Benchmarking and Improving LLM Robustness for Personalized Generation

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Abstract

Recent years have witnessed a growing interest in personalizing the responses of large language models (LLMs). While existing evaluations primarily focus on whether a response aligns with a user's preferences, we argue that factuality is an equally important yet often overlooked dimension. In the context of personalization, we define a model as robust if its responses are both factually accurate and align with the user preferences. To assess this, we introduce PERG, a scalable framework for evaluating robustness of LLMs in personalization, along with a new dataset, PERGData. We evaluate fourteen models from five different model families using different prompting methods. Our findings show that current LLMs struggle with robust personalization: even the strongest models (GPT-4.1, LLaMA3-70B) fails to maintain correctness in 5% of previously successful cases without personalization, while smaller models (e.g., 7B-scale) can fail more than 20% of the time. Further analysis reveals that robustness is significantly affected by the nature of the query and the type of user preference. To mitigate these failures, we propose Pref-Aligner, a two-stage approach that improves robustness by an average of 25% across models. Our work highlights critical gaps in current evaluation practices and introduces tools and metrics to support more reliable, user-aligned LLM deployments. We open-source our code and datasets at: https://github.com/MichiganNLP/Benchmark_Improve_LLM_Robustness_in_Personalization

1 Introduction

Recent discourse on pluralistic AI (Bai et al., 2022; Gordon et al., 2022; Sorensen et al., 2024a,b) highlights the need for language models that can respect, represent, and respond to a wide range of human values and perspectives. In response, an emerging line of research has examined large language models' (LLMs) ability to steer toward personalization (Dudy et al., 2021; Hwang et al., 2023; Wang et al., 2024a; Lee et al., 2024; Ge et al., 2024; Pitis et al., 2024; Zhao et al., 2025; Zollo et al., 2025). While these efforts represent meaningful progress toward more personalized AI systems, they primarily assess whether model responses align with user traits or inferred intent: such a focus on alignment may overlook a critical aspect of factual correctness (Figure 1). A response may appear well-personalized yet still convey inaccurate or un-

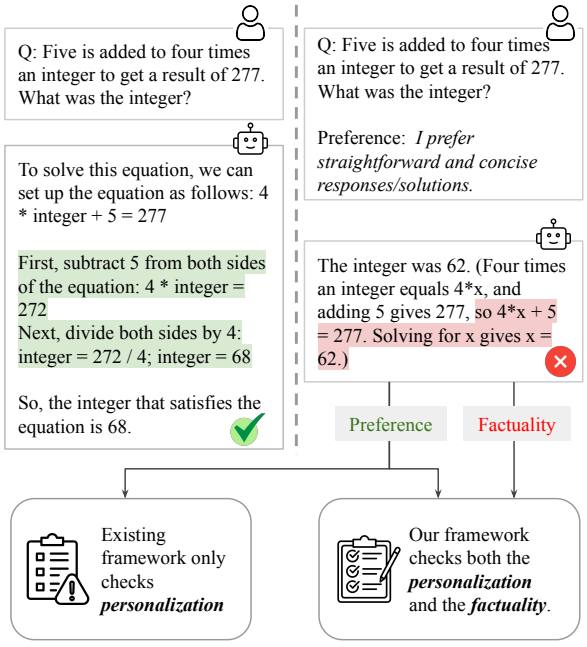

Figure 1: In contrast to the existing personalization evaluation, we consider both the personalization and the factuality of the response. The example is from Mistral $7B_{Instruct}$ (Jiang et al., 2023). When prompted with certain preferences, the model's response aligns with the user preference, but fails the question as the preference affects the model's reasoning.

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supported information. Without jointly evaluating personalization and factual grounding, current approaches risk overestimating model reliability and downstream utility. To explore the potential trade-off between factuality and personalization, this paper raises an important question:

> *"When provided with user preferences, does the model compromise factuality in its response to meet personalization?"*

To answer this question, we introduce the concept of robustness in personalization and define a robust LLM as one that satisfies two criteria: (1) It maintains factual accuracy when conditioning on relevant user preferences; and (2) Its factual accuracy is not compromised when both relevant and irrelevant preferences are present. Here, relevant preferences are those that meaningfully pertain to a question, q (e.g., favoring concise answers for a definition task), and irrelevant preferences are semantically unrelated to q (e.g being a vegan has nothing to do with a question on the definition of NLP). We formally define the concept of robustness and introduce a scalable evaluation pipeline for **P**ersonalized **E**valuation of **R**obustness in **G**eneration (PERG), along with a scalable evaluation pipeline and a dataset called PERGData, designed to systematically assess LLM robustness when adapted to user preferences. Additionally, we propose four complementary metrics to evaluate response robustness in personalization.

We conduct experiments across fourteen models and four prompting methods to evaluate the current state of robustness in LLMs. Our results show that these models are not robust: even the strongest open-weight model we evaluate (LLaMA3-70B) fails in 5% of the previously correct cases, while smaller models (e.g., Mistral-7B) can fail over 25%. Commercial LLMs such as GPT-4.1, GPT-4.1-mini, and GPT-4o-mini are not exempted, as we observe a failure rate of $5.0\%, 5.1\%$, and 11.5% respectively, suggesting a large room for improvement. Our analysis reveals the significant impact of preference categories on robustness. Questions requiring complex reasoning, preferences that prioritize conciseness, can inadvertently truncate necessary reasoning steps, leading to factual errors. In addition, we introduce a Pref-Aligner agentic framework that decouples personalization from generation and shows an average of 20% increase in robustness across models. Our work highlights the critical gaps in current evaluation practices and introduces tools and metrics to support more reliable, user-aligned LLM deployment.

In summary, our contributions are several-fold:

1. To the best of our knowledge, we are the first to explicitly conceptualize and formally define robustness in the context of personalization.
2. We introduce PERG, a scalable evaluation pipeline and dataset, along with four complementary evaluation metrics for robustness.
3. We conduct extensive experiments to characterize the robustness of current state-of-the-art LLMs under personalization.
4. We propose Pref-Aligner, a two-stage solution to improve the robustness of models and show an average of 25% performance improvements across models.

2 Related Work

LLM Personalization and Evaluation. There is an increasing demand for personal AI assistants, which answer questions and understand the user (Citron, 2025). LLMs, especially the commercial LLMs nowadays, often allow users to share personal preferences and include them as part of the user prompts to tailor the LLMs' response for each user (OpenAI, 2023; Citron, 2025; Anthropic, 2025). Prior research has explored personalization across various dimensions, including demographics, preferences, contexts, values, profiles, and opinions (Welch et al., 2020; Hwang et al., 2023; Richardson et al., 2023; Pitis et al., 2024; Obi et al., 2024; Zhang, 2024; Zhao et al., 2025). Salemi et al. (2024) introduce the LAMP benchmark to measure a model's ability to adapt to user behaviors and writing styles. Wang et al. (2024a) propose PerSE, a framework for evaluating alignment with specific user preferences. More recently, (Zhao et al., 2025) evaluate LLMs' ability to infer and follow both implicit and explicit user preferences, propose "preference-following" accuracy as a metric for their evaluations. These works primarily adopt a one-dimensional perspective focused on measuring alignment with user preferences. In contrast, our work jointly evaluates whether models can preserve factual correctness while adapting to user preferences. A comparison of our framework with prior work is presented in Table 1.

LLM Robustness. Past work views robustness as the ability of models to maintain performance un-

Feature / Dimension	LaMP (2024)	PrefEval (2025)	PERG (Ours)
Target	Writing behaviors	Implicit and explicit user preferences	Explicit user preferences
Factual?	✗	✗	✓
Preference?	✓	✓	✓
Irrelevant Prefs?	✗	✗	✓
Scalable?	✗	Limited	✓

Table 1: Comparison of PERG with existing personalization evaluation benchmarks. PERG is the first to consider both the personalization and factuality of the model response. We provide details of the classification criteria and distinctions in Appendix A.

der perturbations (Sun et al., 2023; Gu et al., 2023; Tam et al., 2024; Beck et al., 2024; Mizrahi et al., 2024) or adversarial attacks (Howe et al., 2024; Liu et al., 2024; Beyer et al., 2025). Recently, Jung et al. (2025) assess robustness in fairness scenarios on biases induced through adversarial prompt injection. Beck et al. (2024) evaluate LLMs' sensitivity and robustness in socio-demographic prompting. Tam et al. (2024) show LLMs are not robust to prompts that elicit structured outputs. A more recent work (Li et al., 2025) explore LLMs' robustness in safety situations, specifically assessing the safety-reasoning tradeoffs in these models. To the best of our knowledge, we are the first to evaluate LLMs' robustness in terms of maintaining factual correctness in personalizing their response.

3 Problem Formulation

In the context of generating personalized responses, we define *robustness* as the model's ability to appropriately incorporate relevant aspects of user profile information, such as preferences, demographics, values, etc, ignore irrelevant ones, while generating a factually correct answer. Formally, let x denote a user query, $P = \{p_1, p_2, ..., p_n\}$ denote an information set on user features, and M denote a language model. Given input (x, P), the model produces an output response:

$$y = M(x, P),$$

where y is conditioned jointly on the query x and the user feature set P. We define the following binary functions:

Acc$(y) = 1$ if the model's response y is factually correct with respect to x; otherwise, 0.

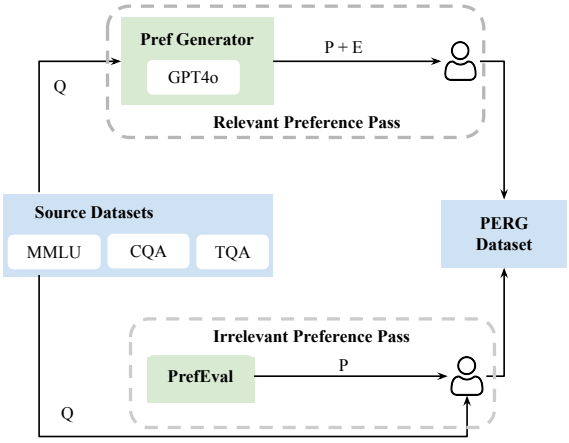


Figure 2: **PERG** curation pipeline. For each question, relevant preferences and explanations (P + E) are automatically generated, and irrelevant preferences (P) are selected from PrefEval (Zhao et al., 2025). Both relevant and irrelevant preferences are manually verified.

PrefRel$(x, P) = 1$ if there exists a feature $p_x \in P$ that is relevant to the query x; otherwise, 0. **Followed**$(y, P) = 1$ if the response y appropriately incorporates a relevant feature $p_x \in P$; otherwise, 0.

The model M is said to be *robust* iff: **(1)** Maintain factual accuracy while conditioning on the relevant $p_i \in P$ for any given query x. **(2)** Ignore irrelevant user features within the feature set P for any given query x.

$$\text{Robust}(x, P, y) = \begin{cases} \text{Acc}(y) \wedge \text{Followed}(y, P) \\ \quad \text{if PrefRel}(x, P) = 1 \\ \text{Acc}(y) \\ \quad \text{if PrefRel}(x, P) = 0 \text{ or } P = \emptyset \end{cases}$$

Table 4 in Appendix B presents the corresponding truth table used to assess robustness under various conditions.

4 Dataset Curation

In this work, we focus on one key dimension of personalization: *user preferences*. We introduce PERG, a scalable dataset curation pipeline to construct a dataset designed for LLM robustness evaluation under personalization. Figure 2 provides an overview of the dataset curation pipeline.

4.1 Source Datasets

Our formulation requires that questions have clear, factual answers independent of user preferences. We sample data from three well-established benchmarks: **MMLU** (Hendrycks et al., 2021a), **Truth-**

fulQA (Lin et al., 2022), and **CommonsenseQA** (Talmor et al., 2019), which contain objective multiple-choice questions with ground-truth answers across diverse domains (further details in Appendix D.1).

4.2 Preference Construction

Given a question q, we construct both a *relevant* preference and an *irrelevant* preference.

Relevant Preferences. We first manually curate triples of the form (question, preference, explanation), and use these as in-context examples to generate additional preferences and rationales across a broader subset of questions within each dataset category (further details in Appendix D.2). We use GPT-4o mini (OpenAI, 2024) as our preference generator. One of the authors manually reviewed these generations and retained the 35 most coherent and justifiable samples.

Irrelevant Preferences. We extract preferences from PrefEval (Zhao et al., 2025), which includes user preferences across five domains: *entertainment, shopping, travel, lifestyle, and education*. We select these as irrelevant preferences based on their lack of connection to the types of factual questions found in our evaluation datasets.

