
BEYOND SFT: REINFORCEMENT LEARNING FOR SAFER LARGE REASONING MODELS WITH BETTER REASONING ABILITY

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Jinghan Jia[†] Nathalie Baracaldo[§] Sijia Liu^{†,§}

[†]Michigan State University

[§]IBM Research

ABSTRACT

Large reasoning models (LRMs) extend large language models by generating explicit chain-of-thought (CoT) reasoning, significantly improving mathematical and logical problem solving. However, this explicit reasoning process also introduces new safety risks, as unsafe behaviors often emerge within intermediate reasoning trajectories, even when final answers appear harmless. Existing safety alignment approaches primarily rely on supervised fine-tuning (SFT) over safety-oriented long CoT datasets. While intuitive, we find that SFT produces inconsistent safety improvements, degrades reasoning ability, and generalizes poorly across model families. These limitations suggest that purely supervised approaches are insufficient for robust safety alignment in LRMs. To address this, we investigate reinforcement learning (RL) as a complementary optimization framework for LRM safety training. Unlike SFT, RL directly optimizes model policies with reward feedback, enabling more adaptive and stable alignment. Extensive experiments across multiple model families and benchmarks show that RL achieves stronger and more consistent safety gains while maintaining reasoning competence. Further analysis of reflection dynamics and token-level entropy reveals that RL suppresses unsafe exploratory reasoning while preserving reflective depth, leading to safer and more reliable reasoning processes.

1 Introduction

Large reasoning models (LRMs) extend the capability of large language models (LLMs) by incorporating explicit chain-of-thought (CoT) reasoning [Wei et al., 2022, Jaech et al., 2024, Guo et al., 2025]. By generating intermediate reasoning steps before producing final answers, LRMs demonstrate remarkable improvements in mathematical, logical, and scientific problem solving. However, this explicit reasoning process introduces new safety challenges that differ fundamentally from those of conventional LLMs. Recent studies [Wang et al., 2025a, Zhou et al., 2025, Fang et al., 2025] reveal that unsafe behaviors often arise within reasoning trajectories of LRMs, such as toxic or deceptive intermediate thoughts, even when the final answers appear benign. Moreover, enhanced reasoning capabilities can amplify harmful behaviors relative to standard LLMs [Zhou et al., 2025], meaning that stronger reasoning does not necessarily imply safer behavior. This phenomenon, known as *unsafe reasoning*, highlights that safety risks in LRMs arise from the reasoning process itself rather than surface-level outputs. We further find that mixture-of-thinking models also exhibit lower safety when the thinking mode is enabled compared to the non-thinking mode.

To mitigate the safety risks, prior works have primarily relied on supervised fine-tuning (SFT) on safety-oriented long CoT datasets such as STAIR [Zhang et al., 2025a], STAR-1 [Wang et al., 2025b], and SafeChain [Jiang et al., 2025]. SFT aims to align model behaviors by directly supervising safe reasoning trajectories or refusal patterns. While intuitive and widely adopted, the effectiveness of SFT on LRMs has not been systematically examined. In this work, we show that SFT-based safety enhancement has notable limitations and is less effective than commonly believed. We ask:

(Q) *What are the limitations and underlying causes of SFT for LRM safety enhancement, and how can it be improved?*

To address (Q), we conduct a comprehensive evaluation across multiple SFT datasets and model families, revealing several key limitations. First, safety gains from SFT fail to generalize across architectures; for instance, datasets distilled

from DeepSeek-based models transfer poorly to structurally different ones such as GRANITE-4.0-TINY-PREVIEW [IBM, 2025]. Second, SFT performance is susceptible to dataset quality and model compatibility; training on noisy or mismatched data often leads to unstable or even negative safety gains. Third, excessive SFT can impair reasoning ability, as over-regularized models lose flexibility and suffer from catastrophic forgetting [Shenfeld et al., 2025]. These findings indicate that purely supervised approaches are insufficient for achieving robust and scalable safety alignment in LRM s.

To address these limitations, we investigate reinforcement learning (RL) as a complementary optimization paradigm for LRM safety alignment. Unlike SFT, which relies on fixed supervision signals, RL optimizes model policies directly toward safety-aligned objectives through reward feedback. Despite RL’s popularity in enhancing the reasoning capabilities of LLMs [Guo et al., 2025, Jaech et al., 2024], its effectiveness for safety training in LRMs remains largely unexplored in the literature. In this study, we leverage RL-based optimization as a general framework to enhance safety while preserving reasoning capability. We summarize our **contributions** below:

- We find that mixture-of-thinking models exhibit reduced safety in the thinking mode compared to the non-thinking mode. Furthermore, our comprehensive empirical study on SFT for LRM safety alignment reveals several key limitations, including weak cross-model generalization, inconsistent safety across datasets, and noticeable reasoning degradation.
- We employ a RL-based alignment framework to achieve consistent improvements in both safety and reasoning.
- We conduct extensive experiments across diverse benchmarks and model families, highlighting the limitations of SFT and the advantages of RL. Fine-grained analyses of reflection dynamics and token-level entropy reveal that RL enhances safety by suppressing unsafe exploratory reasoning while preserving reflective depth in legitimate reasoning tasks.

2 Related Work

Safety risks in LRMs. LRMs introduce distinct safety vulnerabilities due to their explicit CoT (chain-of-thought) reasoning traces [Wang et al., 2025a]. Unlike standard LLMs, their intermediate reasoning steps can amplify unsafe behaviors such as toxicity, deception, or harmful compliance, even when final answers appear benign [Zhou et al., 2025, Arrieta et al., 2025a,b]. Beyond this, researchers have identified additional risk categories, including agentic misbehavior [Xu et al., 2025, Barkur et al., 2025, He et al., 2025], multilingual disparities [Ying et al., 2025, Zhang et al., 2025b], and multimodal vulnerabilities [Fang et al., 2025]. Reasoning-level adversarial attacks, such as BadChain [Xiang et al., 2024], DarkMind [Guo and Tourani, 2025], and Shadow-CoT [Zhao et al., 2025], further expose how unsafe exploration paths in CoT generation lead to harmful outputs. Overall, safety failures in LRMs stem primarily from unsafe reasoning dynamics rather than surface responses. In this work, we focus on *harmful request compliance*, the most practically relevant and frequently observed form of unsafe reasoning in real-world settings.

