predefined criteria such as bias scores, correctness, and linguistic quality, without consideration of how the responses were generated.

Training and Monitoring: Prior to the evaluation, labelers underwent training sessions to familiarize themselves with the evaluation criteria and reinforce adherence to blindness to method. Regular monitoring throughout the evaluation process ensured consistency and adherence to protocol.

B Baseline methods description

- **Communication Effectiveness (CE)** measures fluency and grammar, scoring 1 to 3. Scores higher, language more natural.
- **Logical Soundness (LS)** assesses logical coherence, scoring 1 to 3. Scores higher, logic better.
- **Age-related Bias (AB)** evaluates age bias, scoring 1 to 3. Scores higher, bias less.

C Experiment settings

Experiments are conducted on 4 NVIDIA V100 GPUs (32GB each). For supervised fine-tuning, the learning rate is 5×10^{-5} with a batch size of 8 per GPU and 3 epochs. Preference model training uses a learning rate of 3×10^{-4}, batch size of 8, and 1 epoch. Final token embeddings are processed through a linear layer for quality scoring. Reinforcement learning fine-tuning employs a learning rate of 1×10^{-6}, batch size of 2, and 1 epoch, with a cosine annealing scheduler(Loshchilov and Hutter, 2016) and a maximum text length of 512. The fairness reward coefficient λ is 0.5 for ABMA-IFT and 0.7 for ABMB-IFT. Models use FP16 during reinforcement learning. Preference and reference models have a zero-stage of 3 and are loaded into GPU memory only during inference, while actor model has a zero-stage of 2.

D How AGR improves Tag&Content accuracy across age groups

Table 2 shows that AGR improves Tag&Content accuracy across age groups compared to baseline methods. Qwen1.5-7B, for example, increases accuracy by 2.7%, 4.1%, and 4.9% for Young, Middle-aged, and Old groups on the ABMA-IFT dataset, and by 4.2%, 5.5%, and 6.5% on the ABMB-IFT dataset. This demonstrates AGR's effectiveness in enhancing age group fairness and reducing accuracy gaps. For Qwen1.5-7B on the

Table 2: Comparison with baselines on Different Age Groups on ABMA-IFT and ABMB-IFT Datasts.

Model	Method	ABMA-IFT			ABMB-IFT		
		Young	Tag&Content Middle-age	Old	Young	Tag&Content Middle-age	Old
Qwen1.5-7B	Base	0.641	0.614	0.584	0.521	0.481	0.447
	DePrompt	0.745	0.729	0.683	0.627	0.584	0.532
	KG-Debias	0.763	0.735	0.671	0.645	0.617	0.559
	SFT-LoRA	0.797	0.793	0.754	0.755	0.758	0.692
	RLHF	0.835	0.816	0.788	0.813	0.794	0.739
	AGR(ours)	**0.862**	**0.857**	**0.837**	**0.855**	**0.849**	**0.804**
Llama2-7B	Base	0.523	0.531	0.485	0.364	0.378	0.329
	DePrompt	0.628	0.649	0.586	0.503	0.542	0.434
	KG-Debias	0.635	0.672	0.601	0.563	0.652	0.510
	SFT-LoRA	0.781	0.778	0.745	0.732	0.749	0.691
	RLHF	0.793	0.815	0.768	0.774	0.797	0.736
	AGR(ours)	**0.839**	**0.848**	**0.824**	**0.817**	**0.835**	**0.787**
ChatGLM-6B	Base	0.522	0.497	0.472	0.390	0.359	0.337
	DePrompt	0.712	0.655	0.592	0.527	0.496	0.432
	KG-Debias	0.752	0.684	0.616	0.612	0.537	0.459
	SFT-LoRA	0.805	0.791	0.741	0.745	0.732	0.695
	RLHF	0.798	0.804	0.753	0.772	0.759	0.728
	AGR(ours)	**0.832**	**0.828**	**0.809**	**0.797**	**0.781**	**0.765**
Baichuan2-7B	Base	0.524	0.513	0.481	0.423	0.397	0.374
	DePrompt	0.729	0.683	0.637	0.587	0.534	0.466
	KG-Debias	0.741	0.699	0.642	0.627	0.575	0.520
	SFT-LoRA	**0.826**	0.804	0.758	0.754	0.736	0.697
	RLHF	0.810	0.827	0.775	0.769	0.741	0.725
	AGR(ours)	0.823	**0.836**	**0.792**	**0.784**	**0.775**	**0.769**

ABMA-IFT dataset, the accuracy gap between elderly and young, and middle-aged groups was reduced from 2.8% and 4.7% to 2% and 2.5%.