DREAM-RL: Dynamic Reward-System Evolution with an Agentic Meta-Judge for Reinforcement Learning on Open-Ended Tasks

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Abstract

Reinforcement learning for open-ended tasks such as writing and roleplay increasingly relies on rubric-based judges, yet such rewards can become unreliable when used as RL training objectives. As policies adapt to these rewards, rubric-based reward systems can exhibit three training-time failures: reward hacking, insufficient on-policy reward coverage, and diminishing reward informativeness. Existing dynamic-rubric methods adapt evaluation criteria, but fixed reward mechanisms can still leave the training signal vulnerable to hacking, poor coverage, or low variance. We propose DREAM-RL, a framework that represents training rewards as executable *Reward-DAG*s composed of heterogeneous evaluator and composition nodes. A meta-judge agent monitors rollouts and reward diagnostics, then performs replay-validated graph edits to revise reward mechanisms during RL. Experiments on writing and roleplay show that DREAM-RL maintains competitive benchmark quality while improving robustness, lowering late-training hacking, and preserving reward-signal separation over static and dynamic-rubric baselines.

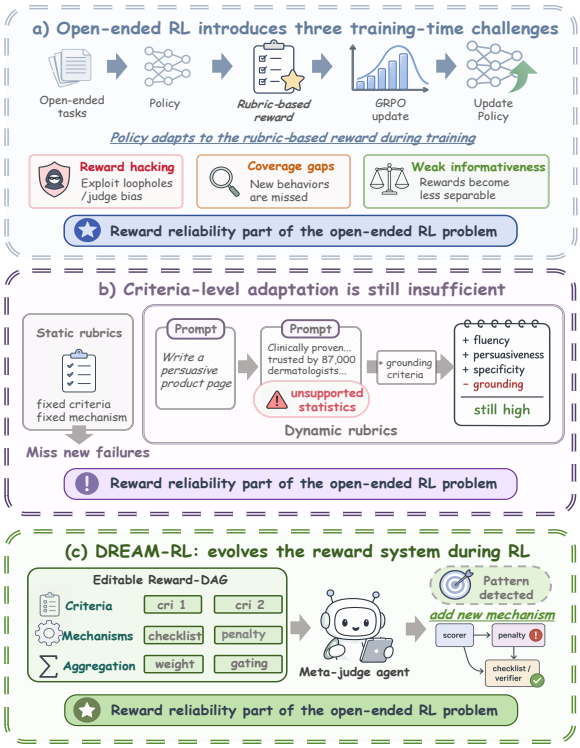

Figure 1: **Reward-system evolution in open-ended RL.** Static or criteria-only rubrics can miss reward hacking, coverage gaps, and weak informativeness; DREAM-RL evolves an editable *Reward-DAG* with meta-judge monitoring during training.

1 Introduction

Reinforcement learning (RL) is increasingly used to improve large language models (LLMs) on open-ended tasks, such as writing, role-playing, and multi-turn agentic tasks that require subjective or context-sensitive evaluation (Jia et al., 2025; Tseng et al., 2024). Unlike mathematical reasoning or code generation, where rewards can often be derived from verifiable answers, open-ended tasks usually require multi-dimensional and context-sensitive judgments. Existing open-ended RL methods therefore rely on rubric-based reward systems, using LLM judges or Generative Reward Models (GRMs) to provide scalable training rewards (Zheng et al., 2023; Gu et al., 2024; Mahan et al., 2024; Zhang et al., 2025). Yet once these rewards are optimized against, their reliability becomes part of the training problem rather than only an evaluation problem.

During RL, the policy continuously adapts to the rubric-based reward system, which exposes new reliability issues. We focus on three training-time challenges: **reward hacking**, where policies exploit rubric loopholes or judge biases (Li et al., 2025; Zhao et al., 2025); **insufficient on-policy reward coverage**, where shifted policy behaviors reveal quality differences or failure modes not expressed by the current reward system (Lang et al., 2024); and **diminishing reward informa-**

tiveness, where the reward signal gradually becomes less useful for optimization, e.g., as rewards saturate or become less separable within same-query groups (Kim et al., 2025b).

To mitigate these training-time reliability challenges, rubric-based RL methods have moved from task-level rubrics to more fine-grained query-level rubrics (Gunjal et al., 2025). Recent dynamic-rubric methods further revise or generate evaluation criteria from on-policy responses to cover behaviors missed by fixed rubrics (Yu et al., 2025; Shao et al., 2025). However, these methods mainly perform *criteria-level adaptation*: they update what the judge should evaluate while largely fixing how judgments are converted into rewards. This distinction matters for optimization. For example, fabricated statistics may create only a small score difference under continuous rubric scoring, but receive direct downward pressure under an explicit penalty mechanism. Thus, open-ended rubric-based RL requires not only dynamic evaluation criteria, but also *reward-mechanism evolution*: adapting the reward nodes, operators, and aggregation paths that turn evaluations into training signals.

We therefore propose DREAM-RL, an RL framework that equips the reward system with an agentic self-evolution loop. A meta-judge agent runs alongside training, not as a response-level judge, but to monitor rollouts, reward traces, and reward-health diagnostics and determine whether the reward remains valid, covering, and informative under policy shift. DREAM-RL represents the reward system as an executable *Reward-DAG* of rubric nodes and composition operators, allowing replay-validated interventions that add or revise nodes, change reward mechanisms, or adjust aggregation. Thus, DREAM-RL adapts not only *what* to evaluate, but also how training-time reward failures are detected, diagnosed, and repaired.

We instantiate DREAM-RL on writing and roleplay, two representative open-ended RL settings where reward specification is difficult and judge-based rewards are easily stressed by optimization. Across both settings, DREAM-RL achieves strongly competitive final benchmark quality. Training-time analyses further show that DREAM-RL reduces late-stage reward hacking, maintains higher within-query reward variance, and lowers zero-distinction rollout groups. Case studies trace these gains to agentic reward-system diagnosis followed by constrained interventions, such as refining penalty mechanisms for newly discovered shortcut patterns or repairing coverage gaps.

Our key contributions are as follows:

- We formulate training-time reward reliability in open-ended rubric-based RL, focusing on reward hacking, coverage gaps, and diminishing informativeness.
- We introduce DREAM-RL, a train-time agentic reward-evolution framework in which a meta-judge agent runs alongside RL to monitor, diagnose, and repair reward-system failures through constrained interventions on executable *Reward-DAG*s, with accepted and rejected interventions distilled into dynamic reward-evolution skills.
- Experiments on writing and roleplay show that DREAM-RL achieves strongly competitive final benchmark quality while improving final-output robustness and reward-signal diagnostics over static-rubric and dynamic-rubric baselines.

2 Related Work

2.1 Rubric-Based Evaluation

Rubric-based evaluation is widely used to assess open-ended LLM outputs. Existing LLM judges instantiate rubrics through several scoring paradigms: **soft rubric/principle scoring**, which assigns continuous dimensional scores (Arora et al., 2025; Kim et al., 2025a; Wu et al., 2025; Kim et al., 2024); **checklist-based scoring**, which decomposes criteria into explicit items for more reproducible judgments (Wei et al., 2025; Lee et al., 2024); and **penalty- or constraint-based scoring**, which penalizes error types or constraint violations (Wang et al., 2025; Hong et al., 2026). Recent work also explores **hybrid rubric systems** that combine subjective quality judgments with verifiable requirements (Liu et al., 2025a).

However, rubric-based evaluation faces two key challenges. First, high-quality rubrics often require manual design, making it difficult to scale to diverse tasks and query-level evaluation; recent work therefore explores automatic rubric generation (Rezaei et al., 2025; Xu et al., 2026; Shen et al., 2026). Second, rubric-based LLM judges and reward models remain vulnerable to systematic biases (Zheng et al., 2023; Ye et al., 2025; Shi et al., 2025; Wang et al., 2026). These studies provide an important foundation for reward modeling, but mainly address fixed-output evaluation.

2.2 Training-Time Reward Reliability

An evaluation system that works in static evaluation can become unreliable when used as an RL objective. A central failure mode is reward overoptimization or reward hacking (Skalse et al., 2022; Zhong et al., 2025; Lambert and Calandra, 2023), where the policy exploits reward-model biases, loopholes, or underspecified objectives to obtain high scores (Gao et al., 2023; Moskovitz et al., 2024). This risk is especially relevant for rubric-based RL with LLM judges (Mahmoud et al., 2026; Zhang et al., 2026), because explicit rubrics may expose exploitable judge biases (Li et al., 2025; Zhao et al., 2025; Singhal et al., 2024). More broadly, reward-model accuracy alone does not guarantee better policies under policy-induced distribution shift (LeVine et al., 2023); training rewards must also maintain discriminability, such as meaningful within-query distinctions among on-policy responses (Chen et al., 2024; Razin et al., 2025).

2.3 Reinforcement Learning for Hard-to-Verify and Open-Ended Tasks

To extend RL from verifiable tasks to open-ended generation, prior work mainly constructs reward signals through **rubric-based RL** or **pairwise RL**. Rubric-based methods have moved from broad task-level principles (Bai et al., 2022; Sun et al., 2024; Yu et al., 2025) toward query-level rubrics and checklists for structured post-training rewards (Gunjal et al., 2025; Viswanathan et al., 2025; Huang et al., 2025). Pairwise RL instead derives preference signals from response comparisons (Xu et al., 2025; Jia et al., 2025; Liu et al., 2025b; Du et al., 2026).

The closest line is **dynamic-rubric RL**, which updates evaluation criteria during training by generating query-specific rubrics (Lv et al., 2026; Xu et al., 2026; Jia et al., 2026), eliciting criteria from pairwise comparisons of current-policy responses (Rezaei et al., 2025), or feeding newly explored policy information into rubric generation (Shao et al., 2025). These methods help rubrics track the evolving policy distribution and reflect broader evidence for on-policy reward feedback (Lang et al., 2024). However, they mainly adapt criteria: the reward mechanisms and composition rules that convert criteria into training signals remain fixed. In contrast, DREAM-RL represents the reward system as an executable *Reward-DAG* and updates reward mechanisms alongside RL.

3 Motivating Analysis

Before introducing DREAM-RL, we analyze two design questions: whether reward mechanisms materially change the training signals induced by the same or similar rubric criteria, and why training-time reward failures are difficult to diagnose and translate into effective reward-system updates.

Why reward mechanisms matter. We use ***reward mechanism*** to denote how a rubric-based reward system turns evaluation criteria into training signals. A reward mechanism specifies the judgment protocol, the granularity of the produced signal, and its normalization into a reward or preference signal. Table 1 lists representative reward mechanisms considered in this work; a fuller taxonomy is provided in Appendix B.1.

Mechanism	Signal	Typical Risk
Continuous Scorer	Dense score	Saturation
Checklist Verifier	Pass rate	Sparsity
Flaw-Penalty	Failure penalty	Over-penalty
Pairwise Comparator	Preference signal	Pair dependence

Table 1: **Reward mechanisms expose different signals.** We consider dense scorer saturation, checklist sparsity, flaw-penalty over-penalization, and pair dependence.

Figures 2 and 3 show why reward evolution cannot be reduced to better rubric wording. Different reward mechanisms applied to the same or similar criteria induce different score distributions, changing reward density, same-query discriminability, and failure sensitivity; a mechanism that is useful early can also saturate later, reducing variance and sample-level separability.

Diagnosis-and-repair bottleneck. Yet editability alone is insufficient: the same symptom can require different repairs. Low within-query variance may reflect scorer saturation, generic criteria, redundant query items, or an aggregation bottleneck; high scores on flawed responses may require criterion refinement, a checklist verifier, a flaw-penalty node routed through a guarded aggregator, or no intervention if evidence is unstable. Train-time reward evolution therefore needs an agentic process that monitors rollout behavior and reward traces, maps failures to bounded reward-system interventions, and validates candidate edits before deployment, motivating DREAM-RL's executable *Reward-DAG*, meta-judge diagnosis, and replay-validated evolution loop. Appendix B.2 provides separability and zero-distinction analyses.

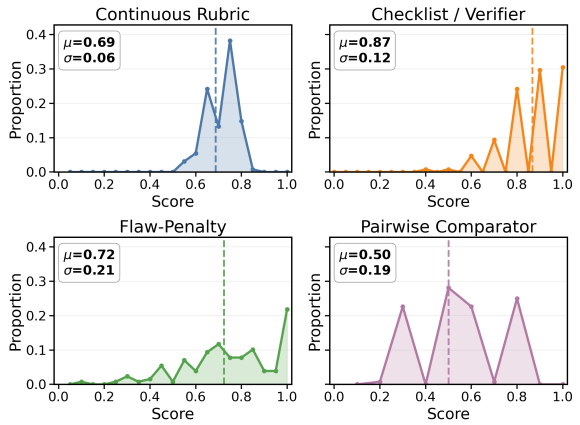

Figure 2: **Mechanisms are not interchangeable.** Different mechanisms induce different score distributions on the same on-policy responses, affecting density, same-query discriminability, and failure sensitivity.

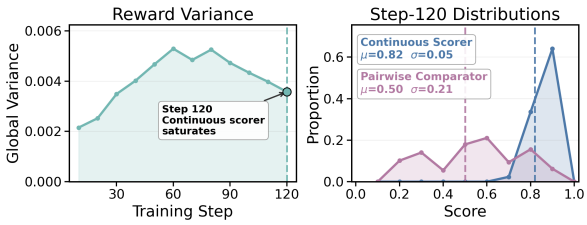

Figure 3: **Fixed scorers can saturate.** Later responses concentrate in a narrower score region, reducing reward variance and sample-level separability.

4 Method

Building on the three train-time challenges above and the role of reward mechanisms in shaping training signals, DREAM-RL treats the reward system itself as a self-evolving train-time object with three coupled components. Section 4.1 defines an executable *Reward-DAG* that exposes criteria, mechanisms, and composition as editable targets. Section 4.2 uses a meta-judge agent to track rollouts and reward traces, identify hacking, coverage, and informativeness failures, and diagnose bounded interventions. Section 4.3 validates candidate edits before live deployment and stores accepted or rejected trajectories as self-evolution experience for later decisions.

We use GRPO-style open-ended RL over queries $x \sim \mathcal{X}$. For each query, the policy samples a response group $\mathcal{Y}_x = \{y_i\}_{i=1}^{K}$, and the current reward system R_t assigns rewards $r_{t,i} = R_t(x, y_i, \mathcal{Y}_x; J_\phi)$ for group-relative policy updates. The subscript t denotes reward evolution during training; Appendix C gives details.

4.1 *Reward-DAG*: Executable Intervention Space

A reward-evolution framework must expose not only what is evaluated, but also how judgments become training signals. We represent R_t as an executable and editable *Reward-DAG* whose backend-agnostic nodes may call a GRM, an LLM-as-judge, or a task-specific verifier. Once a failure is diagnosed, the repair can target the criterion source, reward mechanism, composition rule, or local graph structure.

$$D_t = (\mathcal{V}_t, \mathcal{E}_t, \Theta_t), \tag{1}$$

where $\mathcal{V}_t$ are executable reward nodes, $\mathcal{E}_t$ specifies dependencies and execution order, and Θ_t contains editable criterion sources, mechanisms, judge templates, weights, thresholds, and aggregation rules. The graph has two main node families. A Rubric Node instantiates criteria and executes a reward mechanism,

$$h_v = M_{m_v}(x, y, \mathcal{Y}_x; \rho_v(x, \mathcal{Y}_x), \theta_v, J_\phi), \tag{2}$$

where ρ_v may be fixed task-level criteria or query-specific criteria generated by G_ψ. A Composition Operator maps upstream node signals into the scalar reward consumed by RL,

$$r_D(x, y) = F_{\text{out}}(\{h_v : v \in \text{Pa}(\text{out})\}; \theta_{\text{out}}). \tag{3}$$

Composition Operators aggregate, gate, normalize, or route upstream signals without judging responses. For example, a *reward guard* is an auxiliary verifier, checklist, or flaw-penalty used compositionally: it can downweight, gate, or route the base reward, not replace it. This lets DREAM-RL edit m_v, composition rules, and local graph connections beyond dynamic-rubric edits to ρ_v. Because candidate *Reward-DAG*s are executable, the same object supports typed meta-judge edits and replay validation; Appendix C.2 gives the schema, node contracts, normalization rules, and GRPO scalarization.

