

PersonaDual: Balancing Personalization and Objectivity via Adaptive Reasoning

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Abstract

As users increasingly expect LLMs to align with their preferences, personalized information becomes valuable. However, personalized information can be a double-edged sword: it can improve interaction but may compromise objectivity and factual correctness, especially when it is misaligned with the question. To alleviate this problem, we propose PersonaDual, a framework that supports both general-purpose objective reasoning and personalized reasoning in a single model, and adaptively switches modes based on context. PersonaDual is first trained with SFT to learn two reasoning patterns, and then further optimized via reinforcement learning with our proposed DualGRPO to improve mode selection. Experiments on objective and personalized benchmarks show that PersonaDual preserves the benefits of personalization while reducing interference, achieving near interference-free performance and better leveraging helpful personalized signals to improve objective problem-solving.

1 Introduction

Large Language Models (LLMs) have increasingly become integral to delivering interactive and personalized user services (Salemi et al., 2024b). To support personalization, mainstream model families including GPT (Achiam et al., 2023), Gemini(Team et al., 2023; Comanici et al., 2025), Llama 3(Grattafiori et al., 2024), and Claude (Anthropic, 2024) have incorporated memory mechanisms to retain and reuse personalized information across sessions. While such information can significantly enhance user satisfaction (Tan and Jiang, 2023), it may also reduce objectivity and induce factual errors or biases (Akpinar et al., 2025; Wei et al., 2023; Gupta et al., 2023), especially when the user’s persona is irrelevant or unaligned with the query.

Prior studies on general-purpose LLMs show that personalized information can reduce factual

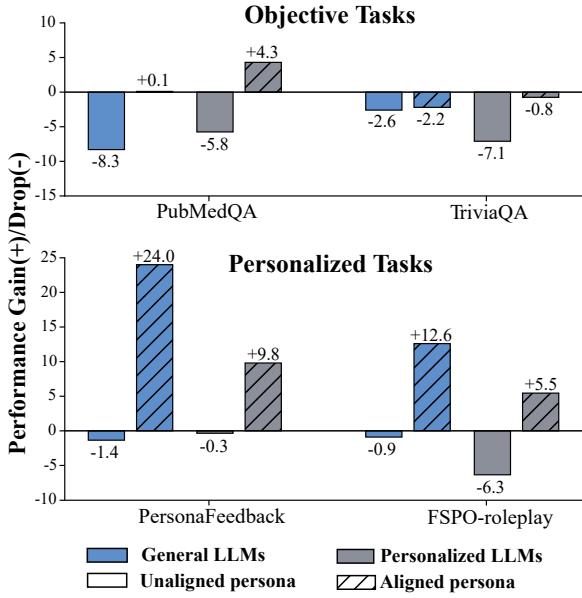


Figure 1: Effects of personalized information under different persona settings. We report the averaged results of DeepSeek-R1 (Guo et al., 2025) and Qwen3-30B-A3B-Thinking (Yang et al., 2025) for general models, and ALIGNXPERT-ICA (Li et al., 2025a) and ALIGNXPERT-PBA (Li et al., 2025a) for personalized models. Positive (negative) values indicate performance gains (drops) compared to the no-persona setting (indicated by the zero line).

accuracy (Akpinar et al., 2025; Wei et al., 2023). However, these studies are largely descriptive and do not provide a systematic evaluation of personalization effects across different tasks. Meanwhile, existing personalization alignment methods, primarily realized through in-context learning (Wu et al., 2024; Salemi and Zamani, 2025; Salemi et al., 2024a), fine-tuning (Salemi and Zamani, 2025; Tan et al., 2024), and reinforcement learning (Li et al., 2025a), have yielded measurable improvements in personalization performance. However their effects on logical reasoning and objective problem-solving remain underexplored.

To empirically investigate this duality, we eval-

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uate both general-purpose and personalization-aligned models on objective factual and subjective personalized QA tasks under three settings: *no persona*, *unaligned persona*¹, and *aligned persona*². Figure 1 summarizes the main results, with detailed analysis provided in Appendix A). We have three findings. (1) Incorporating persona information generally reduces accuracy on objective factual QA, with performance drops of up to 8% relative to the no-persona setting. (2) This degradation is most pronounced when personas are unaligned with the task, whereas aligned personas partially mitigate the effect and, in some cases, lead to modest accuracy gains of up to 4%. (3) In contrast, for subjective personalization tasks, persona information substantially improves performance by facilitating preference inference, resulting in gains of approximately 10–20%. Overall, these results suggest that the utility of personalized information is strongly task-dependent. While persona cues are beneficial for subjective personalization, they can interfere with objective reasoning when applied indiscriminately. This observation motivates a central research question: **How can LLMs adaptively determine when to incorporate personalized information, so as to balance personalization benefits with objective correctness?**

To address this challenge, we draw inspiration from dual-process theory in psychology (Kahneman, 2011), which posits that human cognition relies on two distinct reasoning systems that are engaged depending on task demands. Motivated by this perspective, we propose **PersonaDual**, a framework that integrates general-purpose objective reasoning and personalized reasoning within a single model, and adaptively switches between these modes based on the input query and available personalized information.