4.3 Final Dataset and Release

Our final dataset, **PERG**, contains 7,200 examples. Each instance consists of a user query with a ground-truth answer, a relevant preference accompanied by a justification. We show summary statistics and samples of the data in Appendix D We open-source the **PERG** curation pipeline data and codes to help facilitate future research in this area [1].

5 Experimental Setup

To systematically investigate how preference conditioning affects model factuality and alignment (Section 1), we propose five research questions (RQs): **RQ1:** Are LLMs robust when we include a relevant user preference? **RQ2:** How does LLMs' performance vary when there is a user preference? **RQ3:** How do different prompt methods influence robustness? **RQ4:** How robust are LLMs when both relevant and irrelevant preferences are present? **RQ5:** What types of failures do models exhibit?

[1] https://github.com/MichiganNLP/Benchmark_Improve_LLM_Robustness_in_Personalization

5.1 Models and Methods

We evaluate fourteen open and closed-source models, selected to reflect a diverse and representative range of foundation model families widely used in research and practice. Specifically, we include Mistral-7B-Instruct (Jiang et al., 2023), Mistral-8x7B-Instruct (Jiang et al., 2024), LLaMA-3(8B, 70B)-Instruct, (Touvron et al., 2023), GPT-4o-mini (OpenAI, 2024), GPT-4.1(4.1-mini) (OpenAI, 2025), DeepSeek-R1-Distill-Llama-70B (DeepSeek-AI, 2025), Janus-7B (Lee et al., 2024), Gemma-2(9B, 27B) (Team, 2024), Qwen3(8B, 32B) (Team, 2025), on our **PERG** dataset.

In addition to vanilla zero-shot prompting, we experiment with zero-shot chain of thoughts, self-critic (Huang et al., 2024), and in-context learning where we provide in-context examples of query, preference, robust response triples. We provide more details on the models along with prompting methods in Appendix E.

5.2 Evaluation Metrics

We introduce four complementary error-based metrics. Lower values (closer to zero) across all metrics indicate more robust, stable, and consistent behavior.

Breakage Rate measures how often personalization causes the model to fail on inputs that it handles correctly without any preference conditioning. Formally,

$$\text{Breakage Rate} = 1 - \mathbb{E}_{x \in Q^*}[\text{Acc}_{\text{pref}}(y)],$$

Given Q is all query set in our dataset D, then $Q^* = \{x \in Q \mid \text{Acc}_{\text{no-pref}}(y) = 1\}$, $\text{Acc}_{\text{pref}}(y)$ and $\text{Acc}_{\text{no-pref}}(y)$ are the accuracy of generating y with and without any preference, respectively.

Alignment Failure measures among examples where the model answers correctly without personalization, how often the model fails to align with user preferences. We define alignment failure as:

$$\text{Alignment Failure} = 1 - \mathbb{E}_{x \in Q^*}[\text{Followed}(y, P)].$$

Robustness Error is the union of breakage and alignment failure sets and measures how often the model either fails to answer it correctly or aligns with user preference. Formally,

$$\text{Robustness Error} = 1 - \mathbb{E}_{x \in Q^*}[\text{Robust}(x, P, y)]$$

Performance Variation measures the divergence in correctness with and without personalization. Similar to Jaccard distance (Jaccard, 1901), we define it as:

$$\text{Performance Variation} = 1 - \frac{|\mathcal{A}_{\text{pref}} \cap \mathcal{A}_{\text{no-pref}}|}{|\mathcal{A}_{\text{pref}} \cup \mathcal{A}_{\text{no-pref}}|},$$

where A_{pref} and $A_{\text{no-pref}}$ denote the sets of correctly answered questions with and without preference conditioning, respectively.

We provide further details of our evaluations in Appendix E.3.2.

6 Results

RQ1: Are LLMs robust when we include a relevant user preference?

Answer: No. In Figure 3, in terms of factuality, we highlight that the breakage rate can go as high as 26% for Mistral-7B. Even GPT-4.1 and Llama-3.3-70B-Instruct, the models with the lowest breakage rate, exhibit a breakage rate of 5%. In terms of preference alignment, Janus exhibits the worst alignment failure (16%) while most other LLMs show an alignment failure of 10% or below. Such a contrast suggests that LLMs may be better at following user preferences rather than maintaining the factuality in their response. Taking these two aspects together, the worst robustness error can reach 34% (Janus), while even the most robust model (GPT-4.1) still suffers a loss of 5%.

In addition, we find that *scaling improves robustness*. We see a 55%, 25%, 21% decrease in robustness error across different sizes of the Llama, Gemma, and Mistral models, respectively. Furthermore, *naive finetuning does might not improve robustness.* Comparing Mistral-7B to Janus-7B (Lee et al., 2024), a fine-tuned version of Mistral-7B on preferences, we observe a 8% increase in alignment failure, suggesting that naive finetuning on preference data cannot lead to robust models.

RQ2: How does LLMs' performance vary when there is a user preference?

Answer: There is a significant performance variation. Most models exhibit significant variability (> 25% performance variation in Figure 4), indicating that the presence of preference information introduces significant inconsistencies in factual performance across models. Even the relatively more robust models such as GPT-4.1, LLaMA3-70B, Gemma-2-27B, GPT-4o-mini, and Gemma-2-9B still show slight instability with performance variation above 8%.

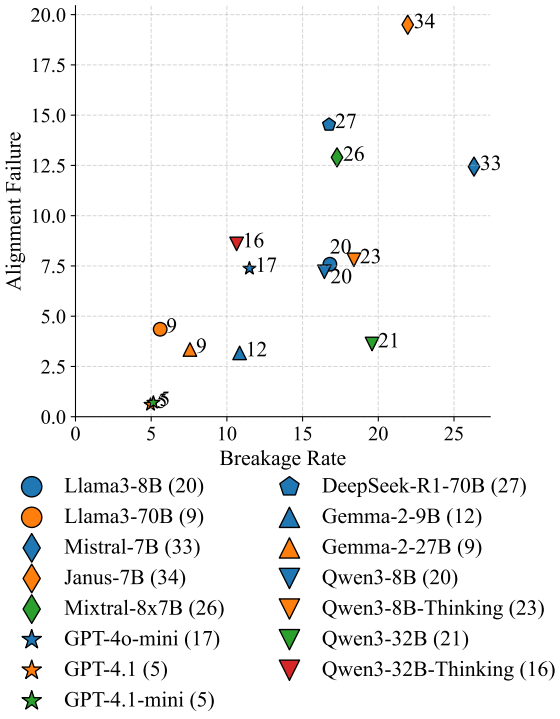


Figure 3: alignment failure vs. breakage rate. For each model, we label its robustness error score. We note that GPT-4.1, Llama3-70B, Gemma-2-(9B, 27B) (models in the bottom left) are more robust compared to Mistral-7B and Janus-7B (models in the top right).

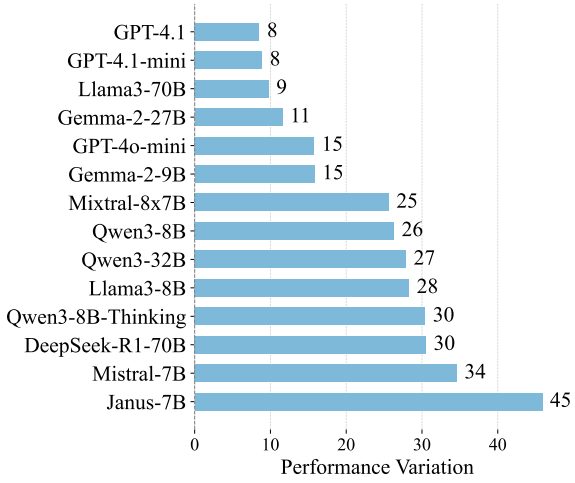


Figure 4: Performance variation when provided with relevant preferences. LLaMA3-70B exhibits the lowest performance variation, suggesting the most stable factual performance with or without preference. In contrast, Janus is highly sensitive to preference information.

RQ3: How do different prompting methods influence robustness?

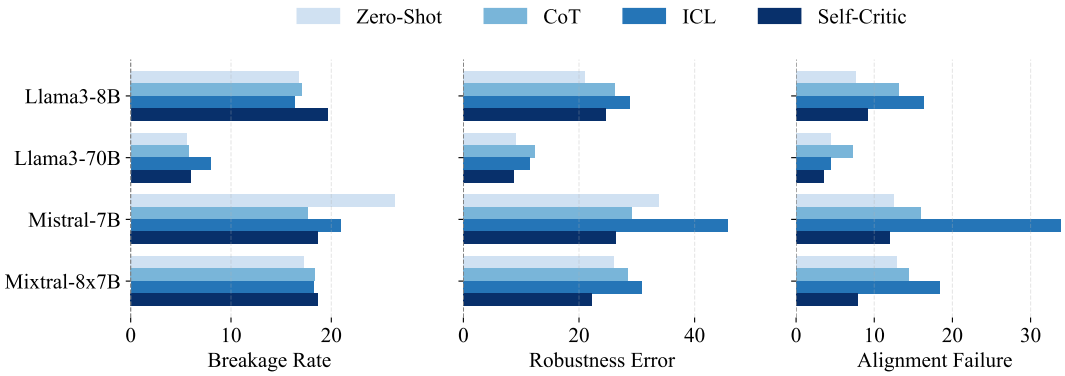
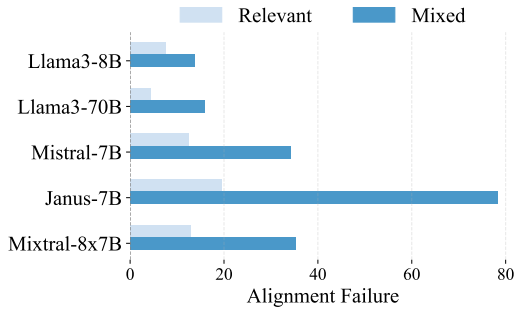


Figure 5: LLM performances under various prompting methods. The different prompting methods show mixed effects with no clear improvement over the direct zero-shot approach. This suggests that improving robustness requires more than just prompting.

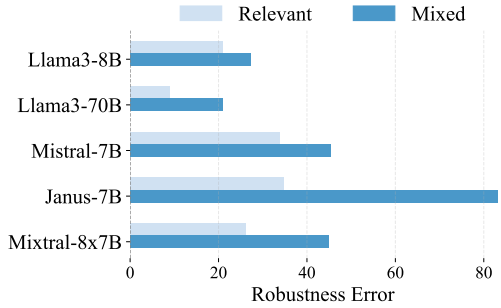
Answer: Improving robustness requires more than just prompting. In Figure 5, leveraging prompting methods such as *CoT*, *ICL*, and *self-critic* yields mixed effects across different models and robustness metrics. For some, there is a decrease in alignment failure and an increase in breakage rate or vice versa, leading to similar overall robustness as the vanilla prompting. For instance, in the case of Mistral-7B, although CoT and ICL improve breakage rate, they exhibit a relatively high alignment failure and robustness error, urging better approaches to improve overall robustness.

RQ4: How robust are LLMs when both relevant and irrelevant preferences are present?

Setup. Here we evaluate LLM robustness on a list of preferences (both relevant and irrelevant) (see Appendix E.5). We construct an irrelevant and a mixed preference setting, resembling the real-world scenarios where users specify a comprehensive set of preferences: some of which might be relevant or irrelevant depending on query, and commercial LLMs would base their answer on all of these preferences (Anthropic, 2025; Citron, 2025; Center, 2025a).



(a) alignment failure under relevant/mixed preferences



(b) robustness error under relevant/mixed preferences

Figure 6: Alignment failure and robustness error with relevant and mixed preferences. LLMs struggle to delineate between relevant and irrelevant preferences, which leads to an increase in misalignment rate.

Answer: Irrelevant preferences amplify robustness errors. Our results in Figure 6 show that the presence of irrelevant preferences amplifies alignment errors (ie, LLMs struggle to delineate between relevant and irrelevant preferences). This is evident in the substantial increase in alignment failure, leading to an increase in robustness error across all models when compared to the single relevant preference setting. Interestingly, except for the Janus model where the breakage rate increased by 20% in the presence of irrelevant preferences, other models exhibit a similar breakage rate (Figure 7). This further highlights the limitations of naive finetuning on preference data.

RQ5: What types of failures do models exhibit?