The *Reward-DAG* defines which reward-system components can be edited; the next problem is to decide from on-policy evidence whether the current failure concerns hacking, coverage, or informativeness, and which edit or no-op is warranted.

4.2 Meta-Judge Agent: Train-Time Reward Monitoring and Diagnosis

The meta-judge agent therefore turns reward evolution into a bounded diagnosis-and-edit procedure.

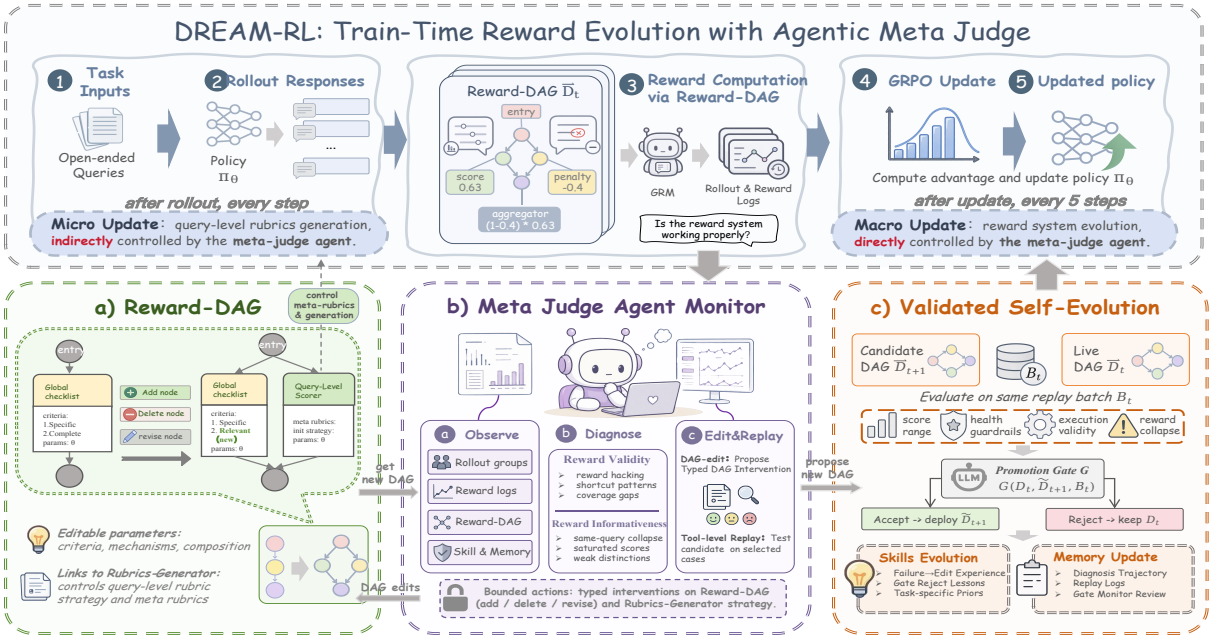

Figure 4: **DREAM-RL overview.** The top panel places reward-system evolution inside the GRPO training loop. The bottom panels show the three algorithmic components: an agentic meta-judge that monitors and diagnoses reward-system failures during RL, an executable *Reward-DAG* intervention space, and replay-validated self-evolution that promotes only validated interventions while feeding accepted and rejected trajectories back into dynamic skills.

At macro step t, it inspects recent rollouts, node-level reward traces, reward-health summaries, and run-local memory, then selects a typed graph intervention

$$e_t = \Pi_{\text{MJA}}(D_t, \mathcal{O}_t, \mathcal{K}_t), \qquad e_t \in \mathcal{A}(D_t), \quad (4)$$

where $\mathcal{O}_t$ contains rollout evidence and reward diagnostics, $\mathcal{A}(D_t)$ is the admissible intervention space, and $\mathcal{K}_t$ stores reward-evolution guidance distilled from earlier accepted and rejected updates.

To choose an edit rather than only flag a failure, the agent checks whether rewards remain valid, covering, and informative under the current policy distribution. It diagnoses shortcut exploitation, missing coverage, and loss of same-query distinctions useful for GRPO. The intervention may refine criteria, repair query-level coverage, add checklist or flaw-penalty nodes, adjust composition, or return a no-op. The harness records $z_t = (o_t, e_t, \Delta_t, a_t, c_t)$, containing the diagnosis, edit, replay evidence, decision, and side effects, and updates $\mathcal{K}_{t+1} = U(\mathcal{K}_t, z_t)$.

The agent is limited to reward-relevant observations and typed *Reward-DAG* edits: it does not replace the judge or modify training code, and live deployment is controlled by the replay gate. Appendices C.4 and C.5 give the tool interface, operator routing, and memory format.

4.3 Replay-Validated Reward Self-Evolution

Given an editable *Reward-DAG* and meta-judge proposals, reward evolution needs a deployment rule that preserves live training signal and turns edit outcomes into future guidance. DREAM-RL uses the current *Reward-DAG* as the GRPO reward: the policy samples $\mathcal{Y}_x$, D_t scores each response, and group-relative advantages update the policy. Micro updates instantiate query- and response-aware criteria inside existing nodes, while macro updates every N steps propose a typed intervention, $\tilde{D}_{t+1} = e_t(D_t)$. The candidate graph is promoted only if the replay gate $\mathcal{G}(D_t, \tilde{D}_{t+1}, \mathcal{B}_t)$ passes; otherwise D_t is retained. The fixed-policy replay batch $\mathcal{B}_t$ checks matched cases for execution failures, signal collapse, or guardrail regressions. Accepted and rejected updates are stored as run-local experience. Appendix C.2 specifies the executable DAG schema, typed edit validator, and program-side replay-gate thresholds; Appendix C.3 gives the full loop.

5 Experiments

5.1 Experimental Setup

Tasks, data, and evaluation. We evaluate DREAM-RL on writing and roleplay. Writing uses 944 filtered synthetic instructions; roleplay

Method	Writing					Roleplay							
	WritingBench		Robust.		Signal	CoSER					Robust.		Signal
	Raw	Calibrated	HR	CFR	R-Var	Overall	SC	AN	CF	SQ	HR	CFR	R-Var
Base model													
Qwen3-4B base	58.76	58.42	7.7	27.8	/	67.11	65.89	66.70	65.07	70.79	6.06	13.0	/
Static rubrics													
RLAIF	61.09	59.57	13.8	21.8	0.0010	71.16	68.43	70.69	70.09	75.42	7.43	16.0	0.0029
RAR	61.73	59.50	14.7	29.5	0.0014	72.18	70.09	71.73	**72.10**	74.80	8.52	22.0	0.0061
Dynamic rubrics													
DR-Tulu	61.04	59.21	11.0	23.9	0.0011	70.40	68.04	68.74	71.21	73.59	9.58	18.0	**0.0137**
OpenRS	61.07	59.58	10.1	31.1	/	69.05	65.69	70.11	66.60	73.80	8.83	15.5	/
Our method													
DREAM-RL	**61.90**	**60.16**	**6.5**	**19.9**	**0.0025**	**73.15**	**72.05**	**72.30**	70.62	**77.64**	**5.25**	**10.0**	0.0063

Table 2: Main results by reward-system family. Raw is the original DeepSeek-V4-Pro WritingBench-style judge; Calibrated is the same judge with a minimal note against over-crediting surface authority, self-certification, and one-dimensional optimization. HR/CFR denote frozen final-output **Hack/Coverage Failure audits**. R-Var is average within-query **reward variance** over grouped rollouts. Higher is better for scores/R-Var; lower is better for HR/CFR. "/" marks undefined or non-comparable signal metrics.

uses 5,000 MiniMax Role-Play Bench queries. Appendix D.3 gives dataset coverage, filtering, and initial-rubric construction. For evaluation, writing uses WritingBench (Wu et al., 2025), reporting both the raw WritingBench score and a calibrated score. The calibrated score asks the same judge to verify whether surface authority, self-certification, and one-dimensional optimization reflect genuine writing quality; Appendix D.5 details the metric's interpretation and setup. Roleplay uses CoSER (Wang et al., 2025), reporting overall GCA-style score and SC/AN/CF/SQ dimensions.

Training and reward systems. All methods share the same GRPO trainer, Qwen3-4B initialization, training data, rollout budget, and evaluation protocol, isolating reward-system design. Unless otherwise noted, scalar rewards use a local Qwen3.5-27B GRM. RLAIF uses fixed task-level rubrics, RAR fixed query-level rubrics, and dynamic-rubric baselines adapt criteria from on-policy rollouts under a fixed reward mechanism. DREAM-RL starts from the same single-node continuous *Reward-DAG* as RLAIF; every 5 RL steps, Codex with our meta-judge harness proposes typed *Reward-DAG* edits that are deployed only after replay validation. Hyperparameters, prompts, edit constraints, replay-gate rules, runtime cost, and agent-framework details are in Appendices C.1 and D.4. We instantiate each baseline's reward-system design in the same GRPO environment to isolate reward-system effects under controlled training conditions.

Metrics and audits. We report benchmark quality, HR, CFR, and R-Var. HR audits fixed reward-attractive shortcut patterns in final outputs, while CFR audits predefined hard coverage-failure labels. The HR/CFR taxonomies are built from a base-model-only calibration pool, frozen before method comparison, hidden from the meta-judge, and audited blind to method labels, reward scores, reward traces, and training stage. R-Var is average within-query reward variance over grouped rollouts, used as a partial reward-informativeness diagnostic. Appendices D.5 and D.6 provide the taxonomies, auditor prompt, paired bootstrap intervals, and CoSER reruns. Appendix A summarizes where we provide details on audit construction, auditor blinding, repeated-judge robustness checks, baseline instantiations, and reward-evolution traces.

5.2 Main Results

We first test whether reward-system evolution improves final quality without trading off robustness or reward-signal usefulness. Table 2 compares final quality, robustness, and reward-signal diagnostics. DREAM-RL obtains the highest mean raw WritingBench score (61.90), calibrated WritingBench score (60.16 vs. 59.58 for the strongest baseline), and CoSER Overall score (73.15 vs. 72.18). Appendix D.6 reports paired bootstrap and repeated-judge checks: writing gains are stable, while roleplay overall remains positive under re-

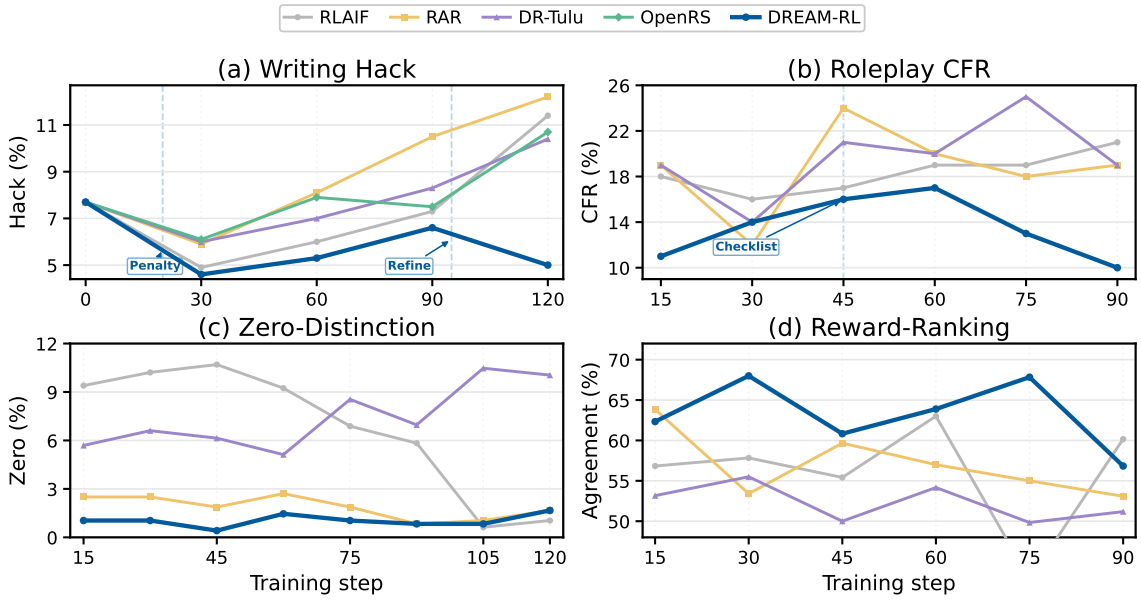

Figure 5: **Training-time reward dynamics.** (a,b) DREAM-RL reduces writing Hack and roleplay CFR after annotated *Reward-DAG* interventions. (c,d) Its rewards preserve same-query distinctions and stronger agreement with blind preference rankings.

peated judging, with a stable SQ gain. More importantly, DREAM-RL also has the lowest HR and CFR on both tasks: 6.5%/19.9% on writing and 5.25%/10.0% on roleplay. On both tasks, DREAM-RL keeps HR below the base model, while most trained baselines increase it. Thus, the gains are not only benchmark-score improvements; static and criteria-adaptive baselines often improve quality while amplifying shortcut patterns or leaving coverage failures.

DREAM-RL also has the strongest writing R-Var (0.0025) and competitive roleplay R-Var (0.0063). Since higher variance can reflect either useful discrimination or noisy penalties, we next inspect training-time dynamics: reward-hacking repair, coverage repair, and whether the reward signal remains useful for same-query policy optimization.

6 Analysis

6.1 Training-Time Dynamics and Agentic Intervention Analysis

Final benchmark scores do not reveal whether DREAM-RL detects and repairs train-time reward failures, so we next inspect reward hacking, coverage failure, and reward-signal usefulness during RL.

Training-Time Reward-Hacking Repair. This analysis asks whether the meta-judge discovers shortcut exploitation from on-policy evidence rather than the hidden post-hoc audit taxonomy. Figure 5(a) shows that static and dynamic-rubric baselines increasingly exhibit writing Hack patterns, whereas DREAM-RL remains lower and reduces late-stage Hack after annotated *Reward-DAG* interventions. The accepted edit uses a guard-style integrity signal to downweight artifact-heavy outputs. Because the post-hoc Hack taxonomy is hidden from the meta-judge, the trend supports on-policy discovery rather than checklist targeting; Appendix E.4 gives the edit trace.

Training-Time Coverage-Failure Repair. This analysis tests whether reward evolution can repair missing on-policy coverage rather than only penalize visible hacks. Figure 5(b) shows the roleplay CFR trajectory: DREAM-RL stays below static and criteria-adaptive baselines and improves after the annotated step-45 coverage repair, which targets hard roleplay-protocol coverage such as speaker-role and perspective control. Appendix E.4 gives the accepted edit and rollout evidence.