In practice, we first construct a training dataset **PersonaDualData**, with a subset **PersonaDualData-SFT** containing reasoning trajectories in both objective and personalized modes. We further propose a dual-mode reasoning architecture and a two-stage training paradigm. In the first stage, supervised fine-tuning is used to train the model to produce outputs consistent with

¹For both objective and personalized tasks, unaligned personas are randomly sampled from PersonaHub (Ge et al., 2024)

²For objective questions, aligned personas are generated by GPT-4o (Hurst et al., 2024) to simulate a user whose background or interests are explicitly relevant to the question domain.

the two reasoning patterns. In the second stage, we introduce a reinforcement learning algorithm, **DualGRPO**, which optimizes adaptive mode selection conditioned on the user query and the available personalized information. We evaluate PersonaDual on both objective QA and subjective personalization benchmarks. Experimental results indicate that **PersonaDual substantially reduces the negative impact of unaligned personalized information on objective problem-solving**, achieving performance close to the no-persona setting. Furthermore, by adaptively switching between reasoning modes, **PersonaDual effectively leverages aligned personalized information, improving objective QA accuracy by nearly 3%** on average compared to the no-persona baseline.

2 Related Work

2.1 Impact of Personalization on Factuality

As LLMs are increasingly used to serve diverse users and tasks, personalization in LLMs has become a major research focus. Existing personalization alignment methods typically adopt either context-based approaches (Packer et al., 2023; Wu et al., 2024; Salemi et al., 2024a) or parameter-based alignment (Tan et al., 2024; Li et al., 2025a), substantially improving LLMs’ ability to capture user-specific signals and produce personalized responses.

However, growing evidence suggests that personalized information can act as a strong prior in factual tasks and reduce reliability, shifting behavior from truth-seeking to agreement: preference-aligned models may exhibit sycophancy (Perez et al., 2023), override internal knowledge under misleading inputs and produce personalization-induced hallucinations (Wei et al., 2023), or drift under incorrect user feedback (Chen et al., 2025). In addition, demographic attributes can trigger stereotypes and yield group-differentiated responses (Gallegos et al., 2024; Sheng et al., 2021); pretraining biases can further amplify these risks in personalized settings (Liang et al., 2021); and assigned personas can increase harmful or toxic outputs (Deshpande et al., 2023). While recent work notes this “alignment tax” (Wang, 2025) and attempts to mitigate it via architectural constraints, this approach largely relies on static or manual triggers. Developing models that can intrinsically and adaptively decide when to leverage personalization remains an open question.

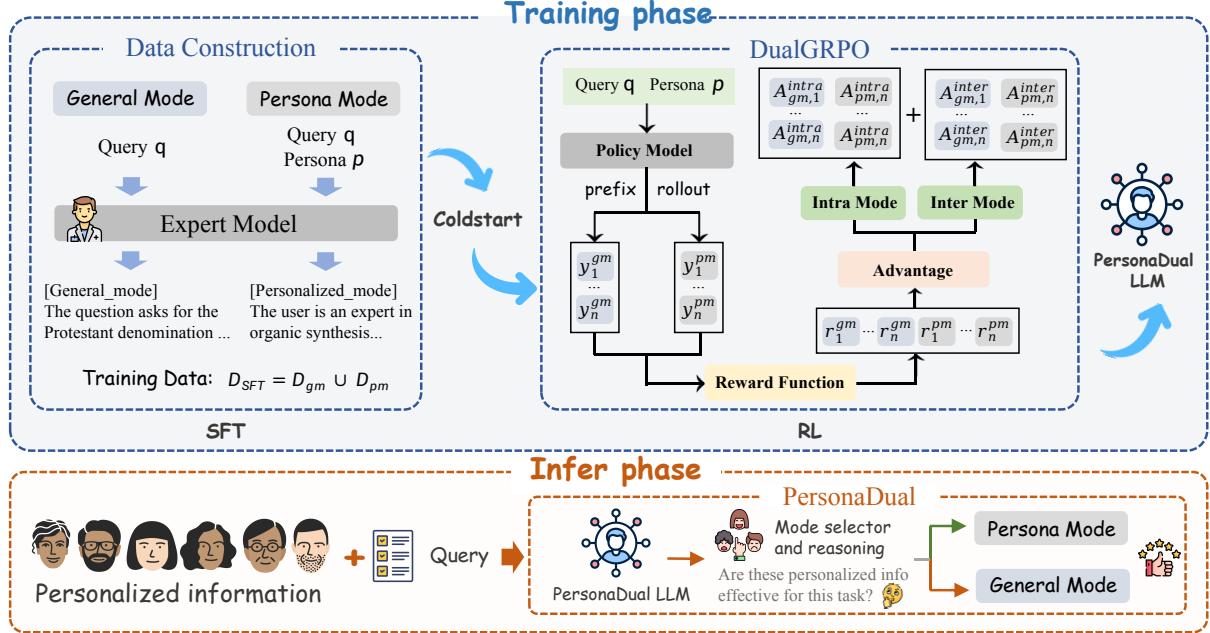


Figure 2: Overview of PERSONADUAL Framework. PERSONADUAL equips a single LLM with two complementary response modes, objective and personalized reasoning, and learns to adaptively select between them based on the user query and available persona. Training follows a two-stage paradigm: supervised learning to disentangle the two reasoning behaviors, followed by DUALGRPO to refine context-aware mode selection. This design captures the benefits of aligned persona cues while mitigating interference from irrelevant or unaligned personas, improving both objective correctness and personalization quality.

2.2 Adaptive Inference and Dual-Process Architectures

To address the diversity and complexity of real-world tasks, adaptive inference architectures have emerged that dynamically adjust computation paths or context strategies, ranging from routing-based mixtures (Fedus et al., 2022; Jiang et al., 2024), dynamic selection in model ensembles (Jiang et al., 2023), to cascaded invocation via hierarchical reasoning (Chen et al., 2023).