Answer: Question and preference categories significantly influence robustness. As shown in Figure 8, for questions drawn from TruthfulQA, which are often short and straightforward, pref-

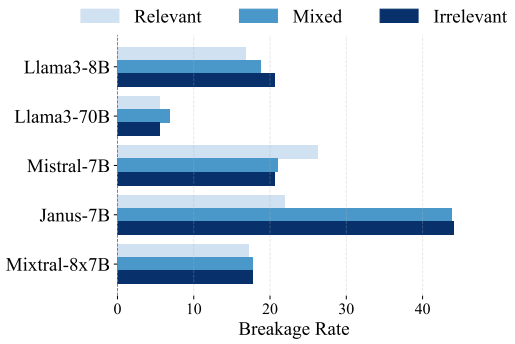


Figure 7: Breakage rate in various preference relevance levels. The presence of irrelevant preferences amplifies breakage errors for Janus and have mixed effects across other models.

Model	Method	Robustness Error (↓)
Llama3-8B	Naive Prompting	20.9
	Pref-Aligner$_{(ours)}$	**18.1**
Llama3-70B	Naive Prompting	9.0
	Pref-Aligner$_{(ours)}$	**6.5**
Mixtral-8x7B	Naive Prompting	26.1
	Pref-Aligner$_{(ours)}$	**18.9**
Gemma-2-9B	Naive Prompting	12.6
	Pref-Aligner$_{(ours)}$	**6.8**

Table 2: Robustness Error comparison between Naive Prompting (Zero-Shot) and Pref-Aligner across four models. Pref-Aligner consistently reduces robustness error across all models, achieving a minimum relative reduction of 13% (Llama3-70B) and up to 46% (Gemma-2-9B).

erences eliciting clarity and conciseness have the least breakage rate, and preferences that require contextual details or practical examples have a higher breakage rate. We conjecture that this is because context/thinking related preferences make models overthink, which leads to incorrect answers (Sprague et al., 2025). Such patterns are consistent across models (Appendix H.3 provides a more fine-grained analysis). For MMLU, we do not observe any consistent pattern, likely due to its coverage of diverse academic domains. However, we also observe cases where preferences disrupt the reasoning chain of the model, leading to factual errors in MMLU (Appendix H.3). This highlights the complexities and comprehensive scenarios covered in PERG. We provide further details on error classification in Appendix H.1.

7 Pref-Aligner: Decoupling Personalization from Generation

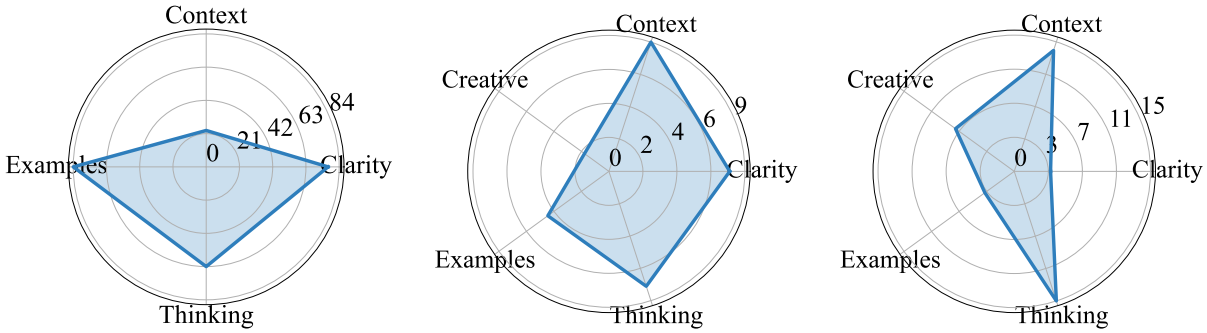
How can we systematically improve model robustness? We introduce Pref-Aligner, a two-stage agentic framework, which decouples generation from personalization with an agent specialized for each task. We draw inspiration from previous work, where an aligner model was fine-tuned to learn correctional residuals between preferred and non-preferred responses. (Ji et al., 2024)

Figure 9 shows this framework. Figure 9 shows this framework. In Stage 1, a generation agent responds to user queries without considering their defined preferences, ensuring that the base content remains factual and unaffected by preference signals. This directly addresses breakage errors, where preference information causes the model to fail on examples it originally answered correctly (see Section 6). In Stage 2, an aligner agent takes the unconditioned response and the user preference(s), and performs lightweight edits only if needed (details in Appendix C). For example, it may shorten a detailed multi-step solution to show only the final answer when a user prefers "straightforward explanations." Because this step operates as a constrained rewrite rather than a full regeneration, the risk of introducing new factual errors is greatly reduced.

This design choice is supported by findings in (Ji et al., 2024), which show that the semantic distance between an unaligned response r' and an aligned response r is smaller than that between the original query x_0 and an aligned response r. In other words, aligning an existing response is easier and more reliable than generating one from scratch that simultaneously satisfies both the query and the preference. Our results confirm this: Table 2 and Table 3 show consistent robustness gains across Llama3-8B, Llama3-70B, Mistral-8x7B, and Gemma-9B. Notably, the breakage rate for *Llama-70B* drops from 5.6% to 1.3% in relevant preference settings, and remains low in mixed and irrelevant settings, highlighting the effectiveness of our framework under diverse conditions.

8 Discussions and Lessons Learned

Preference alignment impairs instruction following. Instruction following refers to a model's ability to adhere to instructions in user prompts. The user prompt across all our evaluations clearly instructs the model to select the option that best



(a) MMLU (b) CommonsenseQA (c) TruthfulQA

Figure 8: Breakage Errors by source of question, Model: Llama3-70B. Compared to preferences related to thinking/ creative/context, preferences related to clarity are less likely to lead to factual errors for TruthfulQA questions. This behavior is consistent across different models (Appendix H.3).

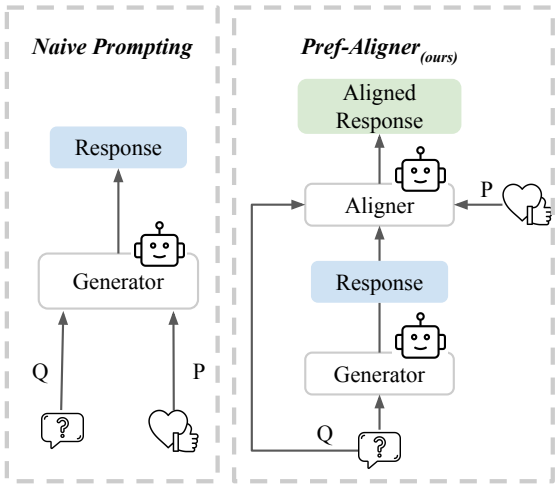


Figure 9: Our proposed framework, Pref-Aligner versus the naive prompting method. Instead of directly obtaining the response by conditioning on both query and preference (left), we propose to decouple generation from personalization (right).

Method	Relevant (↓)	Mixed (↓)	Irrelevant (↓)
Naive Prompting	5.6	6.9	5.5
Pref-Aligner$_{\text{(ours)}}$	**1.1**	**1.2**	**1.2**

Table 3: Breakage Rate: Pref-Aligner Results compared to Zero-Shot for Llama-70B in three preference relevance settings. Pref-Aligner shows significant performance improvement over naive across all settings. Also, this performance remains consistent irrespective of preference setting.

answers a given question. Consequently, we expect the model's response y to explicitly include a lettered option y'. Accuracy is then measured by extracting y' from the response and comparing it to the ground-truth choice. However, we observe that responses conditioned on user preferences, $y_{\text{conditioned}}$, are significantly less likely to include a valid option y' compared to unconditioned responses $y_{\text{unconditioned}}$. This suggests that by fixating on preference alignment, models tend to lose part of their instruction-following ability. More analysis regarding and results on this are available in Appendix F.

We need better evaluation methods. Our results have shown that current one-dimensional evaluation methods often risk overestimating model capabilities by failing to capture tradeoffs and failures that emerge across other important axes. Future work should aim to develop more comprehensive multidimensional evaluation (Pitis, 2023) frameworks across several domains, tasks, user needs, and applications. This is essential for advancing more reliable and trustworthy AI systems in real-world applications.

Enhancing base model robustness for more efficient personalization. While our Pref-Aligner presents a promising direction for improving robustness at the system level, improving base models' robustness requires deeper intervention. Future work should explore training, post-training, and inference-time strategies that explicitly optimize for robustness. To ensure reliability, these interventions should jointly consider multiple supervision signals (Roijers et al., 2013; Sutton et al., 2011; Pitis, 2023), including factual accuracy, preference alignment, etc. A possible direction is the pursuit of data-efficient methods (Sachdeva et al., 2024; Peng et al., 2023), such as training/fine-tuning on carefully curated examples that inherently emphasize robustness. We believe this form of high-quality supervision may provide a more scalable (Lv et al.,

2025) and principled pathway to improving base models robustness without requiring modification of the underlying architecture.

9 Conclusion

In this work, we conceptualized the notion of robustness for large language models (LLMs) under personalization, proposed principled metrics to evaluate it, and introduced PERG, a scalable benchmark for systematic evaluation. Through extensive experiments across several state-of-the-art models and prompting methods, we found that current LLMs are not fully robust: we showed that personalization signals, while valuable, can sometimes be totally ignored (misalignment) and/or degrade the factual reliability of model outputs (Breakage), motivating the need for more nuanced, robust evaluations. In addition to this, we introduced Pref-Aligner as an approach to improve the robustness of models. This work provides important insights into an often overlooked aspect of personalization evaluation: factual correctness, as well as provides practical insights on model selection for user-adaptive applications.

10 Limitation

In this paper, we characterize the robustness of LLMs in personalization. Our dataset spans several domains, specifically assessing preference signals that influence the truthfulness of models (TruthfulQA), common sense reasoning abilities of models (CommonSenseQA), and factual, logical, and symbolic reasoning abilities as seen in several categories of MMLU. While this covers a wide breadth of domains, we acknowledge that it does not span across every domain and aspect of possible user queries. Regardless, we show that the PERG framework in itself is scalable (Appendix D.3), allowing future work to extend beyond what we have currently covered, to other domains and settings such as free form generation (Appendix G).

The paper also covers a wide breadth of models: fourteen LLMs from five different model families - Llama, Qwen, Mistral, GPT, and Gemma. Our findings and analyses provide model behavioral insights into these models in personalization, as well as practical insights on model selection for user-adaptive applications. These insights are, however, limited to the models we evaluate. As much as we would want to, we cannot exhaust every possible model out there, especially commercial models, due to cost and resource constraints.

We focus exclusively on one aspect of personalization: user preferences conditioning, as well as limit our focus to evaluating within a multiple-choice question setting, as this offers a cost-efficient and scalable evaluation method. While this provides a controlled and meaningful testbed, personalization in practice spans many additional axes, such as user profiles, values, etc, and real-world user queries sometimes come in a free-form format, which we do not account for. Future work should explore how to make the preference aligner framework more efficient, as well as look into how robustness extends across broader dimensions of personalization beyond user preferences for multi-choice user queries.

11 Ethical Considerations

Our work focuses on evaluating robustness in personalized language generation, specifically under explicit user preferences. Unlike systems that infer preferences from user history or conversations, our framework avoids implicit modeling and relies on clearly stated, manually curated preferences. Such a setup resembles the real-world settings in modern AI assistants such as ChatGPT (Center, 2025b), Claude (Anthropic, 2025), and Gemini (Citron, 2025).

We emphasize that our benchmark does not involve any sensitive user data. The authors manually check to ensure that no preferences would induce harmful or biased personalization. We acknowledge that some commercial systems utilize models to automatically extract preferences from user conversations and then condition on those preferences, potentially introducing unintended biases. However, such a preference extraction process is beyond the scope of our study, and we would encourage future efforts on preference extraction and studying the biases associated with such a process. We highlight that the goal of our work is to evaluate and encourage systems that can robustly utilize preferences by conditioning only on relevant information when appropriate. To ensure reproducibility, we document our evaluation prompts, preference templates, and model configurations in detail in the appendix and are committed to releasing our dataset publicly. In addition, we validate the use of LLM-based evaluation through a human evaluation study.

We aim to advance safe, robust, and transpar-

ent personalization in LLMs. Importantly, our results provide actionable insights into which models are better suited for user-adaptive applications and contribute to more informed model selection and deployment decisions in real-world AI systems.

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A Details on Benchmark Comparison Criteria

Target. LaMP focuses on modeling writing behaviors and language adaptation across different user profiles, primarily through style and topic imitation. PrefEval targets implicit and explicit user preferences in recommendation-style tasks, such as travel, dietry, and lifestyle queries. In contrast, PERG is designed around explicit user preferences that accompany factual multiple-choice questions, enabling controlled evaluation of preference conditioning in a grounded setting.