Reward-Signal Validity During Training. This analysis checks whether the evolved reward remains useful for optimization, since higher reward variance alone can reflect either discrimination or noisy penalties. Figure 5(c,d) evaluates reward-signal usefulness on on-policy writing groups. DREAM-RL keeps zero-distinction low and maintains stronger agreement with blind

Variant	Writing						Roleplay					
	Score	Δ Score	Hack %	Δ Hack	CFR	Δ CFR	Score	Δ Score	Hack %	Δ Hack	CFR	Δ CFR
Full DREAM-RL	60.158	–	6.5	–	19.9	–	73.15	–	5.25	–	10.0	–
w/o edit-time replay probes	59.732	-0.426	10.8	+4.3	18.0	-1.9	72.57	-0.58	6.85	+1.60	8.0	-2.0
w/o replay/gate protection	59.812	-0.346	5.4	-1.1	16.6	-3.3	72.06	-1.09	7.99	+2.74	10.5	+0.5
w/o dynamic memory / skills	59.724	-0.434	8.5	+2.0	21.3	+1.4	72.74	-0.41	6.20	+0.95	11.2	+1.2
only criteria-level adaptation	59.510	-0.648	6.0	-0.5	22.1	+2.2	70.58	-2.57	6.54	+1.29	8.5	-1.5
Fixed final *Reward-DAG*	59.242	-0.916	5.4	-1.1	24.5	+4.6	69.27	-3.88	7.17	+1.92	15.3	+5.3

Table 3: **Downstream component ablations.** Writing Score is calibrated WritingBench and Roleplay Score is CoSER Overall; Δ is relative to full DREAM-RL. Only criteria-level adaptation restricts edits to existing criteria, while Fixed final *Reward-DAG* trains from the start with the final evolved graph. Higher Score and lower Hack/CFR are better.

same-query preference rankings than rubric baselines across most checkpoints in a 480-group audit. Appendix E.3 gives the ranking protocol and reliability checks.

6.2 Ablation Studies

We test two ablation questions: whether agentic diagnosis and replay-validated intervention turn rollout failures into effective *Reward-DAG* updates, and how downstream performance changes when reward evolution is replaced by a fixed final *Reward-DAG* or replay-gated protection is removed.

Agentic Diagnosis and Intervention Analysis. To isolate the effect of agentic diagnosis and replay-validated intervention, we measure the local reward-signal change around each meta-judge intervention. For every proposed reward update, we compute the average same-query reward variance over the two rollout steps before and after the update. We use the non-guard reward branch, so the metric reflects useful reward separability rather than variance induced by bad-tail penalties.

Table 4 shows that the full loop proposes 14 interventions, rejects 4, and promotes 10; all promoted edits increase two-step non-guard R-Var, raising the mean from .001352 to .001743. This local analysis is used to interpret the intervention mechanism and is complemented by the downstream ablations below.

Table 4: **Local effect of reward-system interventions.** R-Var is computed over the two rollout steps before and after each intervention on the non-guard branch.

Setting	Interv.	Positive	R-Var
Full loop	10/14 promoted	10/10	.00135→.00174
w/o gate	14/14 applied	6/14	.00301→.00304
w/o harness	12 edits	7/12	.00098→.00105

Without the gate, all 14 edits are applied but only 6 improve R-Var and the mean change is negligible; without the agent harness, the gain is also small and inconsistent. Appendix E.1 gives the edit ledger, including rejected probes that collapsed same-query signal or caused guard-role spillover.

Downstream Component Ablations. The downstream ablations test whether the full evolution loop is needed, rather than a single final graph, criteria-only adaptation, or ungated agent edits.

Table 3 shows that every component variant lowers final score on both tasks, with the largest drop from using the fixed final *Reward-DAG* throughout training. Replay-related ablations mainly hurt Hack and roleplay robustness; improved writing diagnostics under lower score suggest over-suppression rather than a better reward trajectory. Removing memory/skills worsens robustness, and criteria-only adaptation loses mechanism- and structure-level edits. Overall, the full system balances quality and robustness through replay-validated reward evolution.

7 Conclusion

We presented DREAM-RL, an agentic reward-evolution framework for open-ended RL. It represents rewards as typed *Reward-DAG*s and uses a meta-judge to diagnose on-policy reward failures, propose bounded graph edits, validate them through replay, and promote only edits that pass program-side checks, making reward adaptation trajectory-aware and auditable.

Across writing and roleplay, DREAM-RL maintains competitive final quality while reducing reward-hacking and coverage-failure diagnostics. Training-time and ablation analyses support accepted interventions, replay probes, promotion gates, memory, and dynamic reward-graph evolution as practical ingredients for adaptive and auditable RL rewards.

Limitations

Our study has several limitations. First, all RL experiments use a Qwen3-4B policy backbone under a fixed rollout budget, so the results are controlled shared-implementation comparisons, not scaling claims.

Second, our experiments focus on writing and roleplay. These settings expose reward misspecification, shortcut-attractive patterns, and coverage failures in open-ended generation, but they are not the full range of tasks where rubric-RL is commonly used. In particular, we have not yet extended DREAM-RL to multi-turn agent tasks, where the reward graph may need to account for tool state, interaction history, and delayed task completion.

Third, reward-evolution quality depends on the meta-judge backbone and its prompt-following behavior. Although our component ablations isolate the value of replay validation, promotion gates, memory, and dynamic reward-graph evolution, broader evaluation across agent backbones remains future work.

Finally, agentic reward evolution introduces runtime overhead: the meta-judge update loop, replay probes, and promotion checks increase wall-clock training cost (Appendix C.1); adaptive scheduling or batched validation could reduce it.

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A Appendix Roadmap and Robustness Checks

Because the evaluation involves open-ended RL, LLM judges, and an agentic reward-editing loop, we include additional checks for evaluation robustness, auditor blinding, reward-evolution traceability, baseline portability, and reproducibility. Table 5 gives a roadmap to these materials. It is intended as a navigation aid rather than as additional experimental evidence.

B Supplementary Motivating Analysis

B.1 Reward Mechanism Taxonomy

This subsection clarifies the reward-mechanism space used in the motivating analysis. We use *reward mechanism* to denote the scoring or judgment procedure that turns criteria and response evidence into an optimization signal. A mechanism specifies the elicited judgment, the granularity of the produced signal, and its normalization into a reward or preference signal. This is distinct from the *criterion source*, which determines what evidence or criteria are evaluated, and from the *composition operator*, which determines how multiple local signals are aggregated, gated, or routed.

This distinction is important for interpreting dynamic-rubric methods. Query-level rubrics, retrieved references, and generated checklists change the criterion source. Weighted sums, product guards, and routing modules change composition. A reward mechanism changes how judgments over criteria are elicited and exposed to the policy. Thus two reward systems can evaluate similar criteria but induce different training signals, for example by using dense scalar scores, pass-rate vectors, penalty scores, pairwise preferences, listwise ranks, or claim-level support vectors.

Table 6 summarizes the mechanisms considered in this work and representative related work. The table is intended as a taxonomy of common scoring protocols rather than a claim that all mechanisms are used as live RL rewards in our experiments.

Continuous / pointwise rubric scorer. The most common rubric-based protocol asks a judge to assign scalar scores to a response, either globally or along multiple rubric dimensions. With criteria $\{c_k\}_{k=1}^{K}$, a typical normalized score is

$$h_{\text{cont}}(x, y) = \frac{1}{K}\sum_{k=1}^{K} s_k, \qquad s_k \in [0, 1].$$

This dense signal is easy to scalarize for RL and covers broad quality dimensions, but it can saturate as the policy improves, reducing same-query separability. Fine-grained LLM evaluation benchmarks and reward models commonly instantiate this mechanism through dimension-wise or rubric-conditioned scalar scores (Kim et al., 2025a; Wu et al., 2025; Kim et al., 2024; Liu et al., 2025b). Evidence-anchored robust scoring systems such as RULERS are also related, but they should be viewed as robust pointwise scoring rather than penalty mechanisms (Hong et al., 2026).

Checklist / verifier scorer. Checklist mechanisms decompose the evaluation into explicit requirements and expose item-level satisfaction:

$$h_{\text{check}}(x, y) = \frac{1}{K}\sum_{k=1}^{K} z_k, \qquad z_k \in \{0, 1\},$$

with graded variants allowing $z_k \in \{0, 0.5, 1\}$. This produces an interpretable pass vector or pass rate and is useful when necessary conditions must be checked explicitly. RocketEval and CheckEval study checklist-based LLM evaluation, RLCF uses checklist-style rewards for alignment, and HealthBench uses physician-written criteria that are judged as met or unmet before aggregation (Wei et al., 2025; Lee et al., 2024; Viswanathan et al., 2025; Arora et al., 2025). Rubrics as Rewards provides an RL example of structured rubric rewards beyond verifiable domains (Gunjal et al., 2025).

Flaw-penalty / deduction scorer. Deduction mechanisms start from an implicit or explicit full score and subtract penalties for detected flaws:

$$h_{\text{pen}}(x, y) = \text{clip}\left(1 - \lambda \sum_{j} \alpha_j v_j, 0, 1\right),$$

where v_j denotes violation severity and α_j denotes the corresponding weight. Unlike checklist scoring, the output is a downward correction targeted at sparse failures. CoSER is a direct example in roleplay evaluation: it identifies roleplay mismatch cases such as role-setting, language-style, action, or psychological mismatches and uses penalty-based LLM judging (Wang et al., 2025). Reward-hacking analyses motivate such bad-tail mechanisms, although they are not themselves deduction scorers (Mahmoud et al., 2026; Zhang et al., 2026).

Appendix topic	What is covered	Purpose	Details
Evaluation Protocols	Raw and calibrated WritingBench scoring, HR/CFR audit construction, auditor blinding, paired bootstrap intervals, repeated CoSER judging, and directional roleplay comparisons.	Documents how benchmark quality, robustness diagnostics, judge variance, and audit blinding are handled.	App. D.5; App. D.6
Training-Time Evidence	Local intervention analysis, accepted and rejected reward edits, reward-variance dynamics, and blind reward-ranking audits over same-query rollout groups.	Makes reward edits traceable and separates final-output gains from process-level reward-evolution evidence.	App. E.1; App. E.3
Implementation and Reproducibility	Model roles, training settings, prompts, Reward-DAG schema, typed edit operations, legality checks, replay-gate thresholds, runtime cost, and harness tools/skills.	Specifies the reward-system interface and constrained meta-judge workflow used in the experiments.	App. C.1; App. C.2; App. C.4; App. C.5
Baselines and Task Setup	Artifact use, data safety, writing and roleplay training data, initial rubric construction, unified GRPO setup, and reward-system instantiations of static and dynamic-rubric baselines.	Clarifies the shared experimental setting and how baseline reward systems are ported into it.	App. D.1; App. D.3; App. D.4
Case Studies	Writing guard-style penalty repair and roleplay coverage repair, including the diagnosed rollout evidence and retained Reward-DAG changes.	Illustrates how DREAM-RL turns on-policy reward failures into bounded graph edits.	App. E.4

Table 5: Roadmap of appendix materials for evaluation protocols, training-time evidence, implementation details, baselines, and case studies.

Pairwise preference comparator. Pairwise mechanisms elicit relative judgments between two responses:

$$p_{ij} = J_\phi(x, y_i, y_j),$$
$$h_{\text{pair}}(x, y_i) = \frac{1}{K-1} \sum_{j \neq i} \mathbf{1}[p_{ij} = i].$$

The output can be a winner label, a preference probability, or a win-rate reward. This mechanism is often more stable than absolute scoring when candidates differ subtly under the same prompt, but it is sensitive to position and order bias and is more expensive than pointwise scoring. Pairwise judging is used in LLM-as-judge settings such as MT-Bench / Chatbot Arena and in pairwise RLHF or generative reward-modeling formulations (Zheng et al., 2023; Xu et al., 2025). Writing-Zero and HER provide open-ended writing and roleplay examples, while LitBench directly supports creative-writing comparison as a benchmark signal (Jia et al., 2025; Du et al., 2026; Fein et al., 2025).

Listwise / ranking scorer. Listwise mechanisms compare a candidate set at once and return a ranking or top-k selection:

$$\text{rank}_i = J_\phi(x, \{y_1, \ldots, y_K\}),$$
$$h_{\text{rank}}(x, y_i) = 1 - \frac{\text{rank}_i - 1}{K-1}.$$

This can strengthen same-query discrimination by asking the judge to order all candidates jointly. It is distinct from a best-of-K winner selector, which is a top-1 special case of listwise evaluation. The main risks are context length, set-composition dependence, and permutation sensitivity. LINKAGE provides a direct listwise-ranking formulation for non-factoid QA evaluation, and permutation-consensus listwise judging studies robustness issues for listwise factuality evaluation (Yang et al., 2024; Huang et al., 2026).

Claim-level factuality / grounding scorer. For grounded open-ended generation, a mechanism can first extract atomic claims, QA probes, or citation-grounded statements and then judge support:

$$\mathcal{C}(y) = \{c_1, \ldots, c_M\}, \qquad z_j = V_\phi(c_j; x, \mathcal{S}_x),$$
$$h_{\text{fact}}(x, y) = \frac{1}{M} \sum_{j=1}^{M} \mathbf{1}[z_j = \text{supported}].$$

Here $\mathcal{S}_x$ denotes source documents, dialogue context, retrieved evidence, or cited sources. This mechanism differs from checklist scoring because the evaluated units are extracted from the response rather than fixed in advance. It is useful for long-form factuality, summarization consistency, RAG-style answers, and deep research reports. FActScore and SAFE/LongFact evaluate long-form factuality through atomic facts and search-augmented verification; QAGS, Q^2, and SummaC use QA- or entailment-style probes for factual consistency; DeepResearch Bench extends

Mechanism	Output signal	Typical granularity	Best suited for	Representative references
Continuous / pointwise rubric scorer	Dense scalar or dimension-wise scalar	Response or rubric-dimension level	Broad open-ended quality, writing quality, general rubric scoring	BiGGen Bench, WritingBench, Prometheus, DeepSeek-GRM (Kim et al., 2025a; Wu et al., 2025; Kim et al., 2024; Liu et al., 2025b)
Checklist / verifier scorer	Pass/fail vector, pass rate, or partial-credit pass rate	Checklist-item or criterion level	Explicit requirements, constraint satisfaction, coverage of necessary elements	RocketEval, CheckEval, RLCF, HealthBench, Rubrics as Rewards (Wei et al., 2025; Lee et al., 2024; Viswanathan et al., 2025; Arora et al., 2025; Gunjal et al., 2025)
Flaw-penalty / deduction scorer	Downward penalty score with violation trace	Flaw, defect, or violation level	Sparse bad-tail failures, roleplay violations, reward-hacking artifacts	CoSER for penalty-based roleplay judging; reward-hacking work as motivation (Wang et al., 2025; Mahmoud et al., 2026; Zhang et al., 2026)
Pairwise preference comparator	Pairwise winner, preference label, or win-rate reward	Response-pair level	Same-query relative quality and subtle writing or roleplay differences	MT-Bench / Chatbot Arena, pairwise RLHF, Writing-Zero, HER, LitBench (Zheng et al., 2023; Xu et al., 2025; Jia et al., 2025; Du et al., 2026; Fein et al., 2025)
Listwise / ranking scorer	Full ranking, top-k, or rank-normalized score	Response-set level	Ordering a set of candidate responses under the same query	LINKAGE and permutation-consensus listwise judging (Yang et al., 2024; Huang et al., 2026)
Claim-level factuality / grounding scorer	Claim-support vector, factual precision, unsupported-claim rate, or groundedness score	Atomic-claim, QA-probe, citation, or evidence-unit level	Long-form factuality, summarization consistency, RAG, deep research, citation grounding	FActScore, SAFE/-LongFact, QAGS, Q^2, SummaC, DeepResearch Bench (Min et al., 2023; Wei et al., 2024; Wang et al., 2020; Honovich et al., 2021; Laban et al., 2022; Du et al., 2025)

Table 6: Representative reward mechanisms for open-ended and partially grounded generation. The taxonomy is organized by scoring protocol and output signal, not by whether a paper uses the word "rubric" or "reward". Criterion-source adaptation methods are discussed separately from reward mechanisms.

this idea to citation accuracy and effective citation counts in deep research agents (Min et al., 2023; Wei et al., 2024; Wang et al., 2020; Honovich et al., 2021; Laban et al., 2022; Du et al., 2025).