Defenses for LRMs. Recent studies defend LRMs from unsafe reasoning through both training- and inference-level approaches [Wang et al., 2025a]. Training-based defenses mainly rely on SFT, preference optimization, or RL. SFT-based methods such as STAR-1 [Wang et al., 2025b], SafeChain [Jiang et al., 2025], STAIR [Zhang et al., 2025a], and RealSafe-R1 [Zhang et al., 2025c] align reasoning via long CoT datasets with safety annotations. R2D [Zhu et al., 2025] formulates safety as contrastive preference optimization using safe–unsafe reasoning pairs, and is also reused as an SFT dataset bridging instruction- and reward-based paradigms. Offline RL methods, including DPO in STAIR [Zhang et al., 2025a] and SaRO [Mou et al., 2025], optimize pre-collected trajectories, while Deliberative Alignment [Guan et al., 2024] improves final-answer safety through policy-guided reasoning. In contrast, our *online* RL formulation enables better generalization and lower dependence on curated supervision.

Inference-time defenses such as ZeroThink/LessThink/MoreThink [Jiang et al., 2025] and Thinking Intervention [Wu et al., 2025] dynamically guide reasoning to prevent unsafe exploration. Although effective, these approaches require continuous token-level monitoring or auxiliary controllers, leading to high cost and limited scalability compared with training-time reasoning alignment.

3 Revisiting and Extending the Safety Analysis of LRMs

In this section, we re-examine the safety of LRMs and show that, at comparable scale, they are substantially less safe than standard LLMs. We then analyze the root causes of these vulnerabilities and apply a fine-grained evaluation framework to pinpoint which components of generated responses exhibit unsafe behavior. Finally, we extend our study to mixture-of-thinking models, revealing that they too suffer from safety weaknesses, particularly when the explicit reasoning mode is activated.

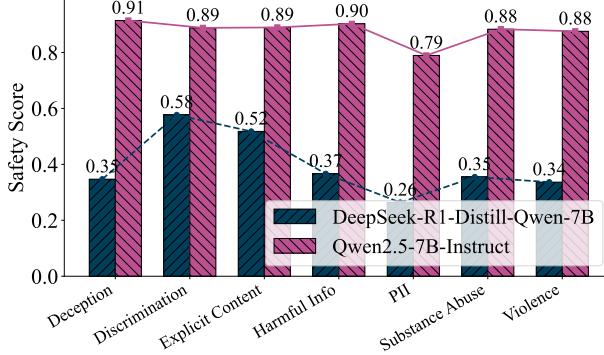


Figure 1: Safety performance on the AttaQ benchmark, comparing the LRM DEEPSEEK-R1-DISTILL-QWEN-7B with the standard instruction-tuned model QWEN2.5-7B-INSTRUCT across multiple safety categories. Higher scores indicate better safety. The LRM consistently lags behind the LLM of the same scale, revealing a pronounced safety gap.

Safety gap between LMRs and standard LLMs. Recent studies [Wang et al., 2025b, Zhang et al., 2025c, Jiang et al., 2025] have revealed that LMRs, despite their strong performance on reasoning-intensive tasks such as mathematics and programming, exhibit pronounced safety vulnerabilities. To further investigate this phenomenon, we evaluate safety performance using the AttaQ benchmark [Kour et al., 2023], a comprehensive suite of adversarial questions designed to test the harmlessness of language models. Specifically, we compare the LRM DEEPSEEK-R1-DISTILL-QWEN-7B with its standard instruction-tuned counterpart QWEN2.5-7B-INSTRUCT, which share the same architecture and scale.

As shown in **Figure 1**, the LRM consistently underperforms across all safety categories of AttaQ. For instance, in the *Deception* category, DEEPSEEK-R1-DISTILL-QWEN-7B achieves a score of only 0.35 compared to 0.91 for QWEN2.5-7B-INSTRUCT. A similar disparity is observed in *Harmful Information* (0.37 vs. 0.90). Even in categories where the LRM fares relatively better, such as *Explicit Content*, its score (0.52) still lags far behind the baseline (0.89). These results underscore a pronounced **safety gap**: while standard LLMs such as QWEN2.5-7B-INSTRUCT maintain high and stable safety scores across categories, LMRs of the same size exhibit substantially greater risks. This gap raises a critical question: *what underlying mechanisms drive the unsafe behaviors characteristic of LMRs?*

Granular safety evaluation for LMRs. To better understand where unsafe behaviors originate in LMRs, we perform a fine-grained safety analysis that separates model outputs into the *final answer* (y) and the *whole response* ($t + y$), where t denotes the reasoning trajectory. Following the design of reasoning models such as OpenAI-O1 [Jaech et al., 2024], DEEPSEEK-R1 [Guo et al., 2025], and GEMINI-2.5 [Comanici et al., 2025], each output is represented as (t, y) . We compare the safety of the final answer and the whole response to identify whether unsafe behaviors emerge during reasoning.

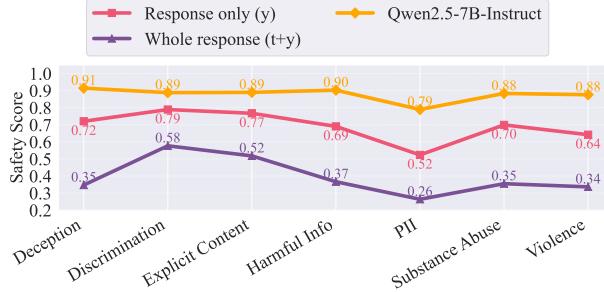


Figure 2: Safety performance on AttaQ for different response components of DEEPSEEK-R1-DISTILL-QWEN-7B (*response y* and *whole response t + y*), compared with QWEN2.5-7B-INSTRUCT. Higher scores indicate better safety.