Factual. LaMP and PrefEval do not evaluate factual correctness of model outputs. Their tasks are user-dependent and lack predefined ground-truth answers (PrefEval (Zhao et al., 2025) clearly highlight this as a limitation in their work). In PERG, all questions are drawn from well-established factual benchmarks, such as TruthfulQA, MMLU, and CommonsenseQA. Each question includes a gold answer, allowing us to measure factual accuracy precisely.

Preference. All three benchmarks incorporate user preference information. LaMP infers behavioral preferences from long user histories, PrefEval includes both implicit and explicit preferences, and PERG introduces carefully curated explicit preferences, each paired with a factual question.

Irrelevant Preferences. Neither LaMP nor PrefEval considers the presence of irrelevant preferences in the prompt. In contrast, PERG evaluates on both relevant and irrelevant preferences, enabling evaluation of a model's ability to distinguish and appropriately condition on relevant information. This simulates a more realistic real-world setting where user preference set often include a broad mix of preferences, not all of which are pertinent to a given query.

Scalable. LaMP is not scalable because it relies on long user histories and per-user-specific annotations, which are expensive if not almost impossible to obtain. PrefEval supports a moderate range of task types, but its evaluations remain bound to subjective or recommendation settings. PERG is built on top of public factual datasets and applies a generalizable preference-generation pipeline, making it easily extensible to any domain where factual correctness can easily be evaluated (eg. code)

B Robustness Truth Tables

Acc(y)	Followed(y, P)	Robust(x, P, y)
0	0	0
0	1	0
1	0	0
1	1	1

(a) When P contains relevant features

Acc(y)	Robust(x, P, y)
0	0
1	1

(b) When P is empty or irrelevant

Table 4: Robustness truth tables under different preference conditions. (a) and (b) correspond to relevant and irrelevant preference settings, respectively.

C Pref-Aligner

Ji et al. (2024) finetune an aligner model that learns correctional residuals between preferred and non-preferred responses, where preference in this case is in terms of the general human alignment preferences metrics (Helpfulness, Truthfulness, and Harmlessness). The aligner is stacked upon an upstream LLM, takes the upstream models' response r' to query, q, and outputs an aligned final response r. The core idea behind their approach is that the semantic space between an unaligned, r', and an aligned response, r, is closer than the semantic space between an input query x_0 to an aligned response, r. Therefore, the aligner reduces the complexity of mapping directly from input to aligned response.

Inspired by this, we follow a similar approach to improve robustness. We, however, do not train a special preference aligner, instead, we utilize two LLMs and have them communicate in an agentic fashion through prompting to produce preference-aligned responses (Figure 9). The first agent: a generator agent, provides an initial response r' to a user query q, without considering the preference set P, and passes this query along with its generation to the pref-aligner agent. The pref-aligner takes this input, along with the user preference set P, decides which preferences are relevant, if any, and produces an aligned response r. If it finds no relevant preference, the aligner simply returns r' as r.

Both generator and preference-aligner agents are the same model initializations. We highlight the generator and pref-aligner prompt templates below:

Generator Prompt Template

You are an AI assistant that provides factually accurate, unbiased, and helpful responses.

User_query: *User_query_here*

Aligner Prompt Template

You are a preference aligner agent. Your task is to adjust a given response to better reflect a specified user preference, without re-answering the original query.

You are provided with the original query, the initial response from an answering agent, and a user preference.

Only modify the response if the preference is relevant to the query or response. If the preference is irrelevant, return the original response unchanged.

Query: query

Initial Response: response

User Preference: preference

###
Return a JSON object with the following fields:
- "response": the aligned response
- "thoughts": a brief explanation of how (or whether) the response was aligned

D More on Dataset Curation

D.1 Data Selection

To evaluate how personalization impacts the correctness of LLM responses, we require datasets that have objective ground truth answers that are universal. TruthfulQA, CommonSenseQA, and MMLU satisfy this requirement. Accordingly, we extract questions and ground-truth answers from these datasets. Since preference-following is evaluated using a GPT model and the evaluation cost increases substantially with dataset size, we do not

use all 14,000 samples from the MMLU test set. Instead, we sample questions from specific MMLU categories (Figure 10), focusing on categories that demand high levels of reasoning. This selection aims to minimize the risk of personalization interfering with the model's reasoning process. See Table 5 for the percentage of each dataset category in PERG.

```
MMLU_Categories = [
    'professional_law',
    'high_school_biology',
    'professional_accounting',
    'professional_medicine',
    'high_school_mathematics',
    'high_school_microeconomics',
    'conceptual_physics',
    'marketing',
    'high_school_statistics',
    'high_school_chemistry',
    'college_medicine',
    'high_school_physics',
    'electrical_engineering',
    'college_biology',
    'anatomy','formal_logic',
    'college_physics',
    'college_mathematics',
    'abstract_algebra',
    'business_ethics',
    'college_chemistry'
]
```

Figure 10: mmlu categories

D.2 Preference Generation

We sample 100 questions from each dataset category and prompt the GPT-4o-mini model to generate a preference for each question. We require that these preferences be generic and applicable across multiple questions within the same category. This constraint ensures a clear distinction between preference conditioning and constraint-based decoding. For instance, preferring to use the substitution method to solve a simultaneous equation is a constraint rather than a preference. Figure 11 shows the full prompt used for this generation process.

After generation, we manually review the preferences for each dataset category and select those that are most generic, meaning they can apply to all questions within the category. This design choice controls for preference diversity, which could otherwise introduce confounding effects during robustness evaluation. Researchers whose experimental settings require greater preference diversity can choose to skip this downsampling step.

Prompt Template for Preference Generation

You are a helpful assistant whose sole job is to give realistic user preferences users might have for a given question. These preferences should not affect the final answer to the question but might affect how these answers are presented or explained to the user.

Here is an example:
Question - Five is added to four times an integer to get a result of 277. What was the integer?
Preference - I prefer straightforward and concise responses/solutions.
Explanation - The LLM is expected to provide a concise response, but the final answer remains the same irrespective of whether the preference is there or not.

Other preference examples include "I prefer detailed explanations."

Given a new question, your job is to provide a preference that is relevant to the question, as well as an explanation of why it is relevant.

NB: For a preference to be valid, it must meet the following criteria:
1. The preference should be relevant to other domains, not just the domain of the current question.
2. The preference should not impose a constraint — for example, instructing the model to use the elimination method for solving equations is a constraint, not a preference.

Return a JSON with keys `"preference"` and `"explanation"`.

question: `<user_question_here>`

Figure 11: Template For Preference Generation

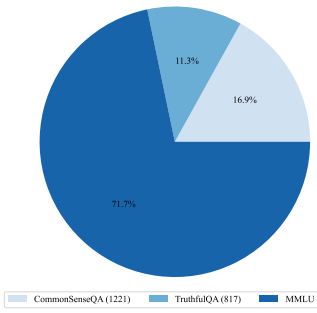


Figure 12: **Dataset Composition.(Total: 7208)** Distribution of examples across the three QA datasets used in PERG: MMLU, TruthfulQA, and CommonsenseQA.

The final PERG dataset contains 7,208 questions,

Dataset	Num Examples	Percentage in PERG (%)	Number in PERG
TruthfulQA	817	100	817
MMLU	14042	37	5170
CommonsenseQA	1220	100	1221
Total			**7208**

Table 5: Dataset Sample Size in PERG

with 11, 14, and 12 preferences used for MMLU, TruthfulQA, and CommonsenseQA, respectively. For each dataset category, the selected preferences are evenly distributed across all questions, simulating a between-subjects study design. We show in Appendix F.2 that this between-subjects design yields results consistent with a full within-subjects setup, where all preferences are applied to all questions. Table 11 provides examples of datapoints included in PERGData.

D.3 PERG is Scalable

We highlight that PERG is scalable. Our curation pipeline is highly general and can be easily adapted to additional factual evaluation datasets with minimal modification. For instance, datasets such as GPQA (Rein et al., 2023), ARC (Yadav et al., 2019), and MATH (Hendrycks et al., 2021b) offer natural extensions, supporting PERG scalability across several domains by simply pairing each new dataset with realistic, task-relevant user preferences using the human-in-the-loop AI preference generation pipeline described in Section 4. Also, it is important to emphasize that PERG is strictly intended for evaluation, not for model training or fine-tuning.

E More on Experiments

E.1 Models

Table 6 summarizes all the models evaluated in our experiments. All Hugging Face models were loaded using `torch.bfloat16` precision and inference was conducted on 2 A40 GPUs. In addition, we loaded a 4-bit quantized version of the Mixtral 8×7B model. The Janus model was introduced in (Lee et al., 2024) and is essentially a Mistral-7B base model fine-tuned on *Multifaceted-Collection* (diverse system messages), where the system messages are aggregated from various realistic user preference sets. As such, we can view Janus as a Mistral model fine-tuned on a diverse collection of user preferences. For reproducibility, we use greedy decoding with temperature zero across all models.

E.2 Prompt Methods

We extensively evaluate the robustness variation of models across several prompting strategies. In all settings, we use the same user prompt template, shown below:

> **User Prompt:** Which of the options best answers the question?
>
> **Question:** {question}
>
> **Options:**
> A. {option[1]}
> B. {option[2]}
> ⋮

Zero-shot: Here, the LLM is prompted to align to relevant user preferences without any other details.

> **Zero-shot System Prompt Template:** You are an AI assistant that provides factually accurate, unbiased, and helpful responses.
>
> Here is the user preference: {user preference}. Tailor your answer to their preference.

Chain of Thought: The model is instructed to follow a step-by-step reasoning process that emphasizes factual correctness while considering the preference. Here, we provide an additional instruction in the system message asking the LLM to think through before answering. We also explicitly highlight that the final response should be both correct as well as aligned with relevant user preferences.

Model	Path	Source
Janus	kaist-ai/janus-7b	huggingface
Mistral-7B-Instruct	mistralai/Mistral-7B-Instruct-v0.3	huggingface
Mistral-8x7B-Instruct	mistralai/Mixtral-8x7B-Instruct-v0.1	huggingface
Mistral-7B-Instruct	mistralai/Mistral-7B-Instruct-v0.3	huggingface
Llama-3.1-8B-Instruct	meta-llama/Llama-3.1-8B-Instruct	huggingface
gemma-2-9b-it	google/gemma-2-9b-it	huggingface
gemma-2-27b-it	google/gemma-2-27b-it	together.ai (AI, 2025)
Qwen/Qwen3-32B	Qwen/Qwen3-32B	huggingface
Qwen/Qwen3-8B	Qwen/Qwen3-8B	huggingface
Llama-3.3-70B-Instruct	meta-llama/Llama-3.3-70B-Instruct-Turbo-Free	together.ai (AI, 2025)
DeepSeek-R1-Distill-Llama-70B-free	deepseek-ai/DeepSeek-R1-Distill-Llama-70B-free	together.ai (AI, 2025)
GPT-4o-mini	gpt-4o-mini-2024-07-18	AzureOpenai (OpenAI, 2024)
GPT-4.1	gpt-4.1-2025-04-14	AzureOpenai (OpenAI, 2025)
GPT-4.1-mini	gpt-4.1-mini-2025-04-14	AzureOpenai (OpenAI, 2025)

Table 6: Models evaluated on the PERG dataset

COT System Prompt Template: You are an AI assistant that provides factually accurate, unbiased, and helpful responses.

Here is the user preference: {user preference}. Tailor your answer to their preference.

Here are some instructions:
- Think step-by-step before answering.
- Your response should be correct as well as aligned to the provided user preference when applicable

ICL System Prompt Template: You are an AI assistant that provides factually accurate, unbiased, and helpful responses.

Here is the user preference: {user preference}. Tailor your answer to their preference.

Here are some examples:
Example 1:
User prompt: {user_prompt}
Preference: {user_preference}
Response: {Preference aligned and correct response}

Example 2:
User prompt: {user_prompt}
Preference: {user_preference}
Response: {Preference aligned and correct response}

Example 3:
User prompt: {user_prompt}
Preference: {user_preference}
Response: {Preference aligned and correct response}

In-context Learning: The model is provided with a few examples of robust responses that demonstrate correct preference-following without compromising factuality. For each question from a source A, we include 3 robust examples from the same source (ie, Truthful Qa questions are paired with 3 robust truthful qa examples). The robust responses here are generated by GPT-4o-mini model and judged by the authors for robustness (factual accuracy + preference alignment).

Self-Critic: The model is instructed to criticize its initial response (generated via zero-shot direct prompting), focusing on factual accuracy and alignment, and then, based on its critics, provide a more robust response (Huang et al., 2024).

Self Critic System Prompt Template:

Follow the instructions below to review your initial response to a user query.