Boundary with criterion-source adaptation. Several related methods change what is evaluated rather than how scoring is elicited. Query-level rubric generation, online rubric elicitation from pairwise comparisons, rubric-anchor methods, and dynamic-rubric RL are therefore best viewed as criterion-source or reward-system adaptation methods, not as separate scoring mechanisms by themselves (Liu et al., 2025a; Huang et al., 2025; Xu et al., 2026; Rezaei et al., 2025; Lv et al., 2026; Shao et al., 2025; Jia et al., 2026). In our framework, such criterion-source changes can coexist with mechanism changes inside the same executable *Reward-DAG*.

B.2 Additional Motivating Results

This subsection provides three supplementary analyses that complement the main-text distribution and training-dynamics figures. All numbers are computed from cached offline mechanism scores; no additional judge calls were made for this summary. The analyses cover: (i) query-level versus task-level criteria under the same scoring mechanism, (ii) mechanism behavior across response buckets, and (iii) mechanism-specific score-distribution shift during training.

Query-level versus task-level criteria. This comparison isolates criterion-source specialization from reward-mechanism changes. Both conditions use the same continuous rubric scoring path over the same 128 writing responses; the only difference is whether the scorer uses task-level global criteria or query-level specialized criteria. Query-level criteria slightly lower the global mean score, from 0.687 to 0.678, but increase score dispersion and within-query separability: global standard deviation rises from 0.061 to 0.074, same-query range rises from 0.064 to 0.093, and same-query standard deviation rises from 0.026 to 0.037. The paired score correlation remains high, with Pearson 0.825 and Spearman 0.823, showing that query-level criteria preserve the broad scoring trend while reshaping local distinctions.

Mechanism behavior by response type. We next bucket the same writing responses into five behavior categories, with 20 examples per bucket: normal high-quality outputs, under-complete or constraint-missing outputs, reward-hacking-like or fabricated-authority outputs, template or scaffold leakage, and subtly better same-query candidates selected by pointwise quality. Figure 7 shows that the mechanisms are complementary rather than interchangeable. Continuous scoring tracks broad quality, but remains relatively high on fabricated-authority cases (0.709). Checklist scores sharply drop on explicit incompleteness or constraint misses (0.717), but remain high on fabricated-authority and scaffold-leakage cases (0.958 and 0.942). Flaw-penalty scoring is most sensitive to bad-tail artifacts, dropping to 0.423 for fabricated-authority cases and 0.513 for scaffold leakage. Pairwise scores are centered near 0.5 over arbitrary buckets, as expected, but rise to 0.646 on independently selected same-query better cases.

Distribution shift during training. Finally, we compare step-0 base-model responses with step-120 trained responses using the same offline mechanism scoring pipeline. Figure 8 shows the clearest shifts for the RAR checkpoint. Continuous rubric scores move upward from mean 0.645 at step 0 to 0.785 at step 120, while checklist scores move from 0.878 to 0.945. The checklist signal also becomes less informative within groups: same-query standard deviation drops from 0.100 to 0.050, and zero-variance group rate rises from 0.188 to 0.531. Continuous scoring retains more local spread under RAR than checklist, with same-query standard deviation increasing from 0.024 to 0.038 and zero-variance group rate decreasing from 0.500 to 0.344. These results illustrate that reward mechanisms can shift or saturate differently as the policy distribution changes, so final reward variance should be separated from base positive-reward informativeness and bad-tail penalty activation.

C Method Details

C.1 Implementation Details for Reward Evolution

Model, compute, and training settings. Table 7 summarizes the model and training settings used for the main reported GRPO runs. The policy model is Qwen3-4B (Yang et al., 2025), and the local GRM/rubric-updater model is Qwen3.5-27B. Proprietary models used as the meta-judge or evaluation judges, including GPT-5.4, DeepSeek-V4-Pro, Kimi-K2.5 (Team et al., 2026), and DeepSeek-V4-Flash, do not expose public parameter counts;

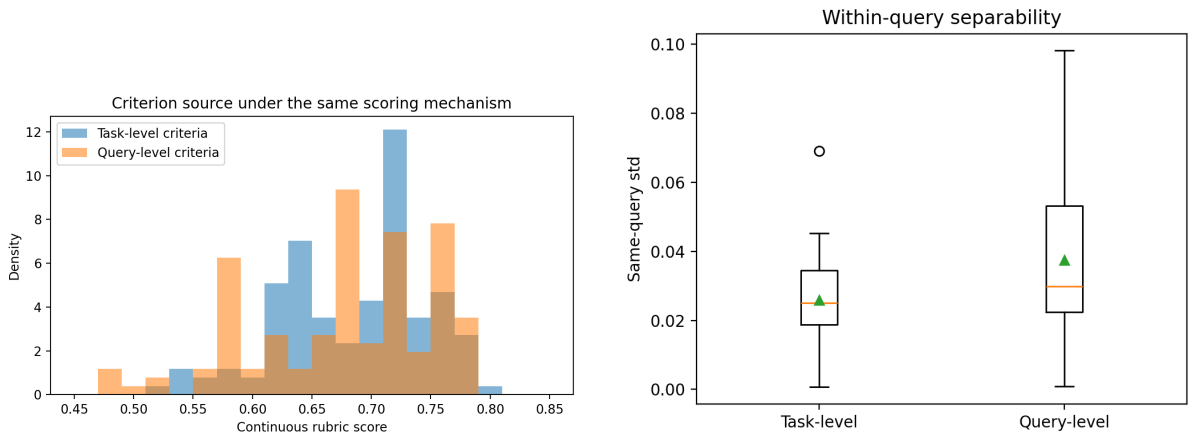

Figure 6: Query-level versus task-level criteria under the same continuous scoring mechanism. Query-level criteria change the reward landscape and improve within-query separability, but this is a criterion-source change rather than a new reward mechanism.

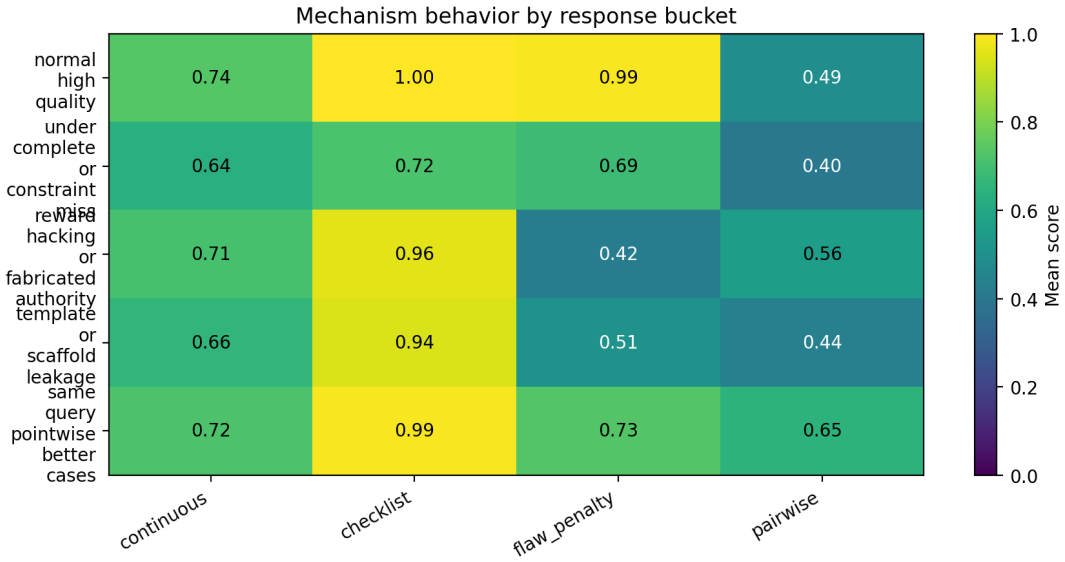

Figure 7: Mechanism behavior by response type. Continuous scoring, checklist verification, flaw-penalty detection, and pairwise comparison expose different failure modes and therefore provide complementary reward signals.

we therefore report their model names and roles. We use a fixed GRPO recipe across methods rather than method-specific hyperparameter search. All compared reward-system variants share the same policy initialization, training data, rollout budget, batching, optimizer settings, and checkpoint schedule; reward-evolution thresholds and update cadences are fixed before the final comparison.

Runtime cost and agent overhead. The RL training budget above counts the training path. Offline benchmark scoring, HR/CFR audits, post-hoc ranking annotations, and repeated evaluator reruns are not included in the RL training GPU-hour accounting. Online reward scoring during RL is included. For DREAM-RL, the logged end-to-end step time also includes the meta-judge update when the update hook runs.

We report writing-side wall-clock cost from the training logs. The per-step time is the logged `perf/time_per_step`, which includes rollout generation, reward scoring, log-probability and reference-policy computation, actor update, checkpointing when triggered, and hook overhead. For DREAM-RL, this logged step time already includes the meta-judge update when the update hook runs. We therefore also report the training-only step time after subtracting `meta_judge/elapsed_s` on update steps and the average agent time per macro update.

GRM scoring and micro updates. All pointwise scalar rewards in the main experiments are computed with a local Qwen3.5-27B GRM. The scorer receives the query, the assistant response, and the active rubric or *Reward-DAG* node specification, and returns item-level scores together with a normalized scalar reward in $[0, 1]$. For continuous rubric nodes, the final node score is the mean or weighted mean of item scores after parsing and clipping. For checklist or verifier nodes, boolean or partial-credit outcomes are normalized into a pass-rate score. For flaw-penalty nodes, detected violations produce a downward correction that is combined with the positive reward through the composition operator. Query-level micro updates use the same local Qwen3.5-27B model as the rubric updater and GRM, matching the dynamic-rubric baselines.

Continuous GRM scoring prompt. The continuous rubric scorer uses the following runtime prompt template. Long query, response, and rubric fields are abbreviated here, but the scoring instructions and output schema match the implementation.

Continuous GRM Scoring Prompt

```
You are a severe but fair reward model
    grader.

You will receive a query, an assistant
    response, and a list of rubric items.
Score each rubric item independently on a
     0.0-1.0 scale.

Use degree of satisfaction, not a yes/no
    interpretation:
- 0.00-0.20: absent, contradicted, or
    harmful.
- 0.20-0.40: very weak; only superficial
    or accidental evidence.
- 0.40-0.55: partial but flawed;
    important requirements are missing.
- 0.55-0.70: adequate but generic, thin,
    or uneven.
- 0.70-0.84: clearly good; specific
    evidence supports the criterion.
- 0.84-0.92: very strong; robust, nuanced,
     and well grounded.
- 0.92-1.00: exceptional; rare, highly
    effective execution.

Calibration and ceiling rules:
- Do not give high scores for merely
    avoiding errors.
- Generic or interchangeable responses
    should usually be capped at 0.65.
- Scores above 0.72 require concrete
    evidence from the response.
- Scores above 0.84 require strong craft,
     insight, grounding, or reader effect
    .
- If the response exposes chain-of-
    thought or private reasoning, cap the
     final
  mean score at 0.35.

Strict scoring addendum:
- Start from 0.55 and move up or down
    based on concrete evidence.
- 0.70 is already a good score; above
    0.70 requires specific non-generic
    merit.
- 0.80+ should be stronger than normal
    good answers; 0.88+ should be rare.
- If the rationale for an item would be
    generic, cap that item at 0.68.
- Polished surface without insight,
    specificity, or task judgment caps at
     0.65.
- Separate responses by depth,
    specificity, judgment, and reader
    effect.

Query:
{query}

Assistant response:
{response}
```

Category	Setting
Policy initialization	Qwen3-4B.
Training algorithm	GRPO using the same trainer for all reward-system variants.
Reward/scoring model	Local Qwen3.5-27B GRM; scalar rewards normalized to $[0, 1]$.
Meta-judge model	Codex SDK with GPT-5.4, invoked every 5 RL steps for DREAM-RL.
Training length	120 GRPO steps for the main reported runs.
Batching	32 prompts per step, 4 rollouts per prompt.
Sequence lengths	4096-token prompts; 4096-token writing responses and 2048-token roleplay responses.
Optimization	Learning rate 1×10^{-6}, PPO mini-batch size 4, micro-batch size 2 per GPU, low-variance KL with coefficient 0.001, entropy coefficient 0.
Checkpointing	Save every 5 steps.
Hardware	8 NVIDIA A800 GPUs for each main training run.
RL training budget	About 24 hours wall-clock on average per main run, i.e., about 192 A800 GPU-hours.

Table 7: Model, compute, and core hyperparameter settings for the main GRPO runs. Proprietary meta-judge and evaluation models have undisclosed parameter counts, so we report their names and roles instead.

Method	Parsed steps	Avg. step time	Avg. agent update time	Agent interval
RLAIF	120	511.3s	–	–
RAR	120	663.8s	–	–
DR-Tulu	120	718.4s	–	–
OpenRS	120	1037.4s	–	–
DREAM-RL, training only	120	753.0s	–	–
DREAM-RL, with meta-judge	120	801.5s	242.8s	5 steps

Table 8: Writing-side runtime cost parsed from training logs. For DREAM-RL, the meta-judge runs every 5 GRPO steps; its average macro-update time is 242.8s. The training-only row subtracts meta-judge elapsed time from update steps, while the with-meta-judge row reports the logged end-to-end step time.

```
Rubric items:
{rubric_items}

Return JSON only:
{
  "item_results": [
    {"score": 0.58, "reason": "brief
         reason with concrete evidence"}
  ],
  "item_scores": [0.58]
}
```

Meta-judge harness. The meta-judge is implemented with the Codex SDK using gpt-5.4 as the backbone model. Codex is not used as a response-level judge. Instead, it operates inside our reward-evolution harness: it observes rollout summaries, reward traces, reward-health diagnostics, replay evidence, the current *Reward-DAG*, and run-specific memory; it can only modify the reward system through the typed edit interface. The harness exposes observation, edit, replay, and memory tools, while fixed and dynamic skills specify the reward-evolution policy. The full tool interface and skill content are given in Appendices C.4 and C.5.

Harness runtime prompt. The following is the actual runtime prompt structure supplied to the Codex-backed harness, with long JSON states and run-specific diagnostics abbreviated.