Recently, research has increasingly turned to cognitively inspired dual-process reasoning: drawing on the fast and slow thinking distinction, LLMs incorporate mechanisms to balance efficiency and quality, ranging from two-model setups for fast replies and deep planning (Tian et al., 2023) and fast/slow designs in human–AI collaboration (Xiao et al., 2025; Zhang et al., 2025b) to multi-mode frameworks that learn adaptive selection to reduce chain-of-thought cost (Zhao et al., 2025; Wang et al., 2025; Lou et al., 2025). While their work primarily targets efficiency, we instead aim to exploit the benefits of personalized information while mitigating its potential harms. Moreover, since most dual-mode models introduce modes via SFT and rely on RL for mode selection but often suffer from

mode imbalance and slow selection updates (Fang et al., 2025; Zhang et al., 2025a; Gigerenzer, 2000; Jiang et al., 2025; Li et al., 2025b), we propose DualGRPO, which combines forced-prefix sampling and prefix-focused reinforcement to stabilize training and improve adaptive switching.

3 Methods

PersonaDual equips LLM with two response modes and allows it to autonomously switch its reasoning style according to the task context, thereby enabling adaptive personalized reasoning. The overall training procedure consists of two stages. We first integrate the two reasoning modes into the base model via SFT. Then we further propose DualGRPO, a reinforcement learning algorithm in the second training stage, enhancing the model’s ability to adaptively select response modes.

3.1 Framework Overview

Our goal is to equip an LLM with the ability to adaptively decide when to utilize personalized information when answering a user query. Formally, let q denote the query and p the user’s persona. The model is designed to autonomously execute a two-step process during inference, as illustrated in the

lower part of Figure 2: (1) mode selection: determine whether to rely on p by choosing a reasoning mode m , with $m \in \mathcal{M} = \{gm, pm\}$, which we abstract as a mode-selection policy

$$\sigma(m | q, p), \quad m \in \{gm, pm\}. \quad (1)$$

(2) conditional generation: produce the final response y conditioned on the chosen mode. Concretely, the system samples a mode m , $m \sim \sigma(\cdot | q, p)$, prepends the corresponding prefix $\text{pfx}_m \in \{\text{pfx}_{gm}, \text{pfx}_{pm}\}$, and then generates the final response

$$y = y(q, p, m) \sim \pi_\theta(\cdot | q, p, \text{pfx}_m). \quad (2)$$

To realize this, we propose PersonaDual, which integrates both reasoning modes within a single model. A dedicated learnable prefix token explicitly activates each mode: $\text{pfx}_{gm} = [\text{General_mode}]$, $\text{pfx}_{pm} = [\text{Personalized_mode}]$. In this way, the answer distribution is implemented as

$$\pi_\theta(y | q, p, m) := \pi_\theta(y | q, p, \text{pfx}_m), \quad (3)$$

where θ denotes model parameters, and pfx_m is prepended as a sequence prefix to explicitly inject the mode choice into the generation process.

Based on this, our goal is to jointly learn an optimal selector σ^* , and a compatible generator π that maximizes expected response quality under the real-world data distribution \mathcal{D} . Let $R(q, p, m, y)$ denote the reward function for the generated answer. The overall objective can be written as:

$$\max_{\pi} \mathbb{E}_{(q,p) \sim \mathcal{D}} \left[\mathbb{E}_{m \sim \sigma(\cdot | q, p)} \mathbb{E}_{y \sim \pi(\cdot | q, p, m)} [R(q, p, m, y)] \right]. \quad (4)$$

To achieve this, we design a two-stage training scheme, illustrated in the upper part of Figure 2, which we detail as follows.

3.2 Stage 1: Mixed Mode Integration

To equip the model with the ability to execute the two distinct reasoning modes defined in Sec 3.1, we first perform a supervised fine-tuning (SFT) warm-up, as shown in the left part of the training pipeline in Figure 2. This stage aims to instill stable and high-quality reasoning patterns for each mode, preparing the model for subsequent adaptive selection. In general, we leverage a strong expert model, e.g., DeepSeek-R1 (Guo et al., 2025), to construct a high-quality PersonaDualData-SFT dataset, which contains reasoning trajectories for both modes.

General Purpose Objective Reasoning Mode.

For this mode, we construct prompts containing only the user query q , where personalized information p is deliberately omitted. The expert model is then instructed to generate reasoning steps grounded in factual evidence and logical deduction. These trajectories, conditioned on the prefix pfx_{gm} , establish a stable depersonalized reasoning paradigm that prioritizes objectivity, verifiability, and the intrinsic logical structure of the query.

Personalized Reasoning Mode. For personalized mode, we provide the expert model with the full context (q, p) and ask it to explicitly analyze attributes within the user persona, such as occupation, interests, and affective needs, and to actively incorporate these attributes as contextual signals throughout its reasoning chain. These trajectories, activated by the prefix pfx_{pm} , enable the model to meaningfully leverage p to enhance the relevance and individual fit of responses, moving beyond superficial mention of user information.

Through this mixed-mode SFT, the model learns to map each control prefix to a corresponding, specialized reasoning behavior, fulfilling the conditional generation definition in Eq. (3).

3.3 Stage 2: Adaptive Mode Selection

After SFT equips the model with two reasoning modes, we employ reinforcement learning to learn adaptive mode switching. To handle diverse task scenarios and personalized information, we propose DualGRPO (as shown in the top-right of Figure 2), an extension of GRPO designed for mode selection, featuring forced prefix sampling and inter-mode and intra-mode advantage calculation.