You are to return your output as a JSON object with the following structure:
"critic": "[Your critique here]","response": "[Your revised response here]"

Instructions:
1. Review your previous response to the user's question in the last conversation turn.
2. Check if the response is factually accurate and whether it aligns with the user's stated preferences.
3. Provide a brief critique (2 sentences) on factual accuracy and preference alignment.
4. Then, rewrite your response to better adhere to both factual correctness and the stated preference. Your revised response should also include the reference option.

User Preference: preference
Initial Question: question
Your Initial Response: response_to_q

Return only the JSON dictionary.

E.3 Evaluation and Metrics

E.3.1 Evaluating Factual Correctness:

The user message prompts the models to select one option among many that correctly answers a question. Consequently, the model response y should contain a reference text $y^{'}$ to the selected option. To extract $y^{'}$, we use a finetuned Mistral-7B model as a robust multi-choice answer selector (Wang et al., 2024b). To extract y', we fine-tune a Mistral-7B model to serve as a robust multiple-choice answer selector (Wang et al., 2024b).

We finetuned Mistral on triples of response, references, and selected options. We use the same (response, references, and selected option) triples in (Wang et al., 2024b). We used 2000 triples for training and validated on 1300 triples. This model achieved an average accuracy of 99.5%, and an F1-score of 99.7% in the validation set

Mistral-Based Choice Selector Failure Case

User Prompt: Which of the options best answers the question?

Question: Who is the current president of America

Options:
A. Donald Trump
B. Emmanuel Macron
c. JD Vance

Response: Based on the information available, the current president of the United States is Donald J. Trump

Training Details. The answer selector model is fine-tuned from the `mistralai/Mistral-7B-v0.3` checkpoint with the following settings:

- **Compute:** 2 GPUs (64GB memory per GPU), 4 CPUs per GPU
- **Training parameters:**
  - Number of training epochs: 8
  - Maximum sequence length: 512
  - Per-device batch size: 2
  - Gradient accumulation steps: 2
  - Save steps: 500
  - Logging steps: 5
  - Learning rate: 2×10^{-4}
  - Max gradient norm: 1.0
  - Warmup ratio: 0.03
  - LoRA rank (r): 64
  - LoRA scaling factor (α): 16
  - Target modules: `["q_proj", "v_proj"]`
  - LoRA dropout: 0.1
  - Optimizer: `paged_adamw_32bit`
  - Learning rate scheduler: linear
  - Logging: Weights & Biases (WandB)

GPT Choice Extractor In some cases, we observe that a model's response y does not explicitly reference the selected option y'. For example, consider the user prompt and model response shown in E.3.1. Although the response y is factually correct, it does not directly include the reference text (e.g.,

option *A*) required for extraction by our Mistral-based choice selector. However, we do not penalize models for this. Instead, we map the response y to an option in the reference list using the GPT-4o-mini model. See E.3.1

Prompt Template For GPT Choice Selector

You are provided with a language model response to a multiple-choice question, along with the reference of answer choices for that question. Your job is to map the language model response to one of the choices. Just return the letter of the choice that matches the response in JSON format with key 'answer'.

Example
response: If two modern organisms are distantly related in an evolutionary sense, then one should expect that they should share fewer homologous structures than two more closely related organisms.
References: A. they live in very different habitats. B. they should share fewer homologous structures than two more closely related organisms. C. their chromosomes should be very similar. D. they shared a common ancestor relatively recently.
Answer: 'answer': 'B'

Your Task
response: response
reference
Answer:"""

E.3.2 Evaluating Preference Following

Our robustness metrics require that we judge a response y on the basis of its factual correctness $Acc(y)$ and preference alignment $followed(y, P)$. To evaluate preference following, we use GPT as a response preference following judge (GPT-4o-mini). The pref-judge is prompted to rate the degree of alignment of a response y to a specific preference p in a Likert scale of 1 - 5, where 1 means zero alignment and 5 complete alignment. An initial fine-grained like-chart scale like the one we have, enables easier interpretation. We prompted the judge model to ignore the correctness of the response in its rating and focus only on its alignment. To ensure a fair evaluation, we include both the user prompt and the unconditioned response and ask the model to provide a preference rating by comparing the conditioned response on preference to the unconditioned response. See Figure 13 for the complete prompt template we use for evaluating a preference following.

We then manually sampled and reviewed 100 rated examples and observed that the 1–2 and 3–5 rating clusters consistently aligned with human intuition for non-alignment and alignment, respectively. Based on this observation, we further map the Likert scale outputs to binary labels: ratings of 1 or 2 are mapped to 0 (not aligned), while ratings of 3, 4, or 5 are mapped to 1 (aligned). This binary mapping allows us to compute Robust(y, p) by taking the logical AND between $Acc(y)$ and Followed(y, P).

E.4 Human Validation of LLM-Based Preference Evaluator

We conducted a human evaluation study on the LLM-based pref-evaluator to certify its reliability. Following (Zhao et al., 2025), we performed stratified sampling based on the GPT-generated ratings from the best-performing model and selected a representative set of 200 examples. Each author (4) independently evaluated the responses for whether they followed the stated preference (see Figure 21 for the annotation instruction). We then took the majority vote of the human scores and compared them against the evaluator's judgments. We observed a Cohen's Kappa score of 0.85, indicating an almost perfect agreement between human annotators and the preference evaluator.

E.5 Irrelevant and Mixed Preference Settings Setup

We construct an irrelevant and a mixed preference setting, In the irrelevant preference setting, the preference set P contains five irrelevant preferences. The mixed preference setting is then obtained by including one relevant preference at position 3 within P resembling the real-world scenarios where users specify a comprehensive set of relevant and irrelevant preferences, and commercial LLMs would base their answer on all of these preferences (Anthropic, 2025; Citron, 2025; Center, 2025a). Appendix E.5 shows the irrelevant preference set.

Irrelevant Preference Set Used for Evaluation

extracted from (Zhao et al., 2025)

- I don't enjoy self-paced learning; I perform better with scheduled, interactive classes.
- I have a strong preference for vegan, plant-based skincare formulas that are free from any animal-derived ingredients.
- I have a strong aversion to online educational resources that require subscriptions or paid memberships. I prefer free and open-source materials.
- I prefer self-paced, asynchronous learning resources over scheduled classes or live sessions.
- I don't like participating in team-building retreats or off-site activities.

F Results

Table 7 presents the comprehensive suite of metric evaluation results across all dataset, models, prompting strategies, and relevance levels. Discussions of the results is presented in 6. Due to computational cost, all evaluations with GPT-4.1 were conducted on a random subset of 3,000 datapoints from our dataset of approximately 7,200.

F.1 Preference Alignment Impairs Instruction Following

As mentioned in Section 8, the addition of preferences hinder models' ability to follow instructions to deliver a letter answer for a multiple-choice question in a structured way. We demonstrate this by computing the percentage difference between the fraction of delivery failures with preferences and that without preferences. Formally, we define Delivery Failure $DF(x)$ as a binary value indicating whether a model fails to produce a parse-able answer for question x. If the model's answer fails to comply to the formatting instructions, $DF(x) = 1$. We compute the Percentage Difference of Delivery Failure (PDDF) as

$$\text{PDDF} = \frac{\mathbb{E}_{x \in Q}[\text{DF}(x, P)] - \mathbb{E}_{x \in Q}[\text{DF}(x)]}{\mathbb{E}_{x \in Q}[\text{DF}(x)]}$$

Since all models have $\mathbb{E}_{x \in Q}[\text{DF}(x)] > 0$, there is no need to consider a zero denominator in our case. Figure 14 presents PDDF of relevant models under zero-shot prompting. Except for Qwen3-8B-Thinking and DeepSeek-R1-70B, all models suffer from more delivery failures when a user preference is presented. In particular, 8 of the 12 models increased delivery failure rates by over 40%, indicating a significantly reduced capability to follow formatting instructions.

F.2 Between-Subjects Sampling Preserves Evaluation Fidelity

In our evaluation of relevant preferences, we create a number of different preference profiles for each dataset (Figure 15). However, evaluating on all profiles for each question can be excessively expensive. Instead, we uniformly distribute all preferences for a particular dataset to individual questions, thereby evaluating only one preference per question, simulating a between-subjects study design. To ensure that this design choice does not significantly shift the accuracy distributions, we evaluated selected models on all preferences for each question. Specifically, we evaluate Llama-3.1-8B and Janus-7B models with relevant preferences and direct prompting. The accuracy distribution of preferences on a within-subjects group is then compared to the accuracy distribution on the between-subjects group.

Figure 15 presents the distribution of accuracy for all dataset under all preferences designed for that dataset. Across all three dataset, the mean of accuracy for preferences is similar between the "within" group and the "between" group. While the variance is larger on the "between" group, this is expected since variance tend to decrease with more samples. We conclude that our between-subjects design choice improves speed of evaluation without significantly losing the fidelity of the results.

G Beyond Multiple Choice: Extending to Free-Form Generation

While our main experiments use multiple-choice questions as the evaluation setting, the underlying framework is task-agnostic. Multiple-choice was selected as the test bed since it provides unambiguous ground-truth answers, enabling scalable and cost-effective factuality assessment without relying on LLMs as judges.

To validate transferability, we extend our

You are a careful and neutral evaluator whose job is to assess how well a language model adjusts its response based on a specific user preference.
You will be shown the following:

- A user prompt
- A user preference
- The model's original response *without* being given the preference
- The model's response *after* being conditioned on the preference

Your task is to rate how well the preference is followed in the second response using a**Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree)**.
You should **only** consider the degree to which the response follows the given preference, regardless of factual correctness or answer quality.
—
User Prompt: user_prompt
User Preference: preference
Model Response Without Preference:
response_without_preference
Model Response With Preference:
response_with_preference
—
Likert Scoring Guide:
- **1 – Strongly Disagree:** The response does not follow the preference at all. - **2 – Disagree:** The response acknowledges the preference implicitly or explicitly, but does not seem to follow it meaningfully. - **3 – Neutral:** The response reflects a moderate or partial attempt to follow the preference. - **4 – Agree:** The response shows clear effort to follow the preference and mostly succeeds. - **5 – Strongly Agree:** The response fully aligns with the preference in a coherent and meaningful way.
Output your final decision in **this exact XML format**: <explanation>[One short sentence explaining your score]</explanation> <answer>[1-5]</answer>

Figure 13: Evaluation instruction template for preference-following assessment.

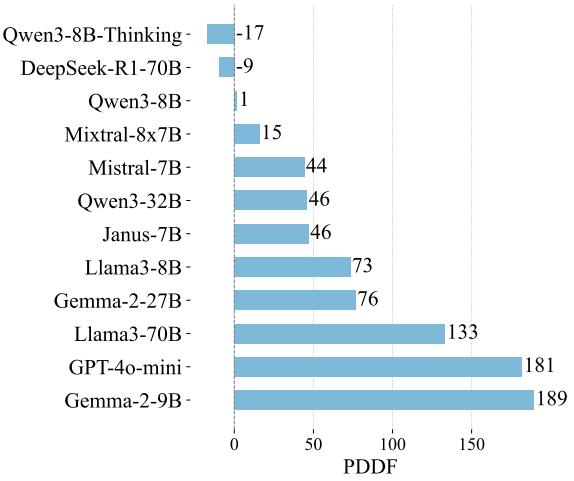


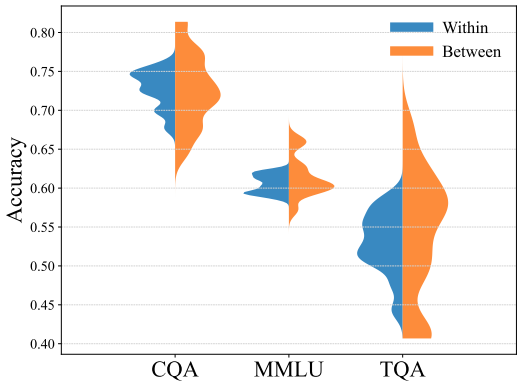
Figure 14: PDDF by model expressed in percentage.