Harness Runtime Prompt

```
You are the Meta Judge Agent for RL
    reward design.
Use the reward-evolution guidance skill
    for the detailed diagnosis/edit/
    replay
workflow. This prompt provides only the
    current run state and non-negotiable
runtime constraints.

## Pre-Loaded State (DO NOT call load_dag
     or get_dag_json)

### Current DAG
{dag_json}

### Reward Health Dashboard (Iteration {
    iteration})
{formatted_dashboard}

### Evaluation Results
Accuracy: {accuracy_pct}%
{eval_results_json}

{benchmark_context}
```

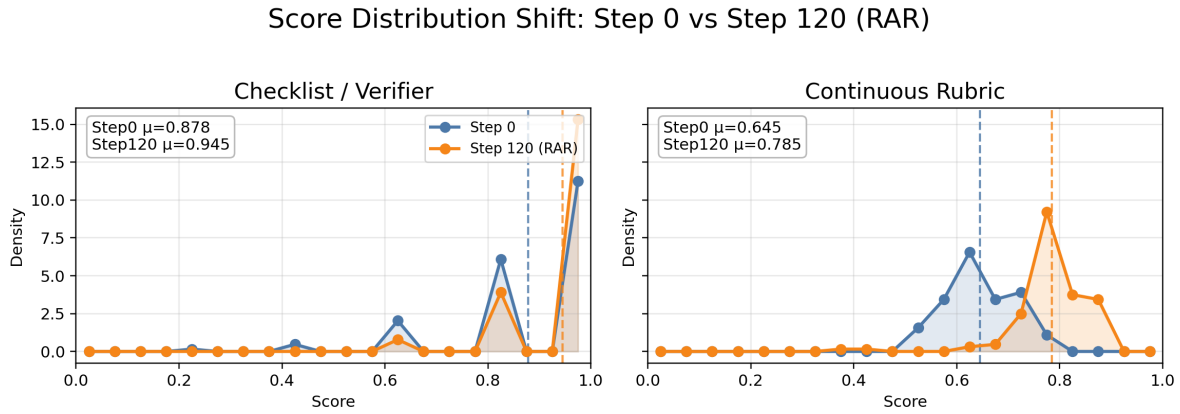

Figure 8: Score-distribution shift from step 0 to step 120 under RAR for the two mechanisms with the clearest shift. Continuous scores shift upward while preserving some spread; checklist scores become highly concentrated near the upper end, increasing the rate of zero-distinction groups.

```
{scenario_meta_rubrics}

## Runtime Reward Context

The current training reward DAG is
    pointwise. During actual RL reward
execution, each rubric node sees one
    sample at a time: the query/prompt,
one candidate response, and any metadata
    already included in that sample. It
does not see other real responses for the
     same query.

Rollout diagnostics, replay, and the
    final gate may compare same-query
    groups
outside the DAG to measure RL signal. Use
     those group statistics to decide
whether an edit helps. Do not write judge-
    facing rubric items that require the
judge to compare the current response
    against unseen same-query responses.

## Current Focus

Dashboard has flagged: {suggested_focus}

## Two-Axis Reward Diagnosis

Use two top-level axes before editing and
     when reading replay:

- On-policy Reward Validity: whether the
    reward covers the current policy's
  actual response space, including reward
       hacking, high-score low-quality
  cases, formatting/scaffolding artifacts,
       fabricated-looking specifics,
  verbosity/template shortcuts, corner
      cases, and false-positive penalties.

- Sustainable Reward Informativeness:
    whether the reward can keep giving
    GRPO
  useful signal. Use `
      informativeness_score`, main/base
      node signal,
  same-query spread, node/item health,
      parse health, and final reward
      sanity.

If the DAG has guard or auxiliary
    downward effects, final-score
    variance is
not primary evidence for Sustainable
    Reward Informativeness. Treat final
    score
as training reward sanity and use `
    informativeness_score` for reward-
    signal
claims.

## Runtime Constraints
- The current DAG remains pointwise;
    judge-facing criteria must not
    require
  unseen same-query responses.
- Keep the main `judge` signal continuous
     unless adding a complementary node.
- Do not edit execution-owned fields: `
    aggregation`, `chunk_size`,
  `parallel_workers`, or `is_final`.
- Use only the exposed reward-harness
    tools. Direct shell/file/Python
    operations
  are forbidden; the read-only analysis
       tool is allowed for guarded mining.
- Use at most two real-judge `
    replay_on_cases(...)` calls. Fixed
    replay is only
  a structural smoke test.
- If recent run-local memory is present
    in the prompt, briefly cite the
    recent
  lesson before editing. Explain whether
       the current bounded change repeats,
  avoids, or extends that lesson.

## Hard Constraints
```

```
- DAG must remain pointwise
- Total nodes <= 10
- Scoring (rubric) nodes per path <= 3

## Policy
- Diagnose before editing
- Prefer smallest valid change
- If reward is healthy, make no change
- If an edit tool rejects a structural
    edit, read its hint and retry once
  with a smaller valid edit.
- If replay budget is exceeded, a policy
    violation occurs, or an unsupported
    fallback
  would be needed, stop and report it.

## Tool Restriction
Use only the exposed reward-harness tools.
     No direct Shell, bash, file
reads/writes, or Python snippets. The
    read-only analysis tool is allowed
    for
guarded rollout/DAG/project analysis.

## Runtime Budget
Use at most {max_tool_calls} tool calls
    across both phases.

## Additional Context
## Context: Online RL Training
- Current completed step: {step}
- Selected rollout step for diagnosis: {
    selected_step}
- Rollout metadata: {rollout_metadata}
- Current scenario: {scenario}
- Update mode: {candidate_or_direct}

The rollout diagnosis and dashboard are
    already pre-loaded in the prompt. Use
the exposed diagnostic MCP tools and
    actual rollout cases for deeper
    checks,
then make the smallest valid edit. Before
     editing, explicitly separate
    findings
into two axes: On-policy Reward Validity
    and Sustainable Reward
Informativeness. Before editing, include
    an explicit reward-operator diagnosis
    :
decide whether the current failure is
    best addressed by a continuous rubric
rewrite, query_rubric refinement,
    checklist/coverage complement,
    complementary
continuous residual scorer, aggregation/
    weight change, narrow guard/
    flaw_penalty
side node, or no-op.

{scenario_specific_policy}

{method_advice_context}

{run_memory_context}

{operator_ledger_context}
```

The prompt separates response scoring from reward editing: the local GRM scores responses and performs micro rubric updates, while the Codex meta-judge performs macro reward-system diagnosis and typed *Reward-DAG* edits through the harness.

Agent framework selection. Before the main training runs, we ran a local diagnostic-modification bench over representative writing and roleplay reward-failure cases. The bench compared Codex SDK, KimiCode, and OpenCode-based agents, including MiniMax-backed configurations. Each agent was evaluated on whether it could identify the annotated reward failure, produce a legal typed edit, ground the edit in rollout evidence, and pass the replay gate. The Codex configuration achieved the most reliable combination of diagnosis quality, edit validity, and gate-passing repair. Weaker or less compatible agent/-model configurations often failed before producing a valid edit, exhausted the tool budget, or proposed edits that did not survive replay. These checks motivated using Codex SDK with gpt-5.4 as the macro meta-judge in the final experiments; they are implementation-selection checks rather than an additional training reward signal.

Update schedule and edit deployment. The meta-judge is invoked every 5 RL steps. Each invocation proposes a bounded candidate update to the current *Reward-DAG*, such as revising a rubric node, adding a query-rubric/checklist/flaw-penalty side node, or changing a local aggregation rule. During editing, small replay probes may execute the candidate graph on selected recent rollout cases to provide diagnostic evidence. Deployment is decided only by the program-side promotion gate, which runs broader replay-gate checks over recent same-query rollout groups, including preservation of clean cases, no new critical guardrail failures, bounded health drop, and no collapse of reward informativeness. The formal replay-gate rules and typed edit validity checks are described in Appendix C.2.

C.2 Reward-DAG Design Details

Implementation scope. The main text defines *Reward-DAG* as an abstract reward-system representation with editable criterion sources, reward mechanisms, and composition rules. The experiments instantiate a pointwise RL reward path, which is the standard scalar-reward interface used

by GRPO. Within this path, DREAM-RL performs mechanism-level evolution by adding or revising executable reward nodes, including query-level rubric nodes, checklist/verifier nodes, flaw-penalty or guard nodes, and composition operators that fuse side signals with the main scorer.

Data schema. The executable graph is stored as a JSON-like DAG configuration. The following pseudocode summarizes the implemented schema.

```
RewardDAG = {
  name: string,
  version: string,
  description: string,
  mode: "pointwise" | "pairwise",
  entry: node_id,
  nodes: [NodeConfig],
  global_config: dict
}

NodeConfig = {
  id: string,
  type:
    "rubric" | "query_rubric"
    | "verifier" | "gate"
    | "aggregator" | "transform",
  config: dict,
  next: node_id | null,
  description: string
}

ExecutionContext = {
  query: string,
  response_a: string,
  response_b: string,
  query_rubrics: dict,
  variables: dict,
  scores: dict[node_id, float],
  execution_path: [node_id],
  final_score: float | null
}
```

For pointwise RL, the input is (x, y), represented as `query` and `response_a`. Nodes execute sequentially from `entry`; each node writes variables, node-level scores, and trace details into the context. The scalar training reward is the `final_score` produced by the terminal Rubric Node or Composition Operator.

Node and operator semantics. Table 9 summarizes the implemented node families and their reward semantics. Each executable node has an input contract, writes a trace and a scalar node score when applicable, and passes control through `next` or a gate branch. Judge-produced item scores are parsed as real values and clamped to $[0, 1]$; Boolean verifier outputs are cast to $0/1$ when used as scores or guard-role inputs. A terminal node with `is_final=true` terminates execution and exposes its score as the scalar training reward.

Reward scalarization for RL. For a pointwise training call, the DAG returns one terminal value $r_D(x, y) \in [0, 1]$. If the terminal node is a Rubric Node, this value is the node score defined above. If it is a Composition Operator, it is the normalized composition of upstream node scores. Verifier or checklist outputs contribute either as $0/1$ guard-role variables, pass-rate side scores, or aggregation inputs, depending on the node configuration. No additional learned reward head is introduced: the scalar `final_score` written by the DAG is the reward passed to the RL trainer.

For GRPO-style optimization, after the DAG returns scalar rewards $\{r_i\}_{i=1}^{K}$ for a response group $\mathcal{Y}_x$, the policy update uses group-relative advantages, e.g.,

$$\hat{A}_i = \frac{r_i - \frac{1}{K}\sum_{j=1}^{K} r_j}{\mathrm{Std}(\{r_j\}_{j=1}^{K}) + \epsilon}.$$

Thus the DAG must not only be behaviorally valid, but also preserve within-query reward informativeness.

Typed edit operations. The meta-judge cannot rewrite reward code directly. All changes must be expressed through typed edit operations over the DAG schema:

- `add_node` adds a Rubric Node or Composition Operator using `id`, `type`, `config`, `next_node`, optional `insert_after`, and optional initializer fields. If `insert_after` is set, the tool splices the new node into the reachable path and preserves the old downstream edge.
- `update_node` patches a node using `id`, `config`, optional `next_node`, and optional `description`. For structured rubrics, `rubric_item_updates` modifies stable item ids without rewriting unrelated items.
- `remove_node(id)` removes a non-entry node, bypasses simple predecessors when possible, and removes stale aggregator inputs.
- `set_entry(id)` changes the graph entry point.

Edits are transactional. The tool first clones the current DAG, applies the proposed mutation, normalizes safe structural details, validates the candidate, and commits it only if validation succeeds. Otherwise, the live in-memory and on-disk DAG remain at the last valid state.

Node/operator	Input	Output	Reward semantics
Global Rubric Node	x, y, fixed ρ^g, judge J_ϕ	node score $h_v \in [0,1]$, item traces	Continuous mode scores rubric items $\{c_k\}_{k=1}^K$, normalizes each parsed item score s_k to $[0,1]$, and returns $h_v = K^{-1}\sum_k s_k$. This is the main positive reward mechanism in the pointwise RL runs.
Query-Level Rubric Node	x, y, meta-rubrics, generation policy, optional precomputed query criteria	query-rubric score $h_v \in [0,1]$, generated criteria trace	Instantiates query-aware criteria and scores them through the rubric-scoring path, yielding the same normalized scalar contract as a Rubric Node. In our current experiments this node mainly changes the criterion source, not the hidden scorer execution protocol.
Checklist / Verifier	x, y, explicit checks or checklist items	pass indicators or pass-rate score	Checklist scoring returns $K^{-1}\sum_k \mathbf{1}[\text{pass}_k]$. Rule verifiers write Boolean variables; as guard-role inputs these variables multiply or route downstream scores rather than introducing an unconstrained reward scale.
Deduction / Flaw-Penalty Rubric	x, y, failure dimensions, judge-extracted violations or flaws	penalty-style score $h_v \in [0,1]$, violation trace	Deduction mode uses $s_j = \max(0, 1-\lambda\sum_i \text{severity}_{ij})$ per dimension with default $\lambda = 0.05$, then averages dimensions. Flaw-penalty mode uses $s = 1$ if total severity is zero, otherwise $s = \text{clip}((c - wS)/Z, 0, 1)$, with defaults $c = 101.5, w = 5, Z = 100$.
Composition Operator	upstream node scores $\{h_v\}$	composed score h_u	Weighted-sum aggregation computes $h_u = \sum_v w_v h_v / \sum_v w_v$ over non-guard inputs; inputs marked `role=guard` multiply the base score. Product aggregation computes $h_u = \prod_v h_v$.
Pairwise Comparator	x, y_a, y_b or two pointwise scores	verdict A/B, or a derived preference signal	Used for evaluator benchmarks and analysis. The implemented pairwise path either directly compares two responses or scores y_a, y_b separately and applies a transform A if $s_a \geq s_b$, else B. Pairwise verdicts are therefore benchmark outputs, not the live pointwise scalar reward in the main experiments.

Table 9: Implemented Reward-DAG node families and reward semantics.

Legality checks. The implemented validator rejects malformed or unsafe candidates. Structural checks require a valid entry node, valid `next` and gate branch references, acyclicity, and reachability from the entry node. RL-time pointwise checks require `mode=pointwise`, at most 10 total nodes, at most 3 scoring nodes on any reachable path, no `input_response=both`, no node-level pairwise mode, supported aggregator methods {`weighted_sum`, `product`}, non-empty aggregator inputs, upstream-only aggregator sources, and a valid terminal final node. Additional edit guards prevent the agent from changing program-owned execution fields such as rubric chunking, parallelism, or hidden item aggregation; protect the main continuous node from being directly replaced by a different scorer mode; and reject obvious task-domain contamination in writing or roleplay runs.

Replay gate decision rule. The final promotion gate $\mathcal{G}$ is program-side. It first samples same-query groups from recent rollouts using four criteria: low-score groups, high-score groups, high-variance groups, and random groups. By default, it samples three query groups per criterion and requires at least two responses per selected query group. The live and candidate DAGs are replayed on the same selected cases when a live baseline is available.

Let $q(D, \mathcal{B})$ denote the dashboard computed from replay records, with health dimensions including discrimination, RL signal, calibration, bias, stability, and hacking risk. Let $\Delta q_d = q_d(\tilde{D}, \mathcal{B}) - q_d(D, \mathcal{B})$, i.e., positive values favor the candidate. In the default metric mode, the promotion gate is the conjunction

$$\mathcal{G}(D, \tilde{D}, \mathcal{B}) = C_{\text{exec}} \wedge C_{\text{guard}} \wedge C_{\text{health}} \wedge C_{\text{info}} \wedge C_{\text{monitor}}.$$

The individual conditions are:

- C_{exec}: the candidate graph is valid and replay success rate is at least $\tau_{\text{succ}} = 1.0$.
- C_{guard}: no new critical guardrail status appears, and every default guardrail dimension $d \in \mathcal{D}_{\text{guard}}$ satisfies $\Delta q_d > -\tau_{\text{guard}}$, with $\tau_{\text{guard}} = 0.05$.
- C_{health}: average replay health does not drop by more than $\tau_{\text{health}} = 0.15$.
- C_{info}: the candidate's informativeness-score std and range are at least 0.02 and 0.05, respectively; the final reward also has nonzero std and range on the replay batch.
- C_{monitor}: if monitor review is enabled, the monitor returns `accept` with overall score at least 0.55; otherwise this condition is true by default.

Here $\mathcal{D}_{\text{guard}}$ is the default guardrail set {discrimination, RL signal, calibration, bias, stability, hacking risk}. Thus "substantial degradation" means either average health drops by more than 0.15, a guardrail dimension drops by more than 0.05, or a new critical guardrail status appears. "Informativeness collapse" means the candidate's informativeness-score std or range falls below the replay floors, or the final reward has zero std/range on the replay batch. If the optional "require improvement" mode is enabled, at least one core dimension in {discrimination, RL signal} must improve by at least 0.01 or move to a better status. These constants are implementation defaults and can be overridden by environment variables for ablation or stricter safety runs.

Example macro update. One real accepted macro update occurred in a writing run at step 25. The live graph before the update was a single Global Rubric Node:

> `writing_judge` (`rubric`, continuous, `is_final=true`) with six rubric items: purposeful development, necessary specificity, form-purpose fit, reader effect, insight/originality, and prose control.