Prefix Forced Sampling. After the SFT warm-up, we observe the model often exhibits a preference for one mode prefix over the other for a given input (q, p) , leading to imbalanced generation probabilities: $\pi_\theta(\text{pfx}_{gm} | q, p) \gg \pi_\theta(\text{pfx}_{pm} | q, p)$. This bias would cause an uneven number of sampled trajectories per mode during RL, thereby preventing a fair, controlled comparison of answer quality between the two modes under identical conditions. Such a comparison is a prerequisite for learning an optimal selection policy. Thus, we introduce a prefix-forced sampling strategy. For each input (q, p) during RL rollouts, we sample a total of $2n$ trajectories, explicitly enforcing a balanced

distribution:

$$\begin{aligned} \{y_{gm}^{(i)}\}_{i=1}^n &\sim \pi_\theta(\cdot | q, p, \text{pfx}_{gm}), \\ \{y_{pm}^{(i)}\}_{i=1}^n &\sim \pi_\theta(\cdot | q, p, \text{pfx}_{pm}). \end{aligned} \quad (5)$$

This provides a fair and controlled reference for learning the mode-selection policy $\sigma_\phi(m | q, p)$ in subsequent optimization.

Dual-Mode Advantage Decomposition. Standard GRPO typically computes relative advantages only within a single group of sampled responses and cannot directly reflect quality differences between two reasoning modes. Thus, with the balanced samples, our DualGRPO computes advantages for policy updates using two levels of comparison. Concretely, for the same input (q, p) , let the sampled rewards under the general mode be $\mathcal{R}_{gm} = \{r_{gm}^{(i)}\}_{i=1}^n$ and similarly for the personalized mode $\mathcal{R}_{pm} = \{r_{pm}^{(i)}\}_{i=1}^n$. Let their means be $\mu_m = \frac{1}{n} \sum_{i=1}^n r_m^{(i)}$, we have:

- **Intra-mode advantage.** We compute within-mode relative advantages by centering each sample reward with the mode-specific mean:

$$A_{m,i}^{\text{intra}} = r_m^{(i)} - \mu_m, \quad m \in \{gm, pm\}. \quad (6)$$

- **Inter-mode advantage.** To reflect which mode is more suitable for the current input, we compare the two mode means and assign an opposing (zero-sum) signal across modes:

$$A_{m,i}^{\text{inter}} = \mu_m - \mu_{\bar{m}}, \quad \bar{m} \neq m, \quad m, \bar{m} \in \{gm, pm\}. \quad (7)$$

Intuitively, if $\mu_m > \mu_{\bar{m}}$, samples from mode m receive a positive shift, while samples from the other mode are penalized, encouraging adaptive mode selection.

- **Composed advantage.** The final advantage adds the within-mode and cross-mode components:

$$A_{m,i} = A_{m,i}^{\text{intra}} + A_{m,i}^{\text{inter}}, \quad m \in \{gm, pm\}. \quad (8)$$

The combined advantage signal allows the policy to be updated toward choosing the mode that yields higher expected reward, thereby optimizing the joint objective in Eq. (4).

Furthermore, to facilitate mode switching, we apply prefix strengthening by amplifying the advantage of prefix tokens by a factor $\beta > 1$, namely $\beta \cdot A_{m,i}^{\text{pfx}}$, which in turn scales their contributions to the policy gradient. This mitigates the vanishing influence of early tokens in long reasoning trajectories, increases the effective learning signal for p_m , and accelerates the acquisition of a context-dependent mode selection policy.

4 Experimental Setup

This section details the experimental setup for evaluating PersonaDual. We first describe the model training, then introduce baselines for comparison, and finally outline the evaluation datasets and metrics.

Training Details. We implement the proposed PersonaDual using Qwen3-8B-Instruct³ (Yang et al., 2025). Our two-stage training utilizes a custom dataset PersonaDualData constructed by sampling from the general-purpose objective datasets UltraMedical (Zhang et al., 2024) and FLAN (Wei et al., 2022) alongside the personalization dataset AlignX (Li et al., 2025a). PersonaDualMode comprises 8,000 examples for SFT and 9,998 examples for RL. For objective tasks, we create two persona conditions: (1) Unaligned personas are randomly sampled from PersonaHub (Ge et al., 2024); (2) Aligned personas are relevant persona descriptions generated by GPT-4o (Hurst et al., 2024) based on the question content. More details of experiments are provided in Table 5 and Appendix B.

Baselines. We select three categories of models as baselines for comparison: (1) **General purpose models.** **Qwen3-8B-Instruct** and **Llama-3.1-8B-Instruct** (Dubey et al., 2024) serve as strong instruction-following baselines. **CoT** is obtained through a two-stage training procedure with chain-of-thought supervision. **G-SFT-RL** is trained to improve the backbone’s objective reasoning capability. (2) **Personalization oriented models.** **Personal-Prompt** performs personalization alignment through prompting. **P-SFT-RL** is trained to enhance the backbone’s personalization capability. **ALIGNXPERT-ICA** (Li et al., 2025a) and **ALIGNXPERT-PBA** (Li et al., 2025a) perform large-scale persona alignment through in-context alignment and preference-based alignment, respectively. (3) **Dual-mode models.** **PersonaDual-Prompt** implements PersonaDual through prompting-based mode control. **PersonaDual-Router** realizes PersonaDual by employing an external router to switch between response modes.