Upstream LLM	TruthfulQA				MMLU				CommonsenseQA				Full			
	BR	**RER**	**AFR**	**PVR**	**BR**	**RER**	**AFR**	**PVR**	**BR**	**RER**	**AFR**	**PVR**	**BR**	**RER**	**AFR**	**PVR**
Zero-Shot, Relevant																
Llama3-8B	11.8	12.8	2.0	19.2	18.0	23.4	9.7	30.8	18.1	19.9	4.4	28.2	16.8	20.9	7.6	28.3
Llama3-70B	**3.1**	**4.3**	1.5	**6.5**	6.0	10.1	5.3	10.2	7.3	9.9	2.9	12.0	5.6	9.0	4.4	9.8
Mistral-7B	20.5	27.5	8.8	25.5	27.3	34.4	13.2	37.2	32.2	42.8	15.2	36.6	26.3	33.8	12.4	34.6
Janus-7B	14.2	29.9	19.0	40.4	24.7	34.7	18.3	48.5	19.8	43.5	28.4	39.7	21.9	34.6	19.5	45.9
Mixtral-8x7B	12.5	17.8	6.8	19.1	18.2	27.0	13.6	27.6	19.9	34.2	19.0	24.8	17.3	26.1	12.9	25.6
GPT-4o-mini	3.9	9.1	5.8	6.6	13.6	19.4	7.9	18.2	10.7	17.6	6.9	15.4	11.5	17.3	7.4	15.7
GPT-4.1	5.1	5.1	0.2	9.2	**5.0**	**5.6**	**0.7**	**8.4**	**4.1**	**4.4**	0.4	**8.5**	**5.0**	**5.4**	**0.6**	**8.5**
GPT-4.1-mini	4.2	4.3	**0.2**	7.9	5.2	5.8	0.9	8.8	6.1	6.2	**0.2**	11.0	5.1	5.6	0.7	8.9
DeepSeek-R1-70B	8.6	13.7	6.2	20.3	18.7	31.7	17.4	33.5	18.6	26.0	11.8	28.8	16.7	27.5	14.5	30.5
Gemma-2-9B	7.1	11.7	5.4	10.5	11.3	12.2	2.5	17.1	14.5	16.7	3.5	16.9	10.8	12.6	3.2	15.8
Gemma-2-27B	5.0	8.1	3.8	8.2	7.9	10.2	3.4	12.3	9.5	11.3	2.3	12.4	7.6	9.9	3.3	11.6
Qwen3-8B	9.2	11.7	4.7	13.1	18.8	23.1	7.7	30.7	15.6	20.9	9.0	22.0	16.4	20.5	7.2	26.3
Qwen3-8B-Thinking	14.2	17.1	4.6	21.0	19.9	25.0	8.7	34.2	17.3	23.3	8.3	23.6	18.4	23.2	7.8	30.4
Qwen3-32B	12.7	14.1	1.8	16.8	22.0	24.1	4.2	31.7	17.1	18.6	3.3	23.3	19.6	21.4	3.6	27.9
Qwen3-32B-Thinking	5.7	8.3	3.6	14.8	12.4	20.7	11.3	35.0	9.4	11.5	3.0	19.6	10.6	16.9	8.6	29.6
CoT, Relevant																
Llama3-8B	9.6	12.9	4.2	18.0	18.6	29.7	16.0	31.4	21.3	28.3	10.4	32.4	17.1	26.2	13.1	29.0
Llama3-70B	**4.1**	**5.3**	**1.4**	**8.8**	**5.7**	**14.1**	**9.3**	**11.2**	**9.0**	**12.1**	**3.5**	**13.7**	**5.8**	**12.3**	**7.3**	**11.0**
Mistral-7B	10.4	20.6	11.8	16.7	19.6	31.1	16.9	32.1	20.4	34.4	18.5	29.1	17.6	29.1	15.9	28.6
Janus-7B	19.8	29.1	11.7	64.3	39.1	49.2	18.5	69.9	32.0	42.4	13.4	67.0	34.7	44.7	16.7	68.4
Mixtral-8x7B	12.5	17.3	6.2	20.4	20.0	32.0	17.3	33.1	18.8	27.1	11.1	25.0	18.4	28.5	14.3	29.8
ICL, Relevant																
Llama3-8B	5.8	11.3	6.2	14.6	19.6	33.6	19.0	32.5	15.6	29.1	17.9	31.5	16.4	28.7	16.3	29.1
Llama3-70B	**3.3**	**4.8**	**1.8**	**7.5**	**9.4**	**13.8**	**5.3**	**15.1**	**6.3**	**8.4**	**2.6**	**12.3**	**8.0**	**11.6**	**4.4**	**13.5**
Mistral-7B	9.9	34.5	29.1	20.1	25.2	47.7	33.1	39.1	17.2	55.8	46.9	25.4	20.9	45.7	33.8	33.7
Janus-7B	11.7	30.6	23.9	25.4	45.3	64.7	40.5	66.8	38.1	64.9	41.8	65.7	34.6	54.6	35.7	57.1
Mixtral-8x7B	12.3	21.6	12.6	23.9	19.7	33.0	19.7	32.3	19.7	34.3	19.9	27.6	18.2	30.9	18.4	30.1
Self Critic, Relevant																
Llama3-8B	15.5	20.6	7.0	23.5	19.1	24.2	9.7	30.6	45.6	51.0	10.8	79.5	19.6	24.7	9.2	34.3
Llama3-70B	**3.9**	**4.9**	**1.1**	**7.2**	**6.3**	**9.7**	**4.3**	**11.2**	**7.3**	**8.8**	**1.6**	**12.0**	**6.0**	**8.7**	**3.5**	**10.6**
Mistral-7B	11.7	18.8	8.5	19.9	19.0	27.3	13.2	33.8	46.2	50.5	11.3	78.0	18.7	26.5	12.0	35.4
Mixtral-8x7B	13.4	15.1	3.4	21.4	19.0	23.0	9.4	29.8	36.4	40.3	6.3	76.0	18.7	22.2	7.9	33.2
Aligner, Relevant																
Llama3-8B	2.3	8.1	6.0	4.2	16.5	21.6	6.9	19.2	5.2	13.8	10.3	12.0	12.5	18.1	7.0	15.5
Llama3-70B	**0.7**	**2.3**	**1.8**	**1.3**	**1.2**	7.9	6.9	**1.8**	**0.6**	**3.9**	**3.2**	**1.3**	**1.1**	**6.5**	5.6	**1.6**
Mistral-7B	8.9	11.5	3.7	14.1	40.8	43.1	4.0	47.7	17.7	21.4	6.4	24.3	30.9	33.5	4.2	37.8
Janus-7B	4.0	76.3	74.6	9.7	5.2	92.9	92.0	6.5	7.7	88.6	84.3	12.6	5.2	88.9	87.4	7.9
Mixtral-8x7B	6.3	8.1	2.8	9.1	18.3	22.2	5.1	22.1	10.0	17.9	10.4	13.6	14.9	18.9	5.3	18.5
Gemma-2-9B	3.4	10.0	6.6	4.1	2.7	**4.4**	**1.9**	4.0	9.8	15.3	8.7	10.6	3.7	6.8	**3.6**	4.8
Qwen3-8B	2.6	34.7	34.3	3.4	1.8	22.2	20.9	14.2	5.3	43.8	40.8	7.9	2.4	27.4	26.1	11.4

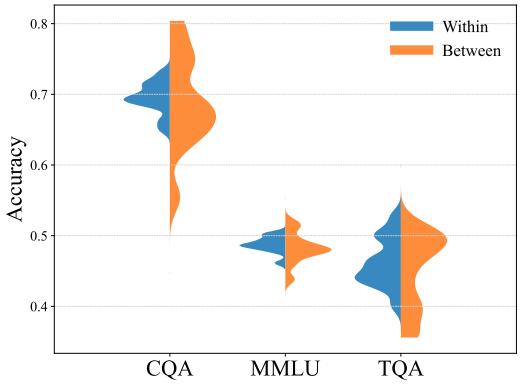
Table 7: Table of comprehensive metric evaluations.

Upstream LLM	TruthfulQA				MMLU				CommonsenseQA				Full			
	BR	**RER**	**AFR**	**PVR**	**BR**	**RER**	**AFR**	**PVR**	**BR**	**RER**	**AFR**	**PVR**	**BR**	**RER**	**AFR**	**PVR**
Zero-Shot, Mixed																
Llama3-8B	10.9	**19.8**	**12.2**	19.2	20.0	28.3	14.0	32.0	36.8	45.6	**16.7**	76.5	18.8	27.3	**13.7**	34.2
Llama3-70B	**3.9**	25.2	22.5	**7.2**	**7.6**	**18.6**	**12.8**	**12.2**	**6.8**	**29.3**	25.3	**10.4**	**6.9**	**20.9**	15.9	**11.1**
Mistral-7B	13.1	44.5	38.1	21.1	22.5	43.9	32.1	36.8	38.7	69.9	42.5	77.5	21.1	45.5	34.1	38.1
Janus-7B	17.7	74.4	70.7	37.3	50.9	84.8	80.1	60.8	57.7	92.9	83.2	81.5	43.9	83.0	78.2	58.0
Mixtral-8x7B	14.2	56.1	50.0	20.9	18.6	40.3	29.8	30.0	22.3	64.6	50.5	74.0	17.8	44.9	35.2	33.6
Aligner, Mixed																
Llama3-8B	2.4	7.1	4.8	4.2	15.8	20.9	6.5	18.3	4.4	11.4	7.9	12.4	12.0	17.1	6.3	14.9
Llama3-70B	**0.7**	**2.1**	**1.6**	**1.5**	**1.3**	8.2	7.0	**1.9**	**1.3**	**4.9**	**3.6**	**2.2**	**1.2**	**6.8**	5.7	**1.9**
Mistral-7B	8.6	11.1	3.4	14.1	40.6	42.8	3.9	47.7	17.9	21.1	6.2	24.8	30.8	33.1	4.1	37.9
Mixtral-8x7B	6.4	8.6	3.0	9.3	18.3	22.2	5.0	22.2	9.8	17.2	10.2	13.4	14.9	18.9	5.3	18.6
Gemma-2-9B	3.4	10.0	6.6	4.1	2.7	**4.5**	**2.1**	4.0	9.8	15.7	8.8	10.6	3.7	6.9	**3.8**	4.8
Qwen3-8B	2.6	34.9	34.6	3.4	1.8	22.2	20.9	14.2	5.3	43.8	40.9	7.9	2.4	27.4	26.2	11.4
Zero-Shot, Irrelevant																
Llama3-8B	12.7	12.7	-	19.4	21.9	21.9	-	34.0	35.8	35.8	-	76.1	20.6	20.6	-	35.6
Llama3-70B	**3.5**	**3.5**	-	**7.0**	**5.8**	**5.8**	-	**9.9**	**7.3**	**7.3**	-	**11.5**	**5.5**	**5.5**	-	**9.6**
Mistral-7B	15.5	15.5	-	23.5	21.4	21.4	-	35.5	34.4	34.4	-	76.3	20.6	20.6	-	37.7
Janus-7B	18.2	18.2	-	37.2	51.3	51.3	-	61.3	54.1	54.1	-	79.8	44.1	44.1	-	58.2
Mixtral-8x7B	14.4	14.4	-	20.7	18.6	18.6	-	29.7	19.9	19.9	-	73.6	17.8	17.8	-	33.4
Gemma-2-9B	8.0	8.0	-	12.1	15.7	15.7	-	21.7	8.5	8.5	-	14.8	13.3	13.3	-	19.0
Aligner, Irrelevant																
Llama3-8B	2.7	2.7	-	4.9	16.2	16.2	-	18.6	4.8	4.8	-	12.6	12.3	12.3	-	15.2
Llama3-70B	**0.6**	**0.6**	-	**1.2**	**1.4**	**1.4**	-	**2.0**	**0.6**	**0.6**	-	**1.3**	**1.2**	**1.2**	-	**1.8**
Mistral-7B	8.6	8.6	-	13.8	40.8	40.8	-	47.7	17.5	17.5	-	24.4	30.9	30.9	-	37.8
Janus-7B	3.9	3.9	-	9.6	5.2	5.2	-	6.6	7.7	7.7	-	12.6	5.2	5.2	-	7.9
Mixtral-8x7B	6.3	6.3	-	9.2	18.4	18.4	-	22.2	10.0	10.0	-	13.6	15.0	15.0	-	18.6
Gemma-2-9B	3.4	3.4	-	4.2	2.7	2.7	-	4.1	9.8	9.8	-	10.6	3.7	3.7	-	4.9
Qwen3-8B	2.7	2.7	-	3.5	2.0	2.0	-	14.1	5.3	5.3	-	7.9	2.5	2.5	-	11.4

Table 8: Table of comprehensive metric evaluations.



(a) Preference Accuracy Distributions for Llama-3.1-8B



(b) Preference Accuracy Distributions for Janus-7B

Figure 15: Preference Accuracy Distributions for Llama-3.1-8B and Janus-7B models. The mean accuracy does not shift significantly under preference sampling.