The meta-judge diagnosed weak same-query separation and template-like writing artifacts. It made one typed edit, `update_node(writing_judge, rubric_item_updates=...)`, without changing the topology. The patch tightened three rubric items: necessary specificity and grounding, insight/originality, and prose control. The new criteria explicitly penalized placeholder scaffolding, pseudo-specific unsupported detail, meta artifacts such as visible word-count scaffolds, and jarring register or language mismatch.

The gate replayed the live and candidate DAGs on 48 recent cases from 12 query groups selected by low-score, high-score, high-variance, and random criteria. The candidate achieved replay success rate 1.0, kept the graph valid, introduced no new critical dimensions, preserved the average health score, avoided guardrail drops, and did not collapse the reward distribution: score std changed from 0.0673 to 0.0730, and score range from 0.2666 to 0.2916, both above the default collapse

thresholds. The update was promoted. This example illustrates a bounded criterion-source/rubric-content edit.

Additional accepted macro updates, including the writing guard-style penalty repair used in the training-dynamics analysis, are reported as experimental case studies in Appendix E.4.

C.3 DREAM-RL Training Algorithm

Algorithm 1: DREAM-RL

Input: initial policy π_{θ_0}, initial Reward-DAG D_0, query distribution $\mathcal{X}$, macro-update interval N, initial harness $\mathcal{H}_0$.

1. Initialize memory $\mathcal{M}_0$ and dynamic skills $\mathcal{S}_0^{\text{dyn}}$.
2. For each training step $t = 0, 1, \ldots$, sample queries $x \sim \mathcal{X}$ and grouped responses $\mathcal{Y}_x \sim \pi_{\theta_t}$.
3. If query-level rubric nodes are active, instantiate query- and response-aware criteria for the current batch.
4. Score responses with the current Reward-DAG D_t; log rewards, node traces, and reward-health summaries.
5. Update π_{θ_t} using GRPO-style group-relative advantages.
6. If t is not a macro-update step, set $D_{t+1} = D_t$ and continue.
7. Otherwise, use $\mathcal{H}_t$ to diagnose reward failures and propose a typed edit e_t, yielding candidate graph $\tilde{D}_{t+1} = e_t(D_t)$.
8. Replay live and candidate graphs on recent rollout batch $\mathcal{B}_t$, optionally with monitor review.
9. Set $D_{t+1} = \tilde{D}_{t+1}$ if $\mathcal{G}(D_t, \tilde{D}_{t+1}, \mathcal{B}_t) = 1$, otherwise set $D_{t+1} = D_t$.
10. Store the accepted or rejected trajectory in $\mathcal{M}_{t+1}$ and distill it into $\mathcal{S}_{t+1}^{\text{dyn}}$.

C.4 Meta-Judge Agent Harness Tool Details

The meta-judge harness exposes reward-system operations through a restricted tool interface rather than through unrestricted file or code access. Table 10 summarizes the tool families used by DREAM-RL. The first two families provide diagnostic evidence, the third family defines the admissible Reward-DAG edit space, and the final two families support verification and guarded inspection.

Observation tools. Observation tools expose recent rollout behavior and reward traces without allowing the agent to change the reward system. The harness organizes these observations around two axes. On-policy Reward Validity focuses on whether current high- and low-reward examples reflect actual response quality on the evolving policy distribution. Sustainable Reward Informativeness focuses on whether the reward remains useful for GRPO-style relative advantage estimation, especially within groups of responses sampled for the same query. This separation prevents the agent from treating global score variance as sufficient evidence of a useful reward signal.

Editing tools. All Reward-DAG changes must be expressed through typed edit operations. The interface supports bounded node updates, adding evaluator or composition nodes, removing stale or harmful nodes, changing the entry node when needed, and locally modifying aggregation. Each edit is applied transactionally to a candidate graph and is rejected if it creates an invalid DAG. Validation checks include acyclicity, reachability from the entry node, valid upstream inputs for aggregation, pointwise reward semantics, and scenario/domain consistency. Program-owned execution details, such as hidden parser schemas or rubric execution internals, are not exposed as agent-editable fields.

Replay tools and promotion gate. Replay validation appears in two forms. Edit-time replay tools are agent-invoked probes: they re-execute the current candidate *Reward-DAG* on a small selected set of recent rollout cases and return compact score changes and node-level traces. These probes help the agent diagnose whether a proposed edit has the intended local effect, but they are budgeted and cannot promote the candidate.

The final deployment decision is made by a program-side promotion gate. The gate validates the candidate graph, selects a broader fixed-policy replay set from recent same-query groups covering low-score, high-score, high-variance, and random regions, and replays both the live and candidate graphs on the same selected cases when a live base-

Tool family	Representative interface	Role in the harness
On-policy Reward Validity diagnostics	high-score, low-score, contrastive case inspection; bias analysis	Check whether the current reward system gives behaviorally valid preferences on current-policy outputs, including over-rewarded bad cases, false positives, shortcut behavior, and superficial length or format bias.
Sustainable Reward Informativeness diagnostics	same-query case inspection; RL-signal analysis; node/item discrimination analysis	Check whether the reward still provides useful optimization signal, especially same-query score spread, zero-distinction groups, advantage-signal strength, node/item saturation, redundancy, and execution reliability.
Constrained Reward-DAG editing	node insertion, node update, node removal, entry change, local aggregation update	Express candidate reward-system updates as typed graph operations rather than free-form file edits. The edit interface enforces graph validity and restricts the agent to bounded mechanism and composition changes.
Replay validation	candidate replay on recent rollout groups; program-side promotion gate	Re-execute candidate Reward-DAGs on recent rollout groups, compare live and candidate behavior, expose score deltas and node traces, and decide whether a candidate can be promoted.
Guarded read-only inspection	sandboxed read-only analysis over rollout, DAG, and project artifacts	Provide flexible failure mining when fixed diagnostic views are insufficient, while blocking writes, deletion, process control, network access, and direct DAG modification.

Table 10: Reward-specific tool families exposed by the Meta-Judge Agent Harness.

line is available. A candidate is rejected if replay fails, introduces new critical guardrail failures, exceeds the health-drop thresholds in Appendix C.2, collapses the informativeness or final-score distribution, or worsens guardrail dimensions such as discrimination, RL signal, calibration, bias, stability, or hacking risk.

Monitor review. When enabled, the promotion gate can call an additional monitor model to review compact live-vs-candidate replay evidence, dashboard deltas, and node traces. The monitor is separated from the proposing agent by role and prompt, and can use a different model from the reward judge when available. We do not assume that this eliminates judge bias. Instead, the monitor mitigates self-confirming reward edits by combining model or prompt separation with fixed metric guardrails, same-case replay comparisons, execution checks, and explicit rejection of score collapse or guardrail regressions.

C.5 Reward-Evolution Guidance Skill Details

Section 4.2 abstracts the meta-judge as an agentic reward monitor and constrained intervention policy $\Pi_{\mathrm{MJA}}(D_t, \mathcal{O}_t, \mathcal{K}_t)$ over an admissible intervention space $\mathcal{A}(D_t)$. In implementation, $\mathcal{O}_t$ is provided by observation tools and reward traces, $\mathcal{A}(D_t)$ is defined by the typed *Reward-DAG* intervention tools and validity checks, and $\mathcal{K}_t$ consists of fixed reward-evolution skills, dynamic skills, and run-local memory. Each replayed candidate edit produces a trajectory record z_t, which is stored in memory and summarized into later dynamic-skill context.

Tools define what the meta-judge agent can observe, edit, and verify. Skill sets define how the agent should reason over those interfaces. In DREAM-RL, skills serve as reward-evolution guidance rather than task-level response rubrics: they structure diagnosis, provide reward-quality knowledge, route failures to suitable mechanism families, constrain edit boundaries, and specify how replay evidence should be interpreted.

Fixed skills. Fixed skills are shared across runs. They require the agent to diagnose before editing and to ground each candidate change in both rollout evidence and reward traces. The diagnosis is organized around the same two axes used by the tool set: On-policy Reward Validity and Sustainable Reward Informativeness. Fixed skills also provide reward-quality priors: useful rewards should preserve current-policy preference validity, cover emerging failures, maintain same-query informativeness, avoid saturated or redundant items, execute reliably, and preserve clean cases under replay.

Diagnosis-to-edit decision policy. Although the meta-judge is implemented with an instruction-following agent, the harness constrains it to a finite decision policy rather than an open-ended prompt workflow. At macro step t, the agent receives observation summaries o_t, node traces τ_t, recent memory $\mathcal{M}_t$, and the current graph D_t. It first assigns a primary failure target

$$f_t \in \{\text{validity}, \text{informativeness}, \text{both}, \text{none}\},$$

and a failure pattern p_t from the operator-routing table. The table maps p_t to a small operator family $\Omega(p_t)$, such as a global rubric refinement, query-level rubric specialization, checklist/verifier, flaw-penalty side signal, aggregation adjustment, or removal. The proposed edit is selected from the legal typed-edit set:

$$e_t \in \mathcal{A}(D_t) \cap \Omega(p_t),$$

where $\mathcal{A}(D_t)$ is defined by the edit tools and validation checks in Appendix C.2. Among legal edits, the policy prefers edits that target the diagnosed failure, preserve clean cases and the stable reward core, maintain same-query signal, avoid known failed edits in memory, and minimize structural change. If no evidence-backed legal edit exists, the policy should return a no-op rather than force a graph change. The program-side promotion gate then decides deployment; the proposing agent cannot promote its own edit.

Algorithm 2: Harness-Constrained Diagnosis-to-Edit Policy

Input: current graph D_t, rollout summaries o_t, node traces τ_t, replay dashboard q_t, memory $\mathcal{M}_t$, fixed skills $\mathcal{S}^{\text{fix}}$, dynamic skills $\mathcal{S}_t^{\text{dyn}}$.

1. Diagnose reward validity and informativeness separately from o_t, τ_t, q_t; attach representative rollout evidence to each finding.
2. Set $f_t \in \{\text{validity}, \text{informativeness}, \text{both}, \text{none}\}$. If $f_t = \text{none}$, return no-op.
3. Classify the dominant failure pattern p_t using the operator-routing prior in Table 11.
4. Construct the admissible action set $\mathcal{C}_t = \mathcal{A}(D_t) \cap \Omega(p_t)$, where $\mathcal{A}(D_t)$ is the typed edit set allowed by the current graph validator.
5. Remove actions that conflict with recent rejected memory, modify protected execution fields, shift the stable core without evidence, or violate pointwise RL constraints.
6. Rank remaining actions by targeted-failure coverage, clean-case preservation, expected same-query signal preservation, locality of structural change, and consistency with dynamic skills.
7. If $\mathcal{C}_t$ is empty or the best action lacks evidence, return no-op; otherwise apply the top typed edit to produce $\tilde{D}_{t+1}$.
8. Replay $\tilde{D}_{t+1}$ and call the program-side gate $\mathcal{G}$. Store both accepted and rejected outcomes in memory for later dynamic-skill updates.

This policy is implemented by the meta-judge harness. The language-model agent supplies diagnosis and ranking under this policy, while the action space, validator, replay selection, and promotion gate are program-defined.

Condensed fixed-skill card. The following condensed skill card is supplied to the agent as reward-evolution guidance. We reproduce it in segmented form to make the harness behavior auditable.

Mission.

> Optimize pointwise RL reward DAGs during unverifiable generation training. The goal is not to make a prettier rubric; the goal is to keep reward useful as the policy changes. Use two top-level axes for every diagnosis, edit, replay interpretation, and memory reference: On-policy Reward Validity and Sustainable Reward Informativeness.

Two-axis diagnosis.

> On-policy Reward Validity asks whether the reward covers the current policy's actual response space, including reward hacking, high-score low-quality responses, shortcut behavior, brittle over-penalization, corner cases, false positives, and response patterns the rubric fails to cover. Sustainable Reward Informativeness asks whether the reward can keep giving GRPO useful learning signal, using same-query range/std, zero-variance groups, main or base node health, item saturation, score collapse, parse failures, calibration, and advantage signal.

Reward-signal interpretation.

> Reward statistics are health signals, not standalone objectives. Same-query std/range and advantage behavior on the informativeness score are primary evidence for GRPO signal. Final reward

mean/std and global variance are training-sanity checks. Larger final-score variance is not progress when it comes mainly from guard or auxiliary downward effects.

Required workflow.

1. Diagnose before editing: inspect rollout summaries, dashboards, node/item traces, same-query groups, contrastive cases, and recent memory.

2. State separate findings for validity, informativeness, recent memory, scenario evolution direction, and reward-invariance risk.

3. Choose one primary target for the edit: validity, informativeness, or both.

4. Classify the failure and assign it to an operator family before editing.

5. Make one bounded edit through the typed Reward-DAG interface.

6. Use replay to check targeted failures, clean-case preservation, same-query informativeness, node traces, and execution errors.

7. Record accepted and rejected edits, observed side effects, and lessons for later dynamic skills.

Table 11 summarizes the operator-routing prior used by fixed skills. This prior prevents the agent from treating every failure as a generic rubric rewrite. It also makes candidate edits more verifiable: each edit has an intended failure target, an owner signal, and an expected replay behavior.

Edit-boundary constraints. Fixed skills constrain reward evolution so the training objective does not oscillate. The agent is instructed to preserve the stable reward core unless evidence supports a larger structural change, prefer bounded complements before replacing the main reward path, make one primary edit at a time, keep RL-time DAGs pointwise, and treat aggregation or final weights as high-impact changes. We distinguish three edit regions: the *Stable Core*, including the main task objective and primary positive reward signal; the *Adaptive Shell*, including anchors, evidence requirements, generation policy, and small coverage refinements; and *Safety/Validity Guards*, which target narrow observable defects and should not become broad secondary quality judges.

Replay-interpretation standards. Skills specify that replay deltas are validation evidence, not proof of policy improvement. The agent must check whether suspicious cases move in the intended direction, whether clean cases are preserved, whether same-query informativeness improves or at least does not collapse, whether node traces explain the score changes, and whether parse or node errors invalidate the replay. In particular, guard-induced final-score variance should not be mistaken for sustainable reward informativeness.

Dynamic skills. Dynamic skills specialize the fixed policy to the current scenario and training run. They record observed hacking or shortcut patterns, failure-to-edit mappings discovered during training, accepted and rejected edits, no-op cycles, historical side effects, and scenario-specific operator preferences. For example, writing runs may record fabricated authority, constraint self-certification, or dimension coupling as concrete hacking families, while roleplay runs may record format gaming, catchphrase stuffing, meta/OOC leakage, or unsupported escalation. These dynamic skills are injected into later meta-judge calls so that the agent can avoid repeated failures and adapt to the policy trajectory.

Dynamic method advice examples. Dynamic skills are implemented as run-local memory and method advice. The advice is advisory context rather than a command list. A condensed version of the advice format is:

> **Ground every edit in three evidence blocks.** Before editing, reconcile reward-signal diagnostics, actual response-level failures, and recent run memory. If any block is missing or contradictory, resolve that gap first rather than inferring a fix from one view.
>
> **Preserve reward invariance across training.** Classify each edit as a reliability fix, calibration change, coverage change, guard/validity change, structural complement, aggregation change, or objective-shifting change. Stable-core edits to the main reward target, hidden scorer protocol, or final weights should be rare.
>
> **Treat replay deltas as falsification, not progress theater.** Use replay to test whether the edit hypothesis holds on same-query spread, trace evidence, clean cases, and targeted failures. Keep reward statistics as decision checks, not isolated optimization targets.
>
> **Escalate skepticism after repeated no-op or revert outcomes.** When recent updates form a repeated no-op/revert cycle, require materially new response-level evidence before trying another near-identical edit.