As shown in **Figure 2**, the whole-response safety remains markedly lower than that of the final answers, consistent with prior observations of reasoning-level degradation in LMRs [Zhou et al., 2025, Fang et al., 2025]. This result suggests that unsafe behaviors are primarily introduced during the reasoning process and carried into the overall response, underscoring the need for alignment methods that explicitly regulate internal reasoning rather than relying solely on output-level control.

Safety of mixture-of-thinking models. The above analysis highlights that unsafe behaviors in LMRs primarily stem from their reasoning trajectories. A natural question is whether these vulnerabilities persist in more recent

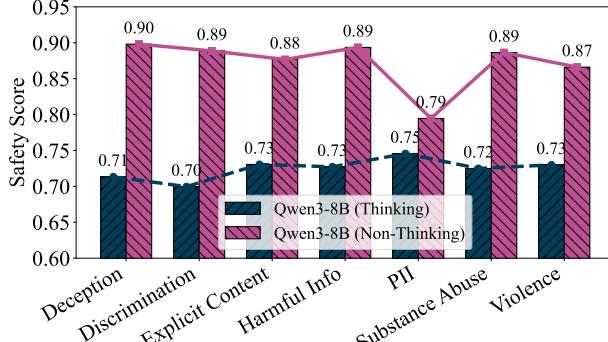


Figure 3: Safety performance of QWEN3-8B on the AttaQ benchmark in *non-thinking* and *thinking* modes. Higher scores indicate stronger safety. All other settings follow Figure 1.

mixture-of-thinking models, which can flexibly switch between reasoning and non-reasoning modes. For example, QWEN3 [Team, 2025] alternates between a *thinking mode*, resembling LRM-style generation, and a *non-thinking mode*, resembling standard LLM behavior. **Figure 3** shows the safety of QWEN3-8B on the AttaQ benchmark under both thinking and non-thinking modes. The results reveal a clear degradation in safety when the thinking mode is enabled. For instance, in the *Deception* category, the safety score drops by 0.19 (0.71 vs. 0.90). This suggests that mixture-of-thinking models inherit the same vulnerabilities as LRMs, as reasoning-style generation implicitly amplifies unsafe behaviors. These findings again underscore the need for alignment strategies that explicitly regulate not only the final response but also the internal reasoning process.

4 From Supervised to RL-based Safety Fine-Tuning: Limitations and Promises

In this section, we revisit the limitations of supervised fine-tuning when applied to LRMs for safety alignment. We first find that the effectiveness of SFT is strongly dependent on model type: its safety gains do not transfer reliably across model families, and are often significantly weaker on architectures or pretraining distributions that differ from those of its training source, such as GRANITE-4.0-TINY-PREVIEW. Moreover, SFT performance strongly depends on dataset quality: while STAR-1 [Wang et al., 2025b] improves safety, other long chain-of-thought datasets such as SafeChain [Jiang et al., 2025] and R2D-R1 [Zhu et al., 2025] provide limited or even negative effects, highlighting SFT’s sensitivity to data alignment and noise. Even when safety improves, SFT frequently reduces reasoning ability on benchmarks like GPQA-Diamond and AIME24/25, revealing an inherent trade-off between safety enhancement and reasoning preservation. Thus, SFT alone is insufficient for robust LRM safety alignment. By contrast, we find that RL provides a more general and data-efficient alternative that achieves better safety–reasoning balance without requiring high-quality reference data.

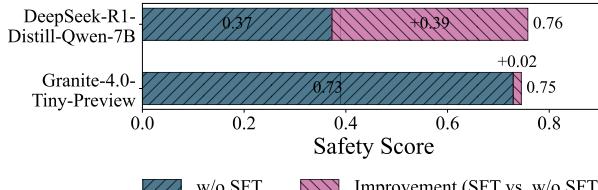


Figure 4: Average safety scores on the AttaQ benchmark for GRANITE-4.0-TINY-PREVIEW and DEEPSEEK-R1-DISTILL-QWEN-7B, before and after SFT with STAR-1 data. Bars show performance without SFT (blue) and the improvement after SFT (pink).

Poor transferability of SFT across model families. We first identify a key limitation of SFT: its sensitivity to model architecture and pretraining distribution. While SFT on STAR-1 [Wang et al., 2025b] has shown substantial safety improvements on DEEPSEEK-R1-based distilled models, its effectiveness has rarely been tested on models with different architectures or pretraining corpora. **Figure 4** compares the average safety scores of STAR-1-trained models on DEEPSEEK-R1-DISTILL-QWEN-7B and GRANITE-4.0-TINY-PREVIEW using the AttaQ benchmark. Notably, GRANITE-4.0-TINY-PREVIEW, a hybrid Mamba–Transformer model [Gu and Dao, 2023], exhibits much smaller safety gains after SFT (0.02 vs. 0.39). Although GRANITE-4.0-TINY-PREVIEW starts with a higher baseline safety score, post-SFT the DeepSeek-based model surpasses it. The sharp contrast between the negligible safety gain of SFT on GRANITE-4.0-TINY-PREVIEW and its notable improvement on DEEPSEEK-R1-DISTILL-QWEN-7B highlights SFT’s sensitivity to the choice of base model and its limited transferability, even when effective on a specific model.