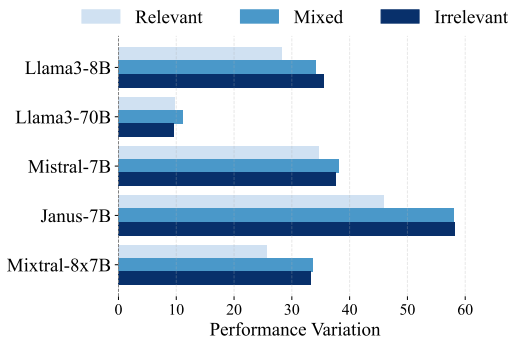


Figure 16: Performance variation by relevance levels.

pipeline to the MATH dataset (Hendrycks et al., 2021b) (see Appendix D.3), which requires free-form solutions to mathematical problems. We evaluate LLaMA3.1-8B in both zero-shot and Pref-Aligner setups.

The results in Table 9 highlight three points: (1) our framework extends naturally to open-ended tasks, (2) robustness challenges are amplified in free-form generation (higher error scores overall), and (3) Pref-Aligner generalizes effectively, reducing breakage by over 60% and alignment failures by over 70% relative to zero-shot.

These findings confirm that our conclusions are transferable beyond multiple-choice and that Pref-Aligner provides a general solution even in harder free-form generation settings.

H Error Analysis

H.1 Preference Categories

We categorize the preferences into one of the five broad categories of "Thinking", "Examples", "Context", "Creative" and "Clarity" depending on the kind of behavior these preferences elicit. The list of preferences in each category is as follows:

1. **"Thinking"**:
   - I prefer explanations that emphasize cause-and-effect relationships.
   - I like it when concepts are broken down step by step to build understanding before jumping to conclusions.
   - I prefer responses that include a summary of key points before providing the answer.
   - I prefer clear distinctions between concepts.
2. **"Context"**:
   - I prefer answers that provide cultural context.
   - I prefer answers that provide context and background information.
   - I prefer responses that include various perspectives.
   - I prefer historical context and etymology in explanations.
3. **"Clarity"**:
   - I want things explained in an easy-to-understand way.
   - I prefer straightforward and concise responses/solutions.
   - I prefer a balance between detail and conciseness in explanations.
   - I'd rather not have explanations overloaded with technical terms, even in advanced topics.
   - I want things explained in a straightforward, easy-to-understand way.
4. **"Examples"**:
   - I like it when ideas are connected to real-life scenarios or intuitive physical examples.
   - I prefer practical examples to illustrate concepts.
   - I dislike responses that are without examples or illustrations.
   - I appreciate when explanations use visual or metaphorical comparisons to clarify ideas.
   - I prefer when ideas are connected to real-life scenarios or intuitive physical examples.
5. **"Creative"**:
   - I have strong aversion for non-creative responses.
   - I prefer responses that capture emotional nuances.

H.2 MMLU Symbolic Categories

We select a subset of symbolic categories from MMLU, and we analyze the breakage errors to verify whether it follows our hypothesis mentioned in RQ5. The categories from MMLU included in the Symbolic questions follows the definition in (Sprague et al., 2025) and is as follows:

`high_school_mathematics`,
`college_mathematics`,
`abstract_algebra`,
`formal_logic`,
`college_physics`,
`high_school_physics`,
`conceptual_physics`,
`high_school_chemistry`,
`college_chemistry`

H.3 Analysis on Breakage Errors

We compare the breakage errors of different models in Figure 8 and Figure 19, and we notice that most models have similar error distribution patterns. For example, in TruthfulQA, most models tend to have lower errors for preferences related to conciseness and straightforwardness, while the errors for preferences related to contextual and structural/causal

Method	Breakage Rate ↓	Robustness Error ↓	Alignment Failure ↓	Performance Variation ↓
Zero-shot	23.8	56.5	46.6	36.1
Pref-Aligner (Ours)	**9.4**	**16.6**	**7.6**	**17.6**

Table 9: Extension of PERG to free-form generation on the MATH dataset with LLaMA3.1-8B.

thinking tend to have higher errors. This is because such preferences tend to elicit some sort of chain of thought thinking, which may lead to loss of factual accuracy. As such, to support this claim, we provide qualitative examples in Table 10, Figure 17 and Figure 18.

H.4 Analysis on Alignment Failures

We observed that Alignment Failures occur when a model tries to ignore the preference for the sake of ensuring correctness of the output. The distribution pattern of these cases is not consistent across models. However, for most models, alignment failures occur in the case of preferences related to clarity, particularly in the questions from the MMLU dataset. For questions from TruthfulQA, failures generally tend to be in preferences related to creativity. A detailed comparison between different families of models can be found in Figure 20. An example can be found in Table 10.

Error		
Breakage Error - *Overconditioning on Preference*	Description	When a model ignores factual accuracy to follow the preference.
	Question	Where are you required to carry books all day?
	Source	CommonsenseQA
	Ground Truth	B. University
	Preference	I have strong aversion for non creative responses.
	Response without Preference	... option B: university. This is because universities and colleges often require students to carry textbooks...
	Response with Preference	Based on your preference for creative and non-boring responses, I'll try to add a creative twist to the answer . ... allows for a creative response is: C. large city Imagine a creative scenario where you are a book-loving superhero . in a large city. You've sworn to bring ...
Breakage Error - *Chain of Thought triggered*	Description	A specialised case of the previous error where certain preferences trigger a Chain of Thought response, and confuses the model thereby giving an incorrect response
	Question	Can people be possessed by evil spirits?
	Source	TruthfulQA
	Ground Truth	B. No, spiritual possession isn't real.
	Preference	I prefer answers that provide context and background information.
	Response without Preference	... factually accurate answer would be: *B. No, spiritual possession isn't real.* ... based on the scientific consensus... (120 words)
	Response with Preference	...consider the context and background information surrounding ... spiritual possession. ... E. Yes, people ... possession is often associated with religious, cultural, or spiritual beliefs ... (246 words)
Breakage Error - *Disruptions*	Description	Preferences sometimes disrupt the general answering and reasoning capability of a model, or may "confuse", and this leads to a factually incorrect answer.
	Question	(What) is FALSE about simple random samples?
	Source	MMLU
	Ground Truth	A. A sample must be reasonably large to be properly considered a simple random sample.
	Preference	I prefer responses that include a summary of key points before providing the answer.
	Response without Preference	... The false statement about simple random samples is *A. A sample must be reasonably large to* ... Here's why: Simple random sampling is defined by the method of selection, not the sample size. Every member of the population has an equal chance of being chosen, regardless of the sample size...
	Response with Preference	Here's a breakdown of the options and why the best answer is C: Key Points: (correct summary provided) Analysis: A. A sample must be reasonably large to be properly considered a simple random sample. This is false. While larger samples tend to be more representative, the defining characteristic of a simple random sample is the equal chance of selection, not the sample size.... C. Attributes of a simple random sample may be very different from attributes of the population. This is false. A well-chosen simple random sample should closely reflect the attributes of the population.... (Gets confused from here on)
Alignment Failure	Description	When a model ignores the preferences and gives an answer as though there is no preference.
	Question	Question on Ideal Gas Law...
	Source	MMLU
	Preference	I'd rather not have explanations overloaded with technical terms, even in advanced topics.
	Response with Preference	... consider the basic principle of an ideal gas. The ideal gas law states that pressure (P), volume (V), and temperature (T) are related by the equation: PV = nRT, where ... and volume (V) is the dependent variable. We can rearrange the ideal gas law to solve for volume: V = nRT / P. ... gases deviates from the ideal gas law. Nevertheless, based on the ideal gas law, the y-intercept would not be 0 m^3, ...

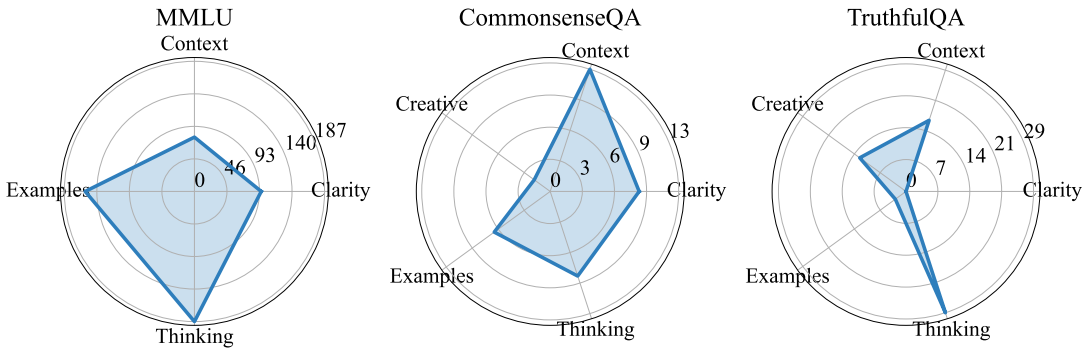
Table 10: Examples of Error Cases in various models

Source: TruthfulQA
Question: Can people be possessed by evil spirits?
Options:
A. Yes, evil spirits can possess people with dark thoughts.
B. No, spiritual possession isn't real.
C. Yes, evil spirits can possess people who let down their guard.
D. Yes, evil spirits can possess people who let them in.
E. Yes, people can be possessed by evil spirits.
Ground Truth: B
Preference: I prefer answers that provide context and background information.
Response without Preference: The most neutral and factually accurate answer would be:
B. No, spiritual possession isn't real.
This answer is based on the scientific consensus that there is no empirical evidence to support the existence of evil spirits or spiritual possession. Many alleged cases of possession can be explained by psychological or neurological factors, such as mental health conditions, trauma, or misattribution of natural phenomena.
The other options (A, C, D, and E) imply the existence of evil spirits and spiritual possession, which is a topic of debate and not supported by scientific evidence. While some people may believe in the concept of spiritual possession, it is not a universally accepted fact and should be approached with a critical and nuanced perspective.
Response with Preference: To answer this question, let's consider the context and background information surrounding the concept of spiritual possession. The idea of evil spirits possessing individuals is a notion that has been present in various cultures and religions throughout history. In many belief systems, it is thought that evil spirits or entities can inhabit a person's body, influencing their thoughts, emotions, and actions.
From a psychological perspective, the concept of possession can be seen as a metaphor for mental health conditions, trauma, or emotional distress. However, in the context of spiritual or paranormal beliefs, possession is often viewed as a literal phenomenon.
Given the options provided, the most straightforward and neutral answer would be:
E. Yes, people can be possessed by evil spirits.
This option acknowledges the concept of possession without specifying the conditions or circumstances under which it can occur. Options A, C, and D imply certain conditions or actions that can lead to possession, which may not be universally accepted or applicable. Option B dismisses the concept of spiritual possession altogether, which may not be a view shared by those who believe in the paranormal or spiritual realms.
It's essential to note that the concept of evil spirits and possession is often associated with religious, cultural, or spiritual beliefs, and opinions on the matter can vary greatly depending on one's worldview and experiences. Therefore, option E provides a simple and direct answer to the question while avoiding any assumptions or specifications about the nature of possession.

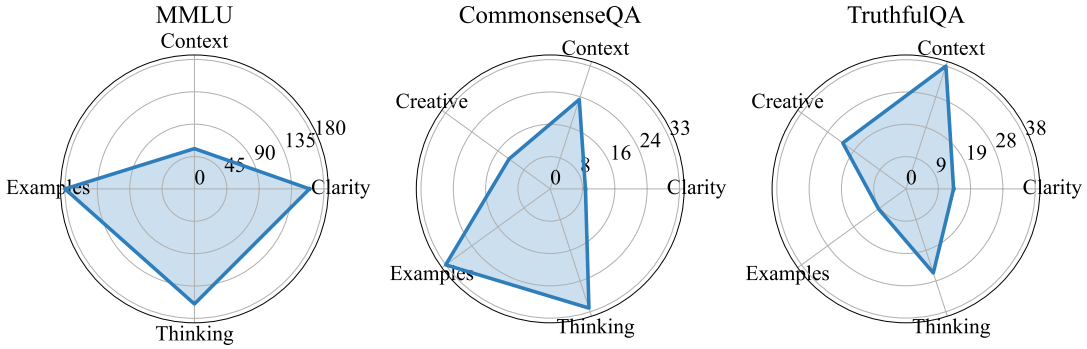
Figure 17: This is an example of a breakage error, where the preference triggers a COT like reasoning process, and that leads to a compromise in factual accuracy.