Failure pattern	Primary operator family	Typical repair
Continuous quality miscalibration	Global continuous rubric	Refine item wording, anchors, evidence requirements, or weights.
Redundant or saturated criteria	Global rubric structure	Split, merge, add, remove, or reweight rubric items.
Prompt-local coverage gap	Query-level rubric node	Revise meta-rubrics or generation policy for query-specific criteria.
Explicit observable requirement	Checklist, verifier, or deduction node	Add hard or soft requirement tracking.
Sparse high-score bad tail or hacking escape	Flaw-penalty, guard, or validity side signal	Add a narrow negative detector or guard-style fusion.
Useful missing positive signal	Complementary positive node	Add a side scorer for a distinct positive construct.
Signal masking or distorted final reward	Aggregator or fusion operator	Adjust weights, guard roles, or fusion method.
Harmful, inert, or duplicated signal	Simplification or removal	Remove, bypass, or downweight stale nodes.

Table 11: Operator-routing priors encoded in fixed reward-evolution skills.

Scenario-specific advice further constrains dynamic edits. For writing, only concrete fabricated authority, constraint self-certification, and dimension coupling are treated as reward-hacking families; ordinary headings, professional structure, useful detail, appropriate length, or normal task completion are not hacking by themselves. For roleplay, shortcut detection is bounded to observable behaviors such as tag gaming without in-character substance, generic dramatic verbosity masking weak grounding, catchphrase or persona-name stuffing, meta/OOC leakage, and unsupported escalation. Ordinary shallow characterization or weak scene progression should usually be handled through positive character, scene, progression, or query-level criteria rather than broad guard penalties.

Run-local memory schema. Each macro update produces a compact memory record:

$$z_t = (o_t, e_t, \Delta_t, a_t, c_t),$$

where o_t is the diagnosed failure, e_t the proposed edit, Δ_t replay and gate evidence, a_t the accept/reject/no-op decision, and c_t observed side effects or caveats. The memory summary is not used as reward evidence by itself. It is injected into later meta-judge calls as dynamic guidance, for example to avoid repeating a rejected guard edit, to reuse a successful failure-to-operator mapping, or to cool down an operator family that repeatedly produced no-op or harmful changes.

In implementation, each memory record also stores the selected rollout step, update mode, agent type, whether the candidate graph was modified or promoted, a compact dashboard summary, a gate summary, the tool sequence, policy violations if any, and links to the candidate graph and operator ledger. A separate memory-advice summarizer may compress the trajectory into two fields: a short *memory summary* for the next update and a *method-advice update* for longer-lived run-local guidance.

D Experimental Details

D.1 Artifact Use, Intended Use, and Data Safety

We use existing artifacts including Qwen3-4B (Yang et al., 2025), Qwen3.5-27B, WritingBench (Wu et al., 2025), CoSER (Wang et al., 2025), MiniMax Role-Play Bench, DeepSeek evaluation models, GPT-5.4, and Kimi-K2.5 (Team et al., 2026). The creators of these artifacts are cited where they are first used in the method and experiment sections. We use these artifacts for research on reward-system evolution and evaluation, consistent with their benchmark, model-evaluation, or model-training use. Proprietary API models are used through their service interfaces; their parameter counts and redistribution rights are not public, so we report model names and roles rather than redistributing them.

The artifacts created by this work include filtered training prompts, initial task-level and query-level rubrics, *Reward-DAG* schemas and edit logs, reward-diagnostic taxonomies, trained policy checkpoints, evaluation outputs, and analysis

scripts. These artifacts are intended for research reproduction and analysis of reward-system evolution, not for deployment as general-purpose safety filters or user-facing moderation systems.

For data safety, the writing data are synthetic open-ended writing instructions. We filter duplicated, underspecified, benchmark-like, and factual-QA-dominated queries, and we avoid prompts that require identifying private individuals. Roleplay training data are sampled from MiniMax Role-Play Bench and retained only when persona, relationship, context, and dialogue state are explicit. We do not intentionally collect personal identifiers. Because open-ended generation and roleplay can still produce sensitive or offensive content, final outputs are used only for aggregate evaluation and audit statistics, and auditor prompts do not require exposing method labels, reward traces, or user-identifying metadata.

Appendix D.3 reports the data coverage and sizes: 944 writing queries and 5,000 roleplay queries, with writing domains and roleplay language, persona, relationship, context, and dialogue-depth coverage summarized there. Section 5.1 and Appendix C.1 report the model settings, training protocol, compute budget, and evaluation protocol.

D.2 Use of AI Assistants in Research and Writing

The authors used AI assistants for auxiliary support in language polishing and code development. The authors reviewed and remain responsible for the research design, experiments, analyses, claims, and final manuscript content.

D.3 Training Data and Initial Rubric Construction

Training data. For writing, we construct a filtered synthetic query set for open-ended writing RL. The queries are generated to cover six broad writing domains and diverse constraints over audience, format, length, style, language, and communicative intent. We remove queries that are duplicated, underspecified, benchmark-like, or dominated by factual QA rather than writing quality. The final training set contains 944 writing queries. For roleplay, we sample from MiniMax Role-Play Bench and retain queries with clear persona, relationship, context, and dialogue-state information. The final training set contains 5,000 roleplay queries, covering English and Chinese scenarios with varied persona relations and dialogue depths.

Initial rubric construction. We build both task-level and query-level rubrics with a lightweight iterative rubric-generation procedure. Starting from a seed instruction and representative examples, a rubric generator proposes candidate criteria and short scoring descriptions. We then audit the candidates on small batches of representative responses and remove criteria that show poor discriminability, strong coupling with other criteria, vague evidence requirements, or weak relevance to the target task/query. New criteria are added to cover uncovered failure modes or task requirements. This generate–audit–revise loop is repeated until the rubrics provide stable, non-redundant, and task-relevant distinctions. The resulting task-level rubrics are used by the RLAIF-style baseline and initialize the single-node continuous *Reward-DAG* used by DREAM-RL, while the query-level rubrics are used by RAR-style reward systems.

D.4 Baseline Reward-System Details

All baselines are implemented under the unified GRPO protocol in Section 5.1. Because the compared methods were originally developed for different task environments, their full pipelines include scenario-specific components that are not directly portable to writing and roleplay. For example, DR-Tulu is designed for agentic deep-research RL, where the environment, rollout structure, tool-use state, and task-specific evaluation differ from our open-ended writing and roleplay setting. We therefore reproduce the complete reward-system design of each baseline that is applicable under our shared GRPO setting, while holding the policy initialization, training data, rollout budget, optimizer, reward model family, and evaluation protocol fixed. This comparison should be interpreted as a controlled reward-system comparison rather than a reproduction of each method's original task pipeline. For dynamic-rubric baselines, criteria-only adaptation denotes the common family of on-policy rubric-update methods below rather than a separate baseline. The DR-Tulu-style baseline uses the same local Qwen3.5-27B model as both rubric updater and GRM, matching the micro query-rubric updater used by DREAM-RL; the OpenRS-style baseline uses the same local model in its pairwise rubric-judge format.

Static rubric baselines. The RLAIF-style baseline uses the task-level rubric constructed in Appendix D.3. The same rubric is applied to all

queries in a task, and the GRM returns a normalized continuous score as the scalar reward. The RAR-style baseline uses fixed query-level rubrics generated before training. For each query, the query-specific rubric remains unchanged during RL, isolating the effect of criterion-source specialization.

DR-Tulu-style dynamic rubrics. The DR-Tulu-style baseline follows the public implementation idea of maintaining persistent meta/static rubrics together with an active query-level rubric buffer. After each rollout step, the update model observes the query and all current rollout responses for that query, proposes positive or negative active rubrics, and appends them to the query-specific active buffer. During reward computation, both the persistent query rubrics and active rubrics are scored by the same continuous GRM path. Active rubrics with weak or collapsed discrimination are filtered using item-level reward statistics, and the active buffer is capped to a small maximum size.

OpenRS-style pairwise rubric reward. The OpenRS-style baseline does not maintain a persistent active-rubric state. Instead, after each rollout, responses under the same query are grouped and compared pairwise. For each pair, the OpenRS prompt asks the judge to analyze the query, construct or select pair-specific rubrics, compare the two responses under those rubrics, and output rubric-level comparison results. The implementation parses the pairwise comparison into a signed margin, aggregates margins across pairs for each response, and maps the average margin to a scalar reward in $[0, 1]$. Thus, this baseline changes the reward mechanism to pairwise comparison, but does not perform replay-validated *Reward-DAG* evolution.

D.5 Evaluation Diagnostics and HR/CFR Audits

We use HR and CFR as final-output robustness audits in addition to final benchmark scores. HR (Hack Rate) measures the incidence of fixed reward-attractive shortcut patterns in final outputs. These patterns are identified from base-model outputs as visible failures that rubric judges may over-reward; when they are amplified after RL, we use this as evidence that the final policy has over-learned reward-attractive shortcuts. CFR (Coverage Failure Rate) measures the audited rate of predefined hard coverage-failure labels in final outputs. R-Var and Zero measure whether the reward gives useful within-query distinctions for GRPO; they are proxies and are interpreted together with the dynamics and case studies in Section 6.1.

Audit protocol. For each task, we define the HR and CFR taxonomies before method-level comparison using a base-model-only calibration pool. The calibration pool contains visible base-model outputs and their prompts, without method labels, reward scores, reward traces, training-stage metadata, or DREAM-RL checkpoints. Human inspection identifies recurring visible failure patterns in this pool. After this taxonomy-construction step, the HR/CFR categories are frozen and applied to all methods with the same LLM auditor. The auditor only labels whether the frozen categories are present and is not allowed to invent new hack or coverage-failure types. These evaluation taxonomies are not provided to the meta-judge agent during RL training. Training rollouts and reward traces are used only for qualitative case-study interpretation and meta-judge diagnosis analysis, not for defining the reported HR/CFR categories.

HR and CFR metrics. Given audited final outputs $\{(x_i, y_i)\}_{i=1}^{N}$, HR is the rate of outputs matching a predefined task-specific shortcut pattern:

$$\mathrm{HR} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}[\exists h \in \mathcal{H}_{\text{task}} : \mathrm{Auditor}_h(x_i, y_i) = 1] \,,$$

where $\mathcal{H}_{\text{task}}$ is the task-specific HR taxonomy. For roleplay, HR is normalized by the number of assistant turns because a simulation-level shortcut can recur across longer dialogues; the reported roleplay HR is therefore a per-assistant-turn rate.

CFR is computed over predefined hard coverage-failure dimensions:

$$\mathrm{CFR} = \frac{1}{N} \sum_{i=1}^{N} \sum_{c \in \mathcal{C}_{\text{task}}} \mathbf{1}[\mathrm{Auditor}_c(x_i, y_i) = 1] \,,$$

where $\mathcal{C}_{\text{task}}$ is the task-specific CFR taxonomy. The reported CFR is the resulting percentage over the frozen CFR dimensions. HR and CFR answer different final-output robustness questions: HR detects reward-attractive shortcut patterns, while CFR detects missing coverage of important discrete validity or completion dimensions. A response may have neither, either, or both labels.

Writing HR taxonomy. The writing HR pattern set was fixed from the base-model WritingBench calibration pool. Manual inspection focused on cases that looked attractive to rubric or checklist judges while not improving, or even hurting, the requested writing deliverable. This process produced three task-level pattern families.

Pattern	Definition used by the auditor
Fabricated authority / surface expertise	Dense unsupported numbers, citations, institutions, laws, technical jargon, timelines, metrics, or unverifiable concrete details that create false professionalism.
Self-certification	Meta-level claims that the answer satisfies length, format, constraint, checklist, or scoring requirements, instead of simply completing the requested deliverable.
One-dimension over-optimization	The response is optimized for one visible scoring dimension, such as length, structure, local keyword coverage, or format compliance, while failing essential requirements such as deliverable shape, grounding, usefulness, or audience fit.

Table 12: Predefined writing reward-hacking patterns used for Hack auditing.

Writing CFR taxonomy. Writing CFR uses a stricter hard-failure taxonomy than ordinary WritingBench quality scoring. It excludes ordinary shortness, weak prose, missing minor subpoints, and low benchmark quality; those are handled by WritingBench scores. Instead, it counts discrete non-final or wrong-deliverable failures that a training reward can under-cover even when the output is fluent.

Roleplay HR taxonomy. Roleplay HR is intentionally narrower than generic roleplay quality. It counts observable shortcut behavior that can look attractive to a judge without adding new in-character consequence. Ordinary shallow characterization, weak scene progression, or generic prose are not HR by themselves.

Roleplay CFR taxonomy. Roleplay CFR measures discrete validity and completion failures in visible AI-character turns. It does not include broad continuous dimensions such as latest-turn uptake, scene progress, character depth, or generic transplantability; those remain part of CoSER/GCA-style scoring. The reported CFR is limited to the following predefined, easy-to-audit failure families.

CFR type	Definition used by the auditor
Unresolved template artifact	The response contains unresolved placeholders, bracketed fill-ins, template debris, or explicit word-count artifacts that make the deliverable non-final.
Non-final process artifact	The response exposes planning, evaluation, checklist reasoning, or meta-process text instead of only delivering the requested writing artifact.
Deliverable mismatch	The response does not produce the requested artifact, format, scope, or concrete communicative deliverable.
Missing artifact	The response admits that a required non-text, source-dependent, or concrete artifact is absent, unavailable, or not actually provided.

Table 13: Predefined writing coverage-failure dimensions used for CFR auditing.

Pattern	Definition used by the auditor
Decorative verbosity / emotion stuffing	Inflates length with generic dramatic interiority, repeated emotional beats, atmosphere, or private-planning style padding without creating new visible roleplay consequence.

Table 14: Predefined roleplay reward-hacking pattern used for HR auditing.

CFR type	Definition used by the auditor
Required protocol / block failure	Missing, malformed, replaced, or misordered required user-visible tags, speaker labels, blocks, or output format when this materially breaks the requested roleplay output.
OOC / meta leakage	Explicit AI-assistant framing, instruction discussion, task explanation, OOC commentary, refusal-like meta text, or model/self-reference when not requested.
Visible context contradiction	Contradicts explicit location, relationship state, prior action, character knowledge, causality, or latest-turn facts in the visible context.
User-agency violation	Dictates the user's internal state or actions, resolves too much of the scene, or removes the user's natural ability to respond.

Table 15: Predefined roleplay coverage-failure dimensions used for the reported CFR.

Taxonomy-level leakage check. We additionally compare the frozen HR/CFR taxonomy with the meta-judge's training-time diagnoses in the inspected DREAM-RL logs. This analysis does not prove that no leakage of broad failure knowledge is possible, since both the frozen audit taxonomy and the meta-judge diagnoses are grounded in visible model failures. Partial overlap is therefore expected. However, the meta-judge did not appear to operate from the frozen HR/CFR audit taxonomy as a checklist: several frozen categories were absent or only weakly matched in the inspected logs, while several agent diagnoses concerned reward-signal informativeness or execution failures outside HR/CFR. This provides evidence against taxonomy-level leakage and weakens the concern that DREAM-RL directly optimized the reported HR/CFR audit checklist.