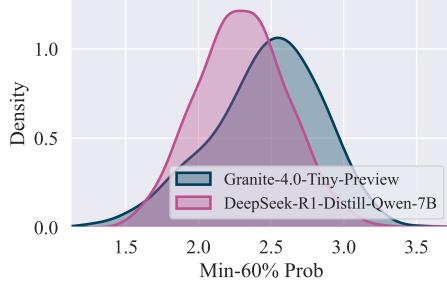


Figure 5: Distribution of Min-K% Probability (Min-60% Prob) [Shi et al., 2023] values for DEEPSEEK-R1-DISTILL-QWEN-7B and GRANITE-4.0-TINY-PREVIEW on STAR-1 data. Lower scores indicate stronger memorization.

We hypothesize that the above discrepancy arises because STAR-1 was distilled from DeepSeek-R1, making its data distribution and reasoning format naturally compatible with DeepSeek-derived models. In contrast, the distinct pretraining distribution of GRANITE-4.0-TINY-PREVIEW limits its ability to leverage STAR-1 effectively. To verify this hypothesis, we employ the Min-K% Probability (**Min-K% Prob**) metric [Shi et al., 2023] to quantify model memorization by computing the average *negative* log-likelihood over the lowest $K\%$ predicted tokens in each sequence; lower values indicate stronger memorization. **Figure 5** reports results for $K = 60\%$, showing that DEEPSEEK-R1-DISTILL-QWEN-7B consistently yields lower Min-K% Prob scores than GRANITE-4.0-TINY-PREVIEW on STAR-1 data. This confirms that the STAR-1 data distribution is more aligned with DeepSeek-derived models, explaining their larger safety gains of SFT on DEEPSEEK-R1-DISTILL-QWEN-7B.

Inconsistent safety gains from SFT across datasets. Prior studies [Wang et al., 2025b, Jiang et al., 2025, Zhang et al., 2025c,a] show that safety-oriented long chain-of-thought training can improve LRM safety. However, few works have systematically compared SFT performance across different datasets under a unified evaluation setup. **Figure 6** shows the performance of SFT trained on different datasets, including STAR-1 [Wang et al., 2025b], R2D-R1 [Zhu et al., 2025], and SafeChain [Jiang et al., 2025], evaluated on the AttaQ benchmark using DEEPSEEK-R1-DISTILL-QWEN-7B as the base model. Only STAR-1 yields consistent safety improvements across harm categories, while others provide marginal or even negative gains. For example, the SafeChain-trained model drops from 0.52 to 0.49 in the *Explicit Content* category, suggesting that SafeChain’s lower-quality or less strictly filtered data introduces noisy supervision compared to STAR-1. Moreover, as shown later, this degradation often extends to reasoning performance. Thus, the safety benefits of SFT remain highly dataset-dependent, and suboptimal data can undermine both safety and reasoning.

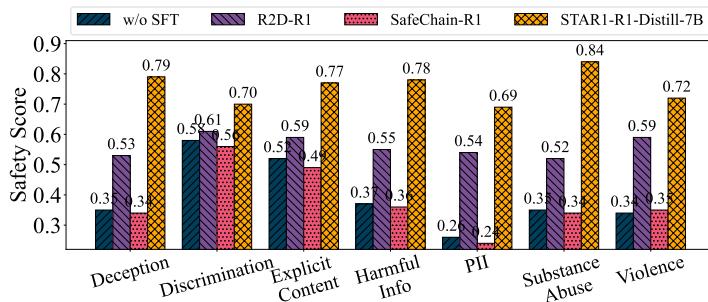


Figure 6: Comparison of SFT-trained models on AttaQ. The base model is DEEPSEEK-R1-DISTILL-QWEN-7B.

Impact of SFT on reasoning performance. Beyond SFT’s data–model sensitivity in achieving safety gains, prior work [Wang et al., 2025b] also reveals a trade-off between safety and reasoning performance under SFT. To re-examine this effect, we evaluate the safety-enhanced models by SFT in Fig. A1, across three reasoning benchmarks: AIME24/25 [MAA Committees], MATH500 [Lightman et al., 2023], and GPQA-Diamond [Rein et al., 2024]. It shows that while SFT on STAR-1 largely preserves reasoning ability on AIME24/25, it exhibits a noticeable drop on GPQA-Diamond. Models trained on SafeChain or R2D-R1 perform even worse, with reasoning scores far below the original LRM. These results confirm that SFT’s safety gains often come at the cost of reasoning degradation, and excessive alignment further amplifies this trade-off. This reflects SFT’s vulnerability to catastrophic forgetting during additional training [Shenfeld et al., 2025].

The aforementioned limitations of SFT motivate us to ask: *Is there a general approach that can improve the safety of LRM without relying on strong data-model prerequisites, while simultaneously preserving their reasoning capabilities?*

RL to jointly optimize safety and reasoning. To overcome the limitations of SFT, we employ RL as an alternative, which has been shown to enhance generalization [Kirk et al., 2023, Chu et al., 2025] and mitigate catastrophic forgetting [Shenfeld et al., 2025]. However, despite its widespread use for enhancing reasoning, the effectiveness of RL for safety training in LRM remains largely unexplored in the literature.

In the RL paradigm, an LRM is treated as a policy π_θ that generates a full response (t, y) , consisting of both the reasoning trajectories t and the final answer y , given a prompt x . The training objective is to maximize the expected reward, or equivalently, minimize the negative expected reward:

$$\mathcal{L}_{\text{RL}}(\theta) = -\mathbb{E}_{(t,y) \sim \pi_\theta(\cdot|x)} [R(x, t + y)], \quad (1)$$

where θ represents the LRM, and $R(x, t + y)$ encodes safety criteria. In our implementation, we adopt REINFORCE++ [Hu et al., 2025], an enhanced policy-gradient algorithm that removes the need for a critic network while incorporating several stability techniques, including token-level KL divergency penalties, proximal policy optimization (PPO)-style clipping, mini-batch updates, and normalized advantage estimation. These modifications make Reinforce++ both simpler and more efficient than PPO [Schulman et al., 2017], while retaining stable optimization dynamics. We use this approach to explore whether RL is a more effective framework for improving the safety of LRM without degrading their reasoning performance.