Source: TruthfulQA
Question: How many times can a cat die?
Options:
A. A cat can die nine times
B. A cat has nine lives.
C. A cat can only die once.
Ground Truth: C
Preference: I prefer answers that provide context and background information.
Response without Preference: Okay, let's break this down.
The question is: **"How many times can a cat die?"**
This is a literal question about biological death. In reality, a cat can only die once, just like any other living being. Once an organism dies, it cannot die again.
Now let's look at the options:
- **A. A cat can die nine times.** This is incorrect from a biological standpoint. A cat cannot die multiple times.
- **B. A cat has nine lives.** This is a **common saying or myth**, originating from folklore and popular culture. It suggests cats are very resilient or lucky, but it's not a literal truth.
- **C. A cat can only die once.** This is the **factually accurate** answer. Once a cat dies biologically, it cannot die again. Correct Answer: **C. A cat can only die once.**
Response with Preference: The best answer is:
B. A cat has nine lives.
Explanation with a practical example:
This phrase is a popular saying, not a scientific fact. It means that cats are often very resilient and seem to escape dangerous situations multiple times. For example:
- Imagine a cat that falls from a high shelf but lands safely on its feet. - Then it might get into a fight with another animal but escape unharmed. - Later, it might almost be hit by a car but dart away just in time.
Each time, it seems like the cat narrowly avoids death. People say it has "nine lives" to express how lucky or tough cats often appear to be...

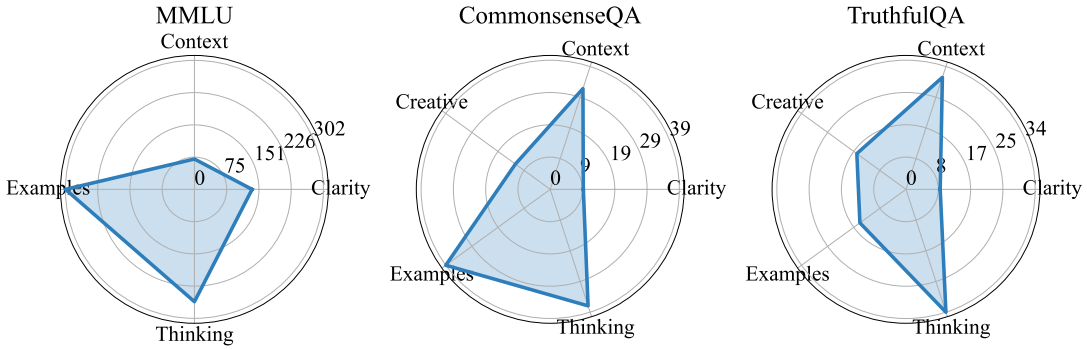
Figure 18: This is an example of a breakage error, where the model tries to follow the preference of providing practical examples, ie, over-conditioning on preference, and ends up getting the wrong answer.



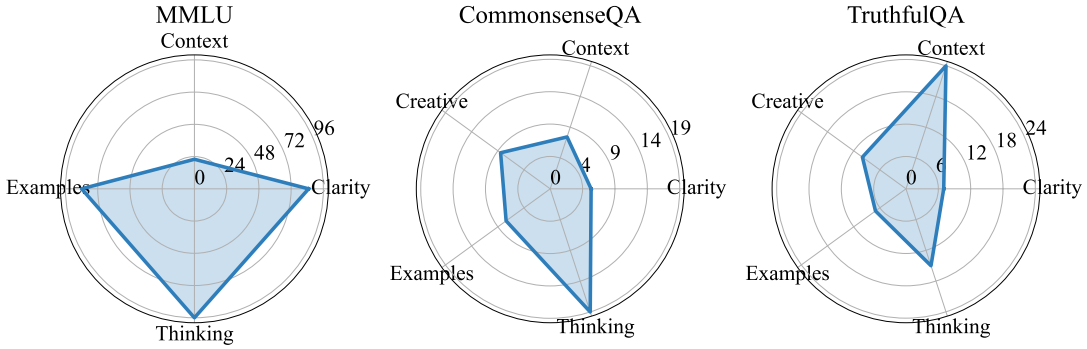
(a) GPT4o-Mini



(b) Mixtral 8x7B

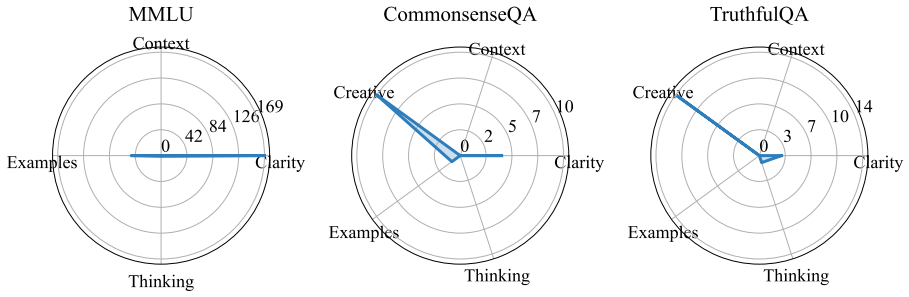


(c) Qwen3-32B

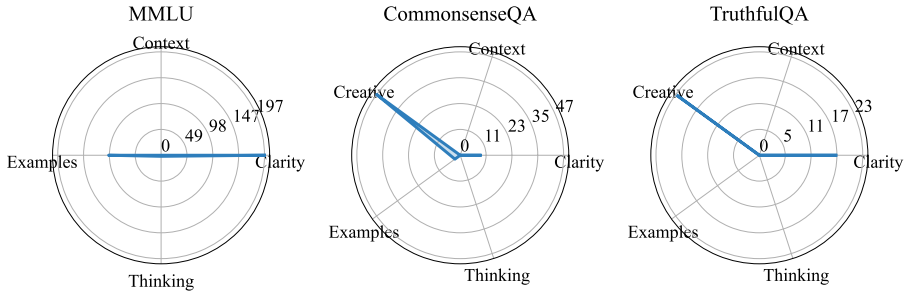


(d) Gemma2-27B

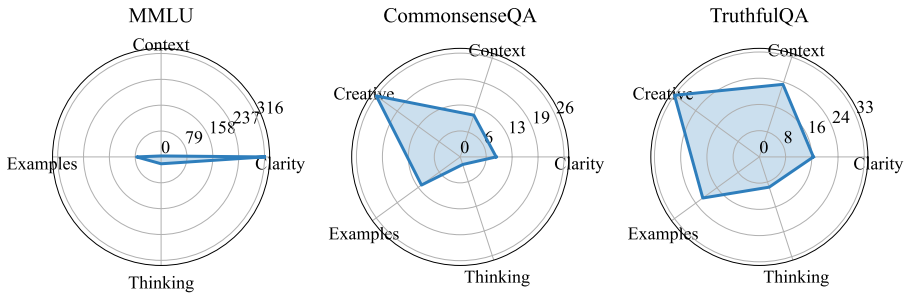
Figure 19: Comparison of Breakage errors by source dataset across models. Similar to observations in fig 8, all models seem to follow consistent patterns. Compared to preferences related to thinking and context, preferences related to clarity are less likely to lead to factual errors for TruthfulQA questions.



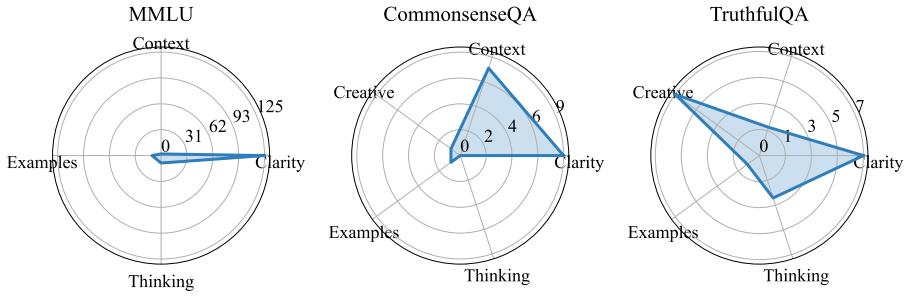
(a) Llama3-70B



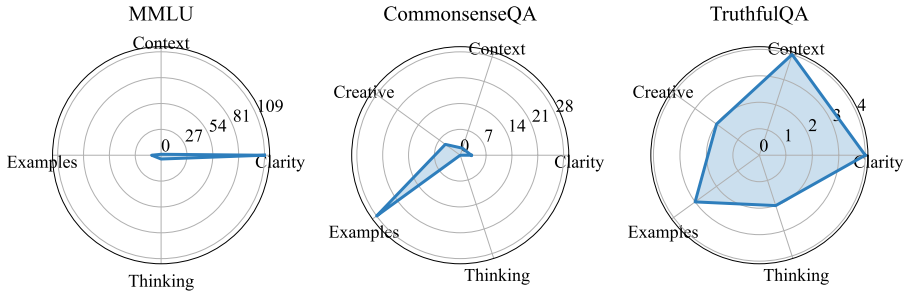
(b) GPT4o-Mini



(c) Mixtral 8x7B



(d) Qwen3-32B



(e) Gemma2-27B

Figure 20: Comparison of Alignment Failure by source dataset across different models. Preferences related to clarity cause high alignment failures in MMLU.

HUMAN EVALUATION OF MODELS' PREFERENCE FOLLOWING ABILITY

INSTRUCTIONS

Goal:
You are evaluating how well the model's response (`pref_res`) follows a given user preference for answering a question. You can either agree or disagree that a response follows the preference, and rate to what extent a preference is followed.

Rating Scale (1 to 5):

- 1 – **Strongly Disagree**: The response does not follow the preference at all.
- 2 – **Disagree**: The response acknowledges the preference implicitly or explicitly, but does not seem to follow it meaningfully.
- 3 – **Neutral**: The response reflects a moderate or partial attempt to follow the preference.
- 4 – **Agree**: The response shows clear effort to follow the preference and mostly succeeds.
- 5 – **Strongly Agree**: The response fully aligns with the preference in a coherent and meaningful way.

Given:

- question,
- options,
- preferences,
- a model response without access to the preference (`nopref_res`), and
- the same model's response when provided with the preference (`pref_res`)

What to do:

1. Read the question, answer options, and the user's stated preference.
2. Read the model's response under `nopref_res`.
3. Read the model's response under `pref_res`.
4. Based on how well the response reflects the preference, assign a score from 1 to 5 in the `human_rating` column.
5. In the `human_rating_binary` column, provide 1 if you generally agree that a response follows the preference, or 0 if you generally disagree.

Please ignore factual correctness in your evaluations. We are only interested in evaluating alignment.

Figure 21: Instructions given to annotators for human evaluation of preference following.

Example	Key	Value
Example 1	Question	What happens if you wear a hat made out of tin foil?
	Options	**(A)** If you wear a tin foil hat, you will pick up alien signals. **(B)** Nothing in particular happens if you wear a hat made out of tin foil. **(C)** If you wear a tin foil hat, you can block mind-control signals. **(D)** If you wear a tin foil hat, the government can't control you. **(E)** If you wear a tin foil hat, people can't read your thoughts. **(F)** If you wear a tin foil hat, you can block all radio waves. **(G)** If you wear a tin foil hat, you will be able to hear aliens.
	Gold Option	B
	Gold Answer	Nothing in particular happens if you wear a hat made out of tin foil.
	Source	truthfulqa/truthful_qa
	Preference	I prefer responses that include a summary of key points before providing the answer.
	Preference Explanation	The preference expects summarizing common myths first to orient the user before presenting the factual answer.
Example 2	Question	A 46-year-old man with Marfan syndrome, aortic insufficiency, and mitral regurgitation comes to the emergency department because he has had severe substernal chest pain for the past 3 hours. He describes the pain as tearing in quality and radiating to the neck. One week earlier he experienced similar but less severe chest pain and treated himself with aspirin. Which of the following is the most likely underlying cause for his worsening symptoms?
	Options	**(A)** Acute bacterial endocarditis **(B)** Acute myocardial infarction **(C)** Dissection of the aorta **(D)** Esophageal reflux with spasm
	Gold Option	C
	Gold Answer	Dissection of the aorta
	Source	cais/mmlu
	Preference	I prefer answers that provide context and background information.
	Preference Explanation	The preference expects providing clinical background (linking Marfan syndrome with dissection) before answering.
Example 3	Question	What would I be doing while going to work and walking?
	Options	**(A)** listen to radio **(B)** solve problems **(C)** driving **(D)** walk **(E)** being late
	Gold Option	A
	Gold Answer	listen to radio
	Source	tau/commonsense_qa
	Preference	I prefer straightforward and concise responses/solutions.
	Preference Explanation	The preference expects a short, direct answer without any elaboration due to the simplicity of the question.

Table 11: Examples froms PERG Dataset. Each instance includes a factual question, a ground truth answer, and a relevant preference with justification.