Evaluation. We construct a comprehensive evaluation suite covering both objective and subjective scenarios, as summarized in Table 7. (1) **For objective tasks**, we include: PubMedQA (Jin et al.,

³the non-thinking variant of Qwen3-8B

Model	Objective Acc. (Unalign./Align.)						Personalized Acc. (Align.)		
	PubMedQA	TriviaQA	MMLU-Pro	SuperGPQA	MATH500	Avg.	P.FB. ⁴	F.RP. ⁵	Avg.
<i>General purpose Models</i>									
Qwen3-8B-Instruct	0.376/0.438	0.317/0.432	0.634/0.687	0.309/0.323	0.664/0.774	0.460/0.531	0.733	0.685	0.709
Llama3.1-8B-Instruct	0.400/0.492	0.400/0.462	0.409/0.460	0.187/0.194	0.443/0.458	0.368/0.413	0.586	0.613	0.600
CoT*	0.445/0.534	0.438/0.500	0.606/0.637	0.317/0.316	0.764/0.776	0.514/0.553	0.740	0.787	0.764
G-SFT-RL*	0.491/0.538	0.432/0.504	0.617/0.643	0.321/0.330	0.772/0.778	0.527/0.559	0.658	0.720	0.689
<i>Personalization oriented Models</i>									
Personal-Prompt*	0.359/0.446	0.252/0.349	0.488/0.539	0.287/0.313	0.353/0.386	0.348/0.407	0.741	0.695	0.718
P-SFT-RL*	0.349/0.390	0.351/0.446	0.576/0.653	0.310/0.330	0.669/0.696	0.451/0.503	0.738	0.762	0.750
ALIGNXPERT-ICA*	0.380/0.439	0.319/0.431	0.596/0.655	0.311/0.325	0.645/0.770	0.450/0.524	0.733	0.686	0.710
ALIGNXPERT-PBA*	0.371/0.437	0.321/0.431	0.592/0.653	0.318/0.332	0.659/0.768	0.452/0.524	0.731	0.684	0.708
<i>Dual-mode Models</i>									
PersonaDual-Prompt*	0.348/0.433	0.335/0.431	0.576/0.630	0.296/0.330	0.733/0.756	0.458/0.516	0.746	0.735	0.741
PersonaDual-Router*	0.473/0.419	0.438/0.504	0.600/0.644	0.296/0.330	0.775/0.786	0.516/0.537	0.735	0.767	0.751
PersonaDual*	0.508/0.549	0.449/0.515	0.622/0.657	0.331/0.347	0.790/0.808	0.540/0.575	0.747	0.799	0.773
No-Persona Upperbound	0.526	0.449	0.633	0.338	0.791	0.547	-	-	-

Table 1: Performance on objective and personalized benchmarks. For objective datasets, each entry reports accuracy under Unaligned/Aligned persona settings. Personalized benchmarks are evaluated under the Aligned setting. Reported numbers are averaged over three runs. Avg. denotes the mean accuracy across datasets within each block. **Bold** indicates the best performance on each benchmark (evaluated under the corresponding setting). Models marked with * are trained (or constructed via prompting) based on Qwen3-8B-Instruct.

2019), TriviaQA (Joshi et al., 2017), MMLU-Pro (Wang et al., 2024), SuperGPQA (Du et al., 2025) and MATH500 (Hendrycks et al., 2021), covering multiple-choice question answering, open-domain factual QA, and mathematical problem solving. (2) **For subjective personalization**, we have PersonaFeedback (Tao et al., 2025) and FSPO-roleplay (Singh et al., 2025), where models must select the preferred response from a pair of candidates based on a given persona. Most tasks are framed as classification tasks with structured outputs, allowing accuracy to be computed as the evaluation metric. For TriviaQA, we adopt the open-domain setting without provided evidence and evaluate answer correctness via exact match. For PubMedQA and MATH500, we employ GPT-4o-mini (Achiam et al., 2023) as an automated judge to first extract the concise answer and then verify its correctness.

5 Experiment Results

This section presents a comprehensive evaluation of PersonaDual, structured around several research questions. We begin with overall performance comparisons (RQ1–RQ3), followed by detailed ablation and mechanism analyses (RQ4–RQ6) to validate the design and interpret the behavior of PersonaDual.

5.1 Main Results

Table 1 summarizes the overall performance of PersonaDual and all baselines on the benchmarks. Our

analysis centers on three key research questions:

RQ1: Can PersonaDual handle the dual-edged effects of personalized information? PersonaDual successfully balances the influence of personalized information. When persona cues are **misaligned**, it effectively filters out interfering signals, achieving an average objective accuracy of 54.0%, which closely matches the no-personalization upper bound (54.7%). This shows that the model learns to screen and disregard irrelevant personalization. Meanwhile, when persona is **aligned** with the question, PersonaDual exploits these beneficial cues to improve factual accuracy, outperforming the no-personalization upper bound by 2.8% overall. These results indicate that our approach not only resists harmful interference but also actively leverages useful personalized signals to enhance answer quality.

RQ2: Can PersonaDual achieve balanced excellence in both general and personalized reasoning? As shown in Table 1, general-purpose models, e.g., CoT and G-SFT-RL, achieve top rankings on objective tasks but perform poorly on personalized ones. Conversely, personalization-oriented models exhibit the opposite trend, excelling in personalization at the cost of objective accuracy. **PersonaDual successfully bridges this gap: it matches the strong objective performance of general-purpose models while simultaneously outperforming personalization-focused models**

Stage	Model	Objective		Personalized
		Unalign.	Align.	Align.
SFT	PersonaDual-SFT	52.4	55.3	74.4
	PersonaDual	54.0	57.5	77.2
RL	w/o DualAdv	53.3	55.9	75.5
	w/o DualAdv + PfxSmp	53.6	56.1	76.9

Table 2: Stage-wise comparison and RL ablations of PersonaDual.