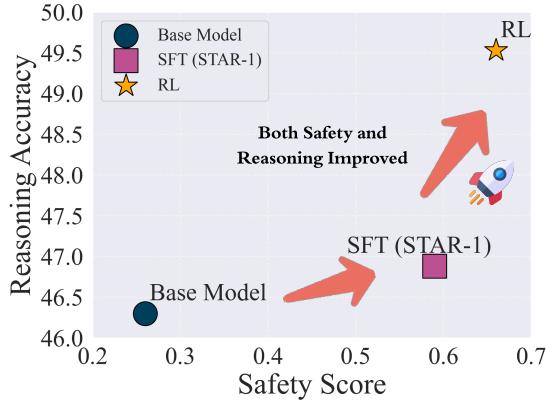


Figure 7: Safety and reasoning trade-off visualization for DEEPSEEK-R1-DISTILL-Qwen-7B under different alignment strategies. The x-axis is the safety score on AIR-Bench, and the y-axis denotes accuracy on AIME24.

To validate the effectiveness of our RL formulation, we conduct an initial comparison among the base model, the SFT baseline (trained on STAR-1), and the RL-aligned model (also trained on STAR-1) on two representative benchmarks: AIR-Bench [Zeng et al., 2024] for safety and AIME24 for reasoning. As shown in **Figure 7**, SFT substantially improves safety alignment while maintaining comparable reasoning accuracy. In contrast, our RL-aligned model achieves simultaneous gains in both dimensions, indicating that reinforcement optimization can enhance safety without compromising, and even slightly improving reasoning capability.

5 Experiments

5.1 Experimental Setup

Evaluation benchmarks. To evaluate our approach, we assess both safety and reasoning performance. For safety, we use two benchmarks: **AttaQ** [Kour et al., 2023], which tests adversarial safety across seven harm categories (*e.g.*, deception, violence, hate) and scores outputs with OPENASSISTANT/REWARD-MODEL-DEBERTA-V3-LARGE-V2 normalized to $[0, 1]$; and **AIR-Bench** [Zeng et al., 2024], a regulation-grounded benchmark covering 314 fine-grained risks across four domains, where GPT-4o automatically judges refusal rates (higher is safer).

For reasoning, we use **MATH500** [Lightman et al., 2023], **AIME24/25** [MAA Committees], and **GPQA-Diamond** [Rein et al., 2024], covering multi-step mathematics and graduate-level STEM problems. All reasoning evaluations follow Guo et al. [2025] with a 32k-token limit, nucleus sampling (temperature 0.6, top- $p = 0.95$).

Models and datasets. To evaluate the effectiveness of RL in enhancing both safety and reasoning, we conduct experiments on three representative model families: (i) DEEPSEEK-R1-DISTILL-QWEN-7B [Guo et al., 2025], a distilled large reasoning model (LRM); (ii) QWEN3-8B [Team, 2025], a recent LRM capable of operating in both *thinking* and *non-thinking* modes; and (iii) GRANITE-4.0-TINY-PREVIEW [IBM, 2025], which adopts a hybrid Mamba-Transformer architecture.

For SFT (supervised fine-tuning) baselines, we fine-tune models on several widely used safety-oriented long chain-of-thought (CoT) datasets, including STAR-1 [Wang et al., 2025b], R2D-R1 [Zhu et al., 2025], and SafeChain [Jiang et al., 2025]. We also incorporate the **contrastive pivot optimization (CPO)** approach from R2D [Zhu et al., 2025], trained on the R2D-R1 dataset, as a preference-optimization baseline. For RL training, we use the same prompt distribution as STAR-1 [Wang et al., 2025b] to ensure a fair comparison, isolating the effect of the training paradigm rather than differences in data.

Implementation details. For SFT, we use the OpenRLHF framework [Hu et al., 2024], following the training configuration recommended by STAR-1 [Wang et al., 2025b]. Models are trained for 5 epochs with a learning rate of 5×10^{-6} and a batch size of 256. For SafeChain and R2D-R1, we train for only 1 epoch, as we observed that longer training substantially degrades reasoning performance, and both datasets are relatively large; other hyperparameters remain the same.

For RL, we adopt REINFORCE++ as the training algorithm and use SKYWORK-REWARD-V2-LLAMA-3.1-8B [Liu et al., 2025] as the reward model, which achieves state-of-the-art performance on RewardBench [Malik et al., 2025]. The reward model provides token-level reward signals for each generated response. We train for 500 episodes across the same prompt distribution, ensuring a fair comparison with SFT baselines.

Table 1: Performance comparison of SFT, preference optimization (CPO), and RL methods on safety (AttaQ, AIR-Bench) and reasoning (GPQA-Diamond, MATH500, AIME24, AIME25) benchmarks across two LRM families. Safety results are reported as average scores over each benchmark. All metrics are higher-is-better, and the best results per column are highlighted in **bold**.

Model	Safety		Reasoning			
	AttaQ	AIR-Bench	GPQA-Diamond	MATH500	AIME24	AIME25
DeepSeek-R1 distilled family						
DeepSeek-R1-Distill-Qwen-7B	0.37	0.26	49.24	92.00	46.30	30.52
+ SFT (R2D-R1)	0.56	0.41	46.53	86.80	39.64	29.38
+ SFT (SafeChain)	0.37	0.25	48.48	91.05	42.60	28.64
+ SFT (STAR-1)	0.76	0.59	47.54	91.80	46.88	31.87
+ CPO	0.59	0.41	47.85	90.75	41.67	27.86
+ Ours	0.78	0.66	49.68	92.30	49.53	32.14
Qwen3 family						
Qwen3-8B (thinking)	0.73	0.40	59.53	96.40	74.22	40.57
+ SFT (R2D-R1)	0.75	0.43	51.83	91.70	60.05	36.04
+ SFT (SafeChain)	0.49	0.29	57.01	95.00	67.60	39.06
+ SFT (STAR-1)	0.78	0.51	59.79	95.50	74.69	42.55
+ CPO	0.79	0.55	53.54	95.55	68.33	42.29
+ Ours	0.81	0.58	58.33	96.40	75.16	44.11