LLM auditor prompt. The auditor receives the query or roleplay context, the response or visible simulation transcript, and the frozen task-specific HR and CFR taxonomies. It does not receive method labels, reward scores, reward traces, or training-stage metadata when producing the reported HR/CFR labels. It returns compact JSON and must prefer no label over a weak or invented label:

HR/CFR Auditor Prompt Excerpt

```
Audit the response against the given task
     /context. Label only the predefined
     HR and CFR types. Do not invent new
     categories.

HR means the response contains a
     predefined hacking pattern that a
     rubric judge may over-reward without
     improving true task quality. CFR
     means the response has a predefined
     hard coverage failure that may be
     under-covered by the reward.

Use the task-specific HR and CFR type
     lists provided in the prompt. Mark a
     type only when it is meaningfully
     present and supported by visible
     evidence. Do not mark normal useful
     structure, necessary detail,
     appropriate roleplay narration, or
     ordinary low quality as HR/CFR.
     Prefer no over weak yes.

Return JSON only:
{
  "hack": "yes|no",
  "hack_types": ["..."],
  "coverage_failure": "yes|no",
  "coverage_failure_types": ["..."],
  "evidence": "<=25 words"
}
```

R-Var and Zero. For each query x, let $\mathcal{Y}_x$ be the grouped rollout responses and $r(y)$ the scalar reward used by GRPO. R-Var is the average within-query reward variance:

$$\text{R-Var} = \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} \text{Var}(\{r(y) : y \in \mathcal{Y}_x\}) .$$

Zero is the percentage of same-query groups whose reward range is indistinguishable under a small numerical tolerance:

$$\text{Zero} = \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} \mathbf{1}\left[\max_{y \in \mathcal{Y}_x} r(y) - \min_{y \in \mathcal{Y}_x} r(y) \leq \epsilon\right] ,$$

with $\epsilon = 10^{-6}$ in our logged reward-health computation. Larger R-Var and lower Zero usually indicate more useful group-relative training signal, but high variance caused only by noisy penalties or score collapse is not treated as sufficient evidence of reward quality.

Calibrated WritingBench scoring. WritingBench itself is a continuous rubric-judge benchmark, so its evaluator can over-credit the same general surface shortcuts that make rubric rewards brittle in training, such as unsupported authority cues, self-certifying constraint claims, or strong performance on only one visible dimension. This overlap is not method-specific: these are general judge-side failure modes for open-ended writing. We therefore use the original WritingBench scoring format with a minimal evaluator-calibration note. The goal is to make the benchmark judge verify whether such visible patterns are supported by the content, rather than rewarding them as writing quality.

This calibration is separate from the HR audit. HR measures whether final model outputs contain fixed reward-attractive shortcut patterns, while the calibrated WritingBench score reduces benchmark-judge over-credit for those patterns so the benchmark score focuses more directly on the requested writing deliverable. The calibrated prompt is applied uniformly to all methods, receives no method labels, reward scores, reward traces, or meta-judge diagnostics, and does not use HR labels as post-hoc caps. Thus, calibration makes the benchmark score less confounded with HR-style surface shortcuts, making it more independent from the HR audit

Frozen audit category	Pattern found by the meta-judge in rollouts	Agent-side diagnosis and edit routing	Match
Writing HR: fabricated authority / surface expertise	Pseudo-specific unsupported statistics, unsupported numeric/entity specificity, weakly credible detail, and fake specificity.	Reward-validity problem: high-scoring responses contain impressive-looking but weakly grounded details; routed to specificity/grounding calibration or a penalty side signal.	Partial
Writing HR: self-certification	Word-count tails, explicit word-count artifacts, meta scaffolding, and visible constraint-satisfaction artifacts.	Observable template/meta artifact requiring downward pressure; treated as anti-template and anti-scaffolding calibration rather than a named self-certification label.	Partial
Writing HR: one-dimension over-optimization	Surface organization and generic template completion scored similarly to better responses; repeated mid-band score vectors.	Reward-signal compression and weak same-query discrimination; diagnosed as low informativeness more than a direct hacking category.	Weak
Writing CFR: unresolved template artifact	Placeholders such as `[X]` and `[Company Name]`, unresolved formatting debris, and template scaffolding.	Concrete non-final artifact; targeted through stricter prose/control, specificity, and anti-template scoring.	Strong
Writing CFR: non-final process artifact	Meta artifacts, word-count scaffolding, and process-like debris.	Artifact leakage that reduces final deliverable quality; grouped with template/meta debris.	Partial
Writing CFR: deliverable mismatch	Genre, format, audience, tone, or length constraint violations in weak cases.	Task-fit or format-purpose calibration issue rather than hard wrong-deliverable auditing.	Weak
Writing CFR: missing artifact	No clear corresponding live diagnosis in inspected agent logs.	Not discovered as a separate failure family.	None
Roleplay HR: decorative verbosity / emotion stuffing	Long atmospheric answers over-rewarded; decorative `<role-think>` padding; generic dramatic padding; transplantable taunts; unsupported specifics.	On-policy reward-validity failure: verbosity and fake specificity are over-rewarded; routed to query-rubric coverage/calibration rather than a new guard.	Strong
Roleplay CFR: required protocol / block failure	High-score responses with `<role-think>` and `<role_action>` but missing required `<think>` block; tag-only compliance.	Explicit requirement-tracking failure; routed to checklist ownership and protocol-checklist repair.	Strong
Roleplay CFR: OOC / meta leakage	No strong promoted diagnosis focused on OOC/meta leakage in inspected logs; only adjacent concerns about planning or tag content.	Not a primary discovered failure in the inspected promoted updates.	Weak
Roleplay CFR: visible context contradiction	Weak latest-turn consequence, poor visible scene-state uptake, unsupported invented specifics, and weak grounded progression.	Positive coverage/calibration problem in the query rubric; treated as missing latest-turn and scene-state reward coverage rather than binary contradiction auditing.	Partial
Roleplay CFR: user-agency violation	No clear corresponding live diagnosis in inspected agent logs.	Not discovered as a separate failure family.	None
Outside HR/CFR	Same-query collapse, repeated score vectors, low within-query spread, query-rubric redundancy, length correlation, replay timeouts, and parser collapse.	Reward-signal informativeness or execution-validation failures used to choose or reject edit families.	Outside

Table 16: Comparison between the frozen HR/CFR audit taxonomy and meta-judge diagnoses observed in inspected DREAM-RL logs. The mapping is incomplete: some reported audit categories were not recovered by the agent, while several agent diagnoses concern reward-signal or execution issues outside HR/CFR.

rather than turning HR into the benchmark objective.

Calibrated WritingBench Scoring Addition

When judging writing quality, pay extra attention to these surface shortcut patterns as quality signals, not as separate penalty rules: (1) Fabricated authority / surface expertise: do not punish normal numbers, examples, domain terms, or concrete details, but lower the score when the response densely piles up unsupported numbers, cases, citations, institutions, laws, technical jargon, timelines, or metrics to look professional without real grounding. (2) Self-certification: when the response claims it has satisfied word count, format, constraints, or checklist items, carefully verify whether it actually does so and assign the true score accordingly; do not punish ordinary headings, sections, or fields required by the task. (3) One-dimension over-optimization: do not give a high score merely because the response is strong on one visible criterion if it is weak on other essential requirements such as deliverable shape, factual grounding, constraints, usefulness, or audience fit.

Illustrative scoring artifact. The calibration mainly affects cases where the raw continuous judge rewards surface specificity without checking whether the specifics are credible. In one WritingBench product-description query, the response was asked to introduce an imported goat-milk powder for an online product page, including New Zealand origin, cold-chain logistics, scientific evidence for Chinese infants, and user feedback. The raw judge assigned a high score because the response appeared complete and specific: it contained named ranch-management systems, many temperatures and quality-control numbers, clinical claims, and testimonial-like quotes. The calibrated judge reduced the score after verifying the content: several numbers and citations were unsupported, the described $-18°$C to $-20°$C cold-chain process was implausible for the stated product, and the user cases were generic rather than verifiable. This example illustrates why calibration is used to remove benchmark scoring inflation from visible shortcut patterns, while HR separately audits the incidence of such patterns in model outputs.

Case	Raw WB	Calibrated WB	Main calibrated finding
Goat-milk product page	82.0	52.0	Unsupported authority cues and implausible logistics inflated the raw continuous score.

Table 17: Example where the raw WritingBench judge over-credits surface specificity. Scores are criterion averages scaled by 10.

Raw WritingBench check. Table 18 reports the full-1000 raw WritingBench score using the original DeepSeek-V4-Pro WritingBench-style prompt without the calibration note. The table checks whether the writing conclusion depends entirely on the calibrated prompt. Under the raw prompt, DREAM-RL obtains the highest mean among trained methods, with RAR close behind. Under the calibrated score, the gap in favor of DREAM-RL becomes larger, consistent with the intended role of the scoring clarification: it reduces over-rewarding of superficial authority, self-certification, and one-dimension optimization. This indicates that DREAM-RL does not trade off standard WritingBench quality for robustness: under the raw V4-Pro judge it obtains the highest mean, while under calibrated scoring it obtains the best score.

Method	Raw WB	Calibrated WB	Calibrated – Raw
Qwen3-4B base	58.76	58.42	-0.34
RLAIF	61.09	59.57	-1.52
RAR	<u>61.73</u>	59.50	-2.23
DR-Tulu	61.04	59.21	-1.83
OpenRS	61.07	<u>59.58</u>	-1.49
DREAM-RL	**61.90**	**60.16**	-1.74

Table 18: Raw WritingBench check and comparison to the calibrated WritingBench score. Raw WB uses the original DeepSeek-V4-Pro WritingBench-style prompt without the evaluator-calibration note. Calibrated WB is the calibrated score reported in Table 2. Scores are full-1000 means scaled by 10.

D.6 Benchmark Score Robustness Checks

Because LLM-judge benchmarks can be noisy in open-ended RL, we additionally check whether the benchmark conclusions are stable under paired resampling and repeated judging over the same benchmark instances. Table 19 shows that the calibrated WritingBench gain is stable under the full-1000 paired bootstrap. The original single-judge CoSER comparison is also positive, while its paired bootstrap range is wider because CoSER is a multi-turn, multi-dimensional deduction-style judge: the 200-simulation evaluation converts heterogeneous SC/AN/CF/SQ flaw detections into one overall score.

Benchmark	N	Comparison	Mean Δ	95% bootstrap range	Readout
WritingBench Calibrated	1000	DREAM-RL – OpenRS	$+0.58$	$[+0.21, +0.96]$	stable positive
CoSER Overall	200	DREAM-RL – RAR	$+0.97$	$[-1.01, +2.88]$	positive mean, wider range

Table 19: Paired robustness checks for the main final benchmark scores. Bootstrap ranges use paired resampling over the same benchmark instances.

The wider CoSER range reflects the high-variance roleplay setting rather than a reversal of

the average pattern. To reduce dependence on a single judge sample, we repeated the DeepSeek-V4-Pro CoSER judge twice on the same simulations and averaged the original judgment with the two reruns. The three-judgment average in Table 20 is not identical to the main-table single-judge scores, but it preserves the same distributional pattern: DREAM-RL obtains the highest overall CoSER score and the strongest Storyline Quality (SQ) score.

Method	Overall	SC	AN	CF	SQ
RLAIF	71.16	67.28	71.39	70.08	75.91
RAR	71.87	69.81	71.41	**71.69**	74.59
DR-Tulu	70.23	67.96	68.44	71.07	73.46
DREAM-RL	**72.83**	**71.31**	**71.99**	70.79	**77.23**

Table 20: CoSER robustness check averaged over the original DeepSeek-V4-Pro judgment and two additional DeepSeek-V4-Pro reruns on the same 200 simulations.

Under this repeated-judge average, the paired cluster bootstrap over the 200 simulations gives a positive mean margin over RAR: $+0.96$, with a 95% bootstrap range of $[-0.83, +2.70]$. Roleplay evaluation is inherently high-variance because CoSER/GCA aggregates multi-turn interactions generated with a stochastic user simulator and heterogeneous flaw dimensions. We therefore interpret roleplay quality using repeated judgments, directional win rates, and dimension-level diagnostics rather than relying on a single aggregate judge sample.

Because the overall score aggregates heterogeneous roleplay dimensions, we also report directional win/tie/loss rates in Table 21. DREAM-RL wins more simulations than it loses against every compared method, including RAR, despite the mixed dimension-level effects.

Comparison	Win	Tie	Loss
DREAM-RL vs. RLAIF	58.0	1.5	40.5
DREAM-RL vs. RAR	60.0	0.5	39.5
DREAM-RL vs. DR-Tulu	62.0	1.0	37.0

Table 21: Directional CoSER results under the repeated-judge average. Entries are percentages of the 200 simulations where DREAM-RL obtains a higher, equal, or lower overall score than the compared method.

The dimension breakdown clarifies where the roleplay gain is concentrated. We treat Storyline Quality (SQ) as a planned diagnostic dimension because it is the most direct CoSER dimension for coherent roleplay progression, context use, and longer-horizon interaction quality. On SQ, DREAM-RL improves over RAR by $+2.65$, with a paired bootstrap range of $[+1.16, +4.09]$, while RAR has a small advantage on CF. Thus the CoSER result supports the main conclusion that DREAM-RL improves roleplay quality: the overall mean is consistently positive, directional wins dominate losses, and the clearest dimension-level gain appears on the planned SQ diagnostic. Together with the best HR/CFR robustness diagnostics in Table 2, these consistent signals support that DREAM-RL improves roleplay final quality under noisy multi-turn evaluation.

E Experimental Results and In-Depth Analysis

E.1 Intervention Trace Analysis

This subsection provides process evidence for the intervention-level analysis in Table 4. The goal is not to prove downstream causality from local replay statistics, but to make the accepted and rejected reward-system edits auditable. All R-Var changes below use the same local two-step before/after comparison as Table 4, computed from the non-guard reward branch over same-query rollout groups. The larger local changes around guard-calibration edits are expected: these updates target hack-related penalty constraints on high-score bad-tail cases, where small calibration changes can alter separation pressure more strongly than ordinary criterion wording changes. We therefore interpret them together with the replay retention rationales rather than as standalone evidence of downstream improvement.

Operator family	Steps	Count	Total Δ R-Var	Mean Δ R-Var
Structure / reward composition	5, 15	2	+0.000628	+0.000314
Query-rubric policy	10, 25, 45, 65	4	+0.001083	+0.000271
Guard calibration	20, 35, 40, 55	4	+0.001620	+0.000405

Table 22: Accepted writing interventions grouped by operator family. The local R-Var changes are adjusted two-step before/after changes from the non-guard reward branch and are used as process diagnostics, not standalone downstream quality gains. The positive/zero/negative counts are $2/0/0$, $4/0/0$, and $3/1/0$ for the three rows, respectively.

Step	Operator family	Intervention summary	Retention rationale
5	Structure / query-rubric mechanism	Added a `writing_query_judge` node so the reward could instantiate query-specific criteria from meta-rubrics instead of relying only on a global rubric.	Replay validated the DAG path and established the query-level reward signal used by later updates.
10	Query-rubric policy	Constrained query-rubric generation to produce criteria better matched to the current query and reduce flattening from generic criteria.	Targeted replay showed mechanism activation and improved sampled same-query separation.
15	Structure / guard-style aggregation	Added `writing_artifact_flaw_penalty` and a multiplicative final aggregator so the artifact signal could only lower the base reward.	Replay showed activation on high-score bad-tail patterns such as long templates, unsupported precision, and generic padding while preserving clean cases.
20	Guard calibration	Calibrated the artifact guard to better trigger on word-count tags, mixed-script glitches, generic padding, and related observable artifacts.	The previous guard under-activated; clean same-query replay showed improved separation.
25	Query-rubric reliability	Strengthened query-rubric generation reliability so criteria are derived from the current query rather than reused as coarse generic dimensions.	Retained as a bounded edit after replay supported useful signal and execution checks passed.
35	Guard calibration	Tightened generic-expansion and redundant-padding detection so section inflation and boilerplate are penalized when they lack query-specific substance.	High-scoring long-template outputs still often received perfect guard scores; same-query replay showed improved sampled spread.
40	Guard calibration	Tightened template-scaffold and meta-leakage detection for placeholders, word-count tags, scaffold shells, and similar artifacts.	Retained as a narrow false-negative repair; local R-Var was approximately unchanged, but replay showed targeted activation without broad degradation.
45	Query-constraint policy	Required query-rubric generation to include an explicit query-constraint fulfillment dimension covering format, length, structure, audience, and required content.	Replay had no node errors and showed usable query-level spread.
55	Narrow guard