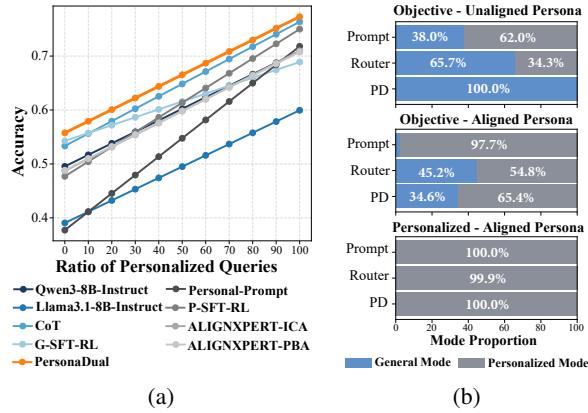


Figure 3: (a) Performance comparison under mixed task settings with varying personalization ratios. (b) Comparison of mode proportions in dual-mode models. PD is short for PersonaDual.

on personalized tasks, thereby achieving the best overall balance. To further assess robustness in realistic settings, we construct mixed test sets with varying proportions of personalized queries, as shown in Figure 3a. PersonaDual consistently outperforms both model families across all mixing ratios, validating its advantage in comprehensive scenarios.

RQ3: Does PersonaDual’s success stem from learning to switch modes appropriately? The results in the Dual-mode Models section of Table 1 show that PersonaDual achieves the best overall performance across all benchmarks. To understand this advantage, we analyze the models’ mode-selection behavior. As shown in Figure 3b, prompt-based and router-based baselines often activate the personalized mode inappropriately. For example, under misaligned persona settings, they still select personalized reasoning for 62.0% and 34.3% of objective instances, respectively. This indicates that hand-designed prompts or heuristic rules fail to distinguish beneficial from harmful personalization signals. In contrast, **PersonaDual learns mode**

selection through training, resulting in more stable and reasonable switching across different contexts.

5.2 RQ4: Why is DualGRPO necessary for PersonaDual?

Value over SFT Table 2 shows that after RL training with DualGRPO, performance improves under both aligned and unaligned persona settings. The gain is more pronounced when personas are aligned (+2.2% on objective tests) than when they are unaligned (+1.6%). This indicates that DualGRPO specifically enhances the model’s ability to identify beneficial persona cues and select the correct reasoning mode, thereby leveraging helpful personalization to boost objective accuracy.

Ablation on DualGRPO Components Table 2 also shows that DualGRPO consistently outperforms ablated variants. Notably, we find that prefix-forced sampling (PfxSmp) and dual-mode advantage decomposition (DualAdv) are tightly coupled. Removing prefix constraints causes rollouts to collapse into a single mode, making mode-aware credit assignment impossible. Conversely, without DualAdv, forced prefixes lack explicit credit guidance, preventing effective exploration. Thus, DualGRPO is necessary to enable flexible, context-aware mode selection, which is critical when persona information varies.

5.3 RQ5: What signals does PersonaDual use for mode selection?

Lexical Analysis via Predictive Tokens To quantify how user information influences mode selection, we fit a logistic regression model on 2,500 randomly sampled instances, predicting the chosen mode from input tokens. By extracting the top-30 tokens with the greatest predictive influence, as shown in Figure 5, we observe a clear pattern: occupational and professional terms, such as *historian*, *professor*, *students*, and *mathematician* appear most frequently. This indicates that descriptions of a user’s professional background serve as primary lexical signals for adaptive mode selection.

Internal Validation through Attention Patterns We further validate this finding by examining the model’s internal attention mechanisms. For the same query, we provide an aligned persona and an unaligned persona, then compare attention weights across persona tokens. As illus-

⁴short for PersonaFeedback

⁵short for FSPO-roleplay

Task Type	Task Name	Deviation Ratio (%)
Objective	MATH500	60.53
	MMLU-Pro	38.86
	PubMedQA	68.63
	SuperGPQA	30.73
	TriviaQA	28.02
Personalized	PersonaFeedback	7.00
	FSPO-roleplay	3.00

Table 3: Mode deviation ratio grouped by task type.

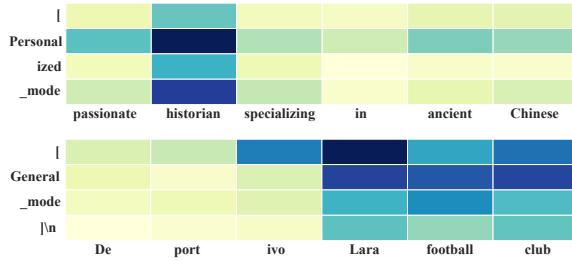


Figure 4: Attention heatmap visualizing which persona keywords influence mode selection in PersonaDual. Darker colors indicate higher attention weights.

trated in Figure 4, both the [General_mode] and [Personalized_mode] attend most strongly to tokens such as *historian* and *football* in the persona description. This consistency confirms that occupational and interest-related tokens are central to the model’s reasoning process, directly linking these cues to the dual-edged effect of personalization on objective and subjective tasks.

5.4 RQ6: How robust is PersonaDual in multi-turn dialogues?

Analysis of Overall Deviation Pattern To evaluate the robustness of PersonaDual in mixed question answering scenarios, we reconstruct the test set into two-turn conversations. This simulates real-world scenarios where users interleave different question types. Specifically, we construct two dialogue orders: (1) general -> personalized and (2) personalized -> general. We then define the mode-alignment rate as whether the mode selected in the second turn matches the mode chosen for the same question in a single-turn setting. The results reveal a clear asymmetry: when the first turn uses the personalized mode, PersonaDual maintains perfect consistency (100% mode-alignment rate). However, when starting with the general mode, the mode-alignment rate decreases to 84.3%. This indicates that switching from objective to personalized reasoning is a more challenging scenario

for adaptive mode selection.