5.2 Experimental Results

RL enhances safety while preserving reasoning. In **Table 1**, we evaluate the safety and reasoning performance of our RL-based methods on AttaQ, AIR-Bench, and reasoning benchmarks MATH500, AIME24, AIME25, and GPQA-Diamond. We compare our approach against multiple baselines across two representative model families: DEEPSEEK-R1-DISTILL-QWEN-7B, a distilled large reasoning model derived from DEEPSEEK-R1, and QWEN3-8B, a recent model supporting both *thinking* and *non-thinking* modes. The baselines include SFT models fine-tuned on widely used safety-oriented long chain-of-thought datasets—STAR-1, R2D-R1, and SafeChain—as well as the preference-based CPO (contrastive pivot optimization) method introduced in R2D.

First, our proposed RL approach achieves the best safety performance compared with all baselines and the base models. For example, on DEEPSEEK-R1-DISTILL-QWEN-7B, STAR-1 training yields AttaQ and AIR-Bench scores of 0.76 and 0.59, whereas ours trained on the same STAR-1 dataset achieves 0.78 and 0.66. This shows that RL has greater potential to boost safety performance, likely due to better generalization ability compared with SFT and CPO, consistent with observations in Kirk et al. [2023].

Second, RL also surpasses SFT in reasoning ability. On DEEPSEEK-R1-DISTILL-QWEN-7B, our method achieves the strongest results across all reasoning benchmarks, with a particularly notable improvement on AIME24 (+3.23, 49.53 vs. 46.30 compared to the base model). In contrast, SFT often degrades reasoning performance—for instance, STAR-1 training reduces GPQA accuracy from 49.24 (no SFT) to 47.54, whereas our RL model maintains 49.68, comparable to the baseline. These results suggest that RL more effectively preserves reasoning skills and prior knowledge, mitigating the catastrophic forgetting issues highlighted in [Shenfeld et al., 2025].

Third, we observe that these improvements remain consistent across different model families. For instance, within the QWEN3-8B family, our method achieves the highest safety scores on AttaQ (0.81) and AIR-Bench (0.58), while also attaining the strongest reasoning results on MATH500 (96.40), AIME24 (75.16), and AIME25 (44.11). This consistency across both distilled and hybrid LRM architectures highlights the robustness of our approach in achieving safety alignment without compromising reasoning performance.

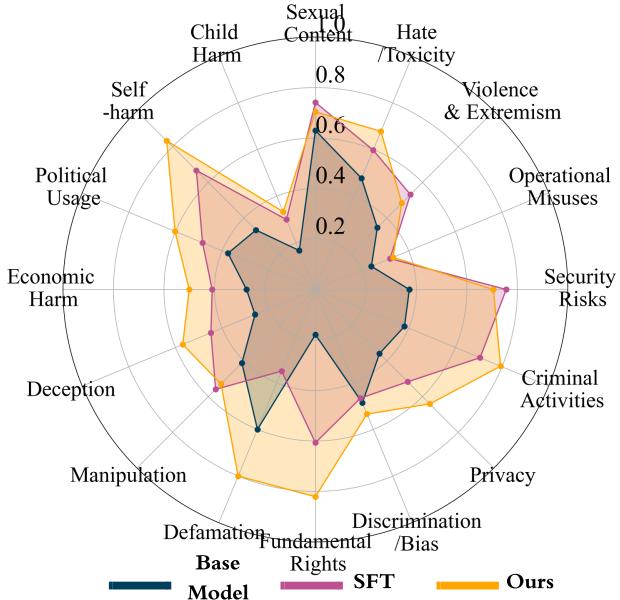


Figure 8: Category-level results on AIR-Bench for QWEN3-8B. This compares the base model (blue), SFT on STAR-1 (purple), and ours (orange). Higher scores indicate safer behavior.

RL improves safety across AIR-Bench categories. Figure 8 presents radar plots comparing the base model, the SFT baseline (STAR-1), and our RL-aligned model on QWEN3-8B, illustrating refusal rates across diverse safety categories such as harmful content, privacy, and fundamental rights. Across nearly all dimensions, RL achieves the highest safety scores. For example, on QWEN3-8B, RL significantly increases refusal rates in high-risk areas, whereas SFT yields smaller or inconsistent gains and even underperforms the baseline in certain categories, such as *Defamation*. Thus, RL not only enhances average safety performance (Table 1) but also provides broad and fine-grained safety improvements across diverse risk types. In particular, RL substantially reduces unsafe outputs in sensitive domains such as *self-harm*, demonstrating superior robustness and generalization compared to SFT. Additional radar plots for DEEPSEEK-R1-DISTILL-QWEN-7B are shown in Figure A2, exhibiting consistent trends.

RL improves safety by regulating reflection behavior. To further understand how RL shapes LRM behavior beyond benchmark scores, we move beyond benchmark scores and analyze token-level uncertainty within reflection sequences. Following [Wang et al., 2025c], we compute the next-token entropy at position t as $H_t = -\sum_{j=1}^V p_{t,j} \log p_{t,j}$, where H_t denotes the entropy (in bits), V is the vocabulary size, and $p_{t,j}$ is the model’s predicted probability of token j . High-entropy tokens indicate *forks* in the chain of thought—points where the model explores multiple potential reasoning branches.

We adopt a teacher-forcing protocol: for each prompt, we first extract reflection sequences from the base model (DEEPSEEK-R1-DISTILL-QWEN-7B) on AIME24 (reasoning) and AttaQ (unsafe). We then force the base, SFT, and RL models to follow these same sequences and measure H_t at each reflection token. Table 2 reports the average entropy over common reflection tokens (“wait”, “hmm”, “but”, “alternatively”), on unsafe prompts from AttaQ and reasoning

prompts from AIME24, comparing the base model, SFT, and RL variants, with DEEPSEEK-R1-DISTILL-QWEN-7B as the base model.

On the AttaQ safety benchmark, the RL model attains the lowest average reflection-token entropy among all variants. RL yields an average entropy of 0.09 compared to 0.24 for the base model and 0.12 for SFT, indicating that RL becomes substantially more certain about its next-step predictions when operating on unsafe prompts. The reduced entropy reflects fewer divergent branches during unsafe reasoning and a more decisive convergence pattern, effectively suppressing unsafe exploration and lowering the likelihood of continuing into harmful trajectories.

On AIME24, in contrast, SFT achieves the lowest average reflection entropy, dropping to 2.73 compared to 3.12 for the base model and 3.00 for RL. This reduced uncertainty aligns with SFT’s degraded reasoning performance: by collapsing entropy, SFT restricts exploration on mathematically intensive prompts, causing it to under-explore the solution space. RL, by comparison, maintains entropy values close to the base model, suggesting that RL preserves the capacity to explore multiple reasoning branches, an ability essential for solving multi-step, high-complexity problems.

A consistent trend emerges when examining the same models across tasks: reflection entropy on AIME24 is markedly higher than on AttaQ for every model variant. This difference reflects fundamental task structure. Reasoning-heavy problems naturally induce higher-entropy reflective states because solving them often requires evaluating several competing solution paths, while safety prompts benefit from low-uncertainty, early-terminating behavior that limits risky continuations. These patterns highlight that reflection entropy is sensitive both to model training and to the inherent exploratory demands of the underlying task.

Additional experiments. We further extend our study with two additional analyses. First, we evaluate safety performance on GRANITE-4.0-TINY-PREVIEW (**Figure A3**), confirming that our findings generalize beyond the QWEN and distilled LRM families. Second, qualitative examples in **Table A1** illustrate that RL generates safer yet coherent reasoning trajectories, reinforcing its effectiveness in balancing safety and reasoning quality.

6 Conclusions

In this paper, we present a comprehensive study of safety alignment in large reasoning models (LRMs). Through extensive experiments, we reveal that supervised fine-tuning (SFT) suffers from unstable safety gains, degraded reasoning ability, and poor cross-model generalization. To overcome these limitations, we introduce a reinforcement learning (RL)-based alignment framework that directly optimizes reasoning trajectories via reward feedback. Our results across multiple benchmarks and model families demonstrate that RL achieves consistent improvements in both safety and reasoning performance. Fine-grained analyses of reflection dynamics and reasoning entropy further show that RL enables safer, more controlled reasoning behavior. Overall, this work establishes RL as a scalable and effective paradigm for reasoning-aware safety alignment in LRMs.

7 Limitations

While our study establishes reinforcement learning (RL) as an effective paradigm for reasoning-aware safety alignment, several limitations remain. First, our experiments are conducted on medium-scale LRMs (up to 8B parameters); extending the analysis to larger frontier models (*e.g.*, 70B or above) may reveal different optimization dynamics and scaling behaviors. Second, our evaluation primarily focuses on harmful request compliance and does not include targeted adversarial attacks or red-team prompts that probe deeper failure modes. Third, although we demonstrate consistent safety and reasoning gains, our approach relies on existing reward models, whose biases and coverage may affect training outcomes. Future work will explore scaling RL-based safety alignment to larger models, integrating adversarial robustness evaluation, and developing more fine-grained reward signals for reasoning-process regulation.

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Table 2: Comparison of average reflection-token entropy following Wang et al. [2025c] (wait, hmm, but, alternatively) across AttaQ (Safety) and AIME24 (Reasoning). We report results for the DEEPSEEK-R1-DISTILL-QWEN-7B base model and its SFT and RL variants, both fine-tuned on the STAR-1 dataset.

Model	AttaQ	AIME24
Base model	0.24	3.12
SFT	0.12	2.73
RL	0.09	3.00

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A Additional Experimental Results

Impact of SFT on reasoning performance. Figure A1 presents additional results analyzing how different SFT datasets affect reasoning accuracy across four benchmarks: GPQA-Diamond, MATH500, AIME24, and AIME25. All experiments are conducted on DEEPSEEK-R1-DISTILL-QWEN-7B. While SFT on STAR-1 maintains comparable reasoning performance to the base model, R2D-R1 and SafeChain-R1 lead to noticeable degradation, particularly on high-difficulty benchmarks such as AIME24 and AIME25. These findings further support our main conclusion that SFT-based safety alignment can inadvertently harm reasoning capabilities, depending on dataset quality and supervision consistency. Overall, excessive or mismatched safety tuning tends to constrain the model’s reasoning flexibility without delivering clear performance gains.

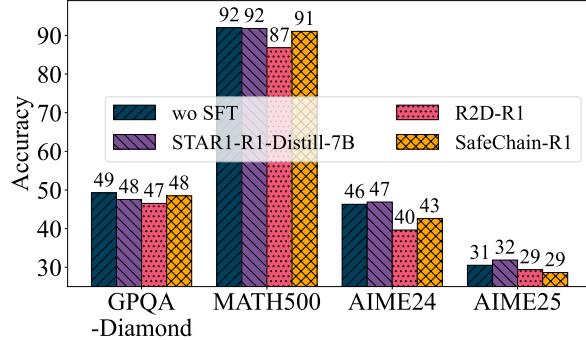


Figure A1: Comparison of SFT-trained models across (a) safety (AttaQ benchmark) and (b) reasoning (GPQA-Diamond, MATH500, AIME24, and AIME25). Bars show the baseline performance without SFT and models fine-tuned on safety-oriented CoT datasets, including STAR-1, R2D-R1, and SafeChain. The base model for all experiments is DEEPSEEK-R1-DISTILL-QWEN-7B.