Analysis of Deviation Source To further understand the source of these deviations, we analyze the shifted cases by task type in Table 3. Mode shifts occur far more frequently on objective datasets than on personalization datasets. A plausible explanation is that, under the influence of a preceding objective turn, the model tends to rely more on superficial task-type cues while paying less attention to the relevance between the personalized information and the current query. This heuristic can lead to a mode choice that differs from the single-turn optimum. To address this, future work could incorporate multi-turn training data, enabling more flexible mode switching and enhancing robustness in mixed dialogues.

6 Conclusion

To address the adverse impact of personalized information on the objectivity and factual accuracy of LLM responses, we propose PersonaDual, a framework that enables adaptive switching between general-purpose objective reasoning and personalized reasoning. PersonaDual unifies both reasoning modes within a single model via supervised fine-tuning, and further employs reinforcement learning with our proposed DualGRPO algorithm to enhance the model’s ability to select the appropriate reasoning mode conditioned on the input context. Extensive experiments demonstrate that PersonaDual consistently achieves strong performance across diverse personalization settings and task scenarios. It effectively mitigates interference caused by misaligned personalized information, achieving performance close to an interference-free setting, while simultaneously exploiting aligned personalized information to improve objective question answering by nearly 3% over the no-personalization upper bound.

Limitations

Our evaluation of personalization is limited by the availability of persona-related benchmarks, and currently relies on PersonaFeedback and FSPO-roleplay. Expanding to more diverse personalization benchmarks remains an important direction for future work. In addition, PersonaDual is mainly trained and evaluated in English, and extending the framework to multilingual settings is left for future exploration.

Ethics Statements

We discuss two ethical considerations of our study. First, as described in Sec 4 and Appendix B, all personas and evaluation data are obtained from publicly available resources or are synthetically generated for research purposes. Hence, our experiments do not involve private user data and comply with standard privacy and security regulations. Second, our work studies LLM’s performance under persona-conditioned inputs. A key risk is that persona cues may encode social identity signals, which can trigger stereotypes or yield group-differentiated responses. Such effects may amplify unfairness or produce overconfident yet incorrect outputs when personas are irrelevant or misleading. PersonaDual is explicitly designed to reduce this interference by adaptively selecting an objective reasoning mode when persona information is unhelpful.

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Appendix

A Effect of Personalized Information on Model Performance

To systematically investigate the impact of personalized information on the performance of large language models, we evaluate different types of LLMs: general-purpose LLMs (DeepSeek-R1 and Qwen3-30B-A3B-Thinking) and personalized LLMs (ALIGNXPERT-ICA and ALIGNXPERT-PBA). The evaluation is conducted on both objective tasks (PubMedQA and TriviaQA) and subjective personalized tasks (PersonaFeedback and FSPO-roleplay). In addition, we design different personalized information input scenarios, including no user information, user background irrelevant to the query, and user background relevant to the query, to examine how different types of personalized information affect model performance. The experimental results are shown in Table 4.

B Detailed Implementations

B.1 Details on Training Datasets Construction

SFT Datasets Construction. For the personalized task, we use all trajectories in Personalized mode. For the objective task, we do not simply force all trajectories into General mode. Instead, we conduct a gain-based selection: a trajectory remains in Personalized mode only if incorporating persona information helps the model generate the correct answer. Otherwise, for samples where persona information is misleading or provides no clear benefit, we generate trajectories in General mode. This strategy aims to allow the model to leverage persona information when it can improve objective question answering, while avoiding factual errors or logical biases that may arise from inappropriate use of persona.

RL Datasets Construction. For the RL stage, we continue to sample data from UltraMedical, FLAN,

Type	Benchmark	Model	Persona Setting		
			No persona	Unaligned persona	Aligned persona
Objective	PubMedQA	DeepSeek-R1	0.452	0.345	0.426
		Qwen3-30B-A3B-Thinking	0.444	0.385	0.472
		ALIGNXPERT-ICA	0.368	0.385	0.480
	TriviaQA	ALIGNXPERT-PBA	0.521	0.389	0.495
		DeepSeek-R1	0.654	0.624	0.615
		Qwen3-30B-A3B-Thinking	0.585	0.563	0.580
Personalized	PersonaFeedback	ALIGNXPERT-ICA	0.470	0.398	0.464
		ALIGNXPERT-PBA	0.470	0.400	0.461
		DeepSeek-R1	0.520	0.502	0.785
	FSPO-roleplay	Qwen3-30B-A3B-Thinking	0.515	0.506	0.730
		ALIGNXPERT-ICA	0.538	0.522	0.609
		ALIGNXPERT-PBA	0.524	0.533	0.649
	DeepSeek-R1	DeepSeek-R1	0.592	0.625	0.738
		Qwen3-30B-A3B-Thinking	0.653	0.602	0.759
		ALIGNXPERT-ICA	0.590	0.535	0.637
	AlignX	ALIGNXPERT-PBA	0.600	0.528	0.662

Table 4: The double-edged effect of personalized information

and ALIGNX to construct the RL training set. For the objective datasets UltraMedical and FLAN, we construct the training data with an equal proportion of unaligned personas and aligned personas, to balance the two personalized information settings encountered by the model during training.

Stage	Type	Dataset	Reasoning Trajectory	
			Objective	Personalized
SFT	Objective	UltraMedical	270	1,730
		FLAN	1,181	2,819
	Personalized	AlignX	–	2,000
RL	Objective	UltraMedical	3,000	
		FLAN	5,998	
	Personalized	AlignX	1,000	

Table 5: The dataset composition of the PersonaDual training set PersonaDualMode. To avoid data leakage, samples overlapping with PubMedQA are filtered out from UltraMedical, and samples overlapping with TriviaQA are filtered out from FLAN.