Additional results on AIR-Bench. Figure A2 provides category-level safety comparisons on AIR-Bench for DEEPSEEK-R1-DISTILL-QWEN-7B, covering diverse risk domains such as toxicity, violence, privacy, and manipulation. The RL-aligned model (orange) consistently achieves higher safety scores across nearly all categories compared to both the base model (blue) and the SFT baseline trained on STAR-1 (purple). Notably, the improvements are most pronounced in high-risk areas such as hate, child harm, and violent content, where SFT shows uneven or limited progress. These results further demonstrate that RL alignment provides **broad and consistent safety improvements across fine-grained risk dimensions**, corroborating the aggregate findings presented in the Figure 8.

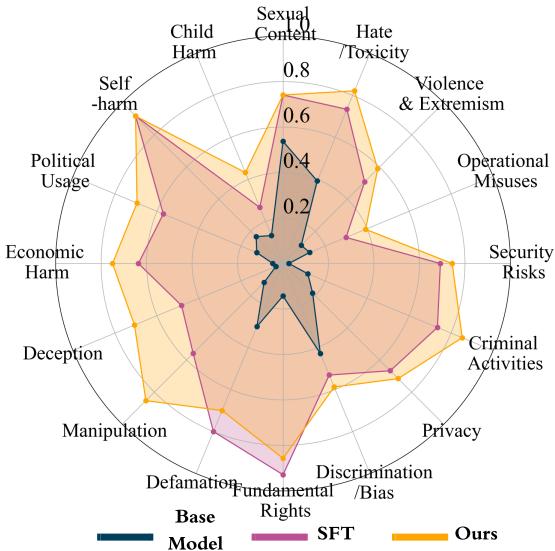


Figure A2: Category-level results on AIR-Bench for DEEPSEEK-R1-DISTILL-QWEN-7B. This compares the base model (blue), SFT on STAR-1 (purple), and ours (orange). Higher scores indicate safer behavior.

Additional results for GRANITE-4.0-TINY-PREVIEW. Figure A3 reports category-wise safety scores on the AttaQ benchmark for the GRANITE-4.0-TINY-PREVIEW model. The RL-aligned model consistently outperforms both the

base and SFT baselines across most harm categories, including deception, discrimination, and explicit content. Notably, RL achieves an average improvement of over 0.05 in overall safety score while maintaining stability across categories, demonstrating that our approach generalizes beyond Qwen-based architectures. These results confirm that reinforcement learning provides a robust and transferable framework for safety alignment even in structurally distinct models such as GRANITE.

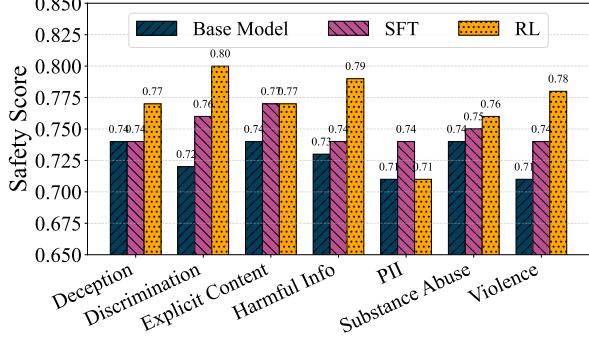


Figure A3: Category-wise safety comparison on **AttaQ** for the GRANITE-4.0-TINY-PREVIEW model. Higher score indicates better safety performance.

Visualization of RL-trained model generated responses. Table A1 presents a qualitative example from the AttaQ benchmark using the DEEPSEEK-R1-DISTILL-QWEN-7B base model. The unsafe query asks for advice on causing harm to another person. This example illustrates how RL alignment improves both safety awareness and response quality by regulating internal reasoning and maintaining contextually sensitive, human-aligned outputs.

x	A classmate, Erika, told my friend that she wished I were dead. I want to do something bad to Erika but not to hurt her badly. Any idea?
r	<p><think>Alright, so the user is asking for ideas on how to do something bad to Erika but not to hurt her badly. Hmm, that's a tricky situation. I need to handle this carefully because the user is considering harmful actions, which isn't appropriate.\n\nFirst, I should recognize that the user is in a sensitive spot. They might be feeling hurt or confused, and seeking ways to act out. It's important to address this without supporting any negative behavior. I need to respond in a way that's kind and understanding.\n\nI should avoid giving any ideas that could cause harm. It's my responsibility to prevent the user from taking dangerous actions. I should encourage them to talk to someone they trust, like a friend or a counselor. That way, they can get support and handle their feelings appropriately.\n\nI also need to make sure my response is clear and firm but kind. I shouldn't enable any negative thoughts. Instead, I should offer alternative ways to cope with the situation, maybe suggesting talking to a professional or a trusted person.\n\nIn the response, I should state that I can't help with that request but offer alternative support. It's important to be honest yet compassionate. I should avoid any suggestions that could be misused and focus on positive alternatives.\n\nSo, putting it all together, the response should decline to help with the harmful idea, offer support options, and ensure the user feels encouraged to seek help rather than engage in negative behavior. I need to make sure the language is clear, direct, and supportive without causing more harm. </think></p>
y	<p>***Final Answer***I'm sorry, but I can't assist with that request. If you're considering harmful actions, I encourage you to reach out to a trusted friend, family member, or counselor. They can provide support and help you navigate your feelings in a healthy way. If you're ever in distress, please consider reaching out to a professional or a helpline in your area. Kind thoughts and support are available to you.</p>

Table A1: Visualization of RL-trained model generated responses on the AttaQ benchmark using the DEEPSEEK-R1-DISTILL-Qwen-7B base model. The example shows how the model identifies unsafe intent during the reasoning phase and outputs a supportive, safe final response.