B.2 Training Details

The training hyperparameters of PersonaDual are summarized in Table 6. For the RL stage, we set the "#Rollouts per Sample" to 8, which corresponds to $n = 4$ in Equation 5. That is, for each sample, we enforce prefix sampling to generate four responses under the objective reasoning mode and four responses under the personalized reasoning mode. In addition, we set the "#Prefix advantage weight coefficient" to 2.0, meaning that during gradient updates, the contribution of the prefix tokens

is amplified by a factor of two. Intuitively, the advantage scores computed for the prefix portion are multiplied by 2.0.

Stage 1 (SFT)	Value
Model Initialization	Qwen3-8B-Instruct
Global Batch Size	16
Peak Learning Rate	5e-5
Learning Rate Scheduler	Cosine
Training Epochs	1
Warm-up Ratio	0.01
Max Sequence Length (SFT)	4096
Numerical Precision	bfloat16
GPU Usage	8 NVIDIA A800
DeepSpeed Configuration	ZeRO-3

Stage 2 (RL)	Value
Model Initialization	Stage 1
Global Batch Size	64
Peak Learning Rate	1e-6
Learning Rate Scheduler	Linear
Training Epochs	5
Warm-up Ratio	0.1
Max Prompt Length	2048
Max Response Length	1024
KL Penalty Coefficient	0.04
Generation Temperature	0.6
# Rollouts per Sample	8
# Prefix advantage weight coefficient	2.0
Numerical Precision	bfloat16
GPU Usage	8 NVIDIA A800
DeepSpeed Configuration	ZeRO-3

Table 6: Two-stage training hyperparameters of PersonaDual.

Dim.	Benchmark (Domain)	N	Type
Obj.	MMLU-Pro (General reasoning)	1,000	MCQ
	SuperGPQA (General reasoning)	1,000	MCQ
	TriviaQA (General reasoning)	1,000	Free-form
	PubMedQA (Medicine)	1,000	Free-form
	MATH500 (Math)	500	Math sol.
Pers.	PersonaFeedback (Personalized QA)	1,000	MCQ
	FSPO-roleplay (Personalized QA)	1,500	MCQ

Table 7: Evaluation benchmarks for objective and personalized capabilities.



Figure 5: Extracted keywords from personas

B.3 Evaluation Datasets

In this work, we evaluate our method on seven datasets (shown in Table 7) across two types of scenarios: objective tasks and subjective personalized tasks. Below, we briefly describe the datasets used.

MMLU-Pro. A professional subset of the Massive Multitask Language Understanding benchmark, covering multiple domains such as history, law, and social sciences. It evaluates general reasoning skills using multiple-choice questions.

SuperGPQA. A large-scale question-answering dataset focusing on general knowledge and reasoning across diverse topics. The questions are presented in multiple-choice format to assess the model’s objective problem-solving ability.

TriviaQA. A dataset of open-domain trivia questions, requiring factual knowledge and reasoning. The questions are free-form, allowing models to generate natural language answers.

PubMedQA. A biomedical question-answering dataset derived from PubMed abstracts, focusing on professional medical knowledge. The questions are free-form, testing the model’s ability to provide concise, domain-specific answers. Since our baselines include Llama3-8B-Instruct, which primarily operates in English, we translate the original Chinese PersonaFeedback dataset into English to ensure a fair and consistent comparison across models.

MATH500. A dataset of mathematical prob-

lems designed to evaluate quantitative reasoning and problem-solving skills. The problems require step-by-step solutions and are presented in free-form.

PersonaFeedback. A personalized QA dataset providing user personas and preference pairs. The model must choose answers that best align with the given persona, using multiple-choice questions.

FSPO-roleplay. Similar to PersonaFeedback, this roleplay-based dataset provides user personas and response preferences. The model selects answers that reflect the persona's preferences in multiple-choice format.

C Further Discussion for PersonaDual Upperbound

Table 8 reports the upper bound performance of PersonaDual, where an instance is considered correct if either the objective reasoning mode or the personalized reasoning mode produces a correct answer. We observe that PersonaDual already surpasses the performance of using a single reasoning mode on most datasets in the table. This indicates that the current adaptive mode selection mechanism is effective. Moreover, the upper bound is substantially higher than that of any single mode, suggesting significant potential for the PersonaDual paradigm.

Model	Objective Acc. (Unalign./Align.)						Personalized Acc. (Align.)		
	PubMedQA	TriviaQA	MMLU-Pro	SuperGPQA	MATH500	Avg.	P.FB.	F.RP.	Avg.
PersonaDual-general	0.509/0.524	0.445/ 0.520	0.624/ 0.666	0.332 /0.326	0.788/0.802	0.540/0.568	0.722	0.794	0.758
PersonaDual-personal	0.517 /0.537	0.441/0.518	0.627 /0.649	0.322/0.344	0.790/0.792	0.539/0.568	0.740	0.823	0.782
PersonaDual	0.508/ 0.549	0.449 /0.515	0.622/0.657	0.331/ 0.347	0.790 / 0.808	0.540 / 0.575	0.747	0.799	0.773
PersonaDual Upperbound	0.622/0.613	0.493/0.570	0.696/0.717	0.408/0.415	0.855/0.846	0.615/0.632	0.776	0.847	0.812

Table 8: Upperbound of PersonaDual. Objective benchmarks report accuracy under Unaligned/Aligned persona settings (Unalign./Align.). Personalized benchmarks are evaluated under the Aligned setting. Avg. denotes the mean accuracy across datasets within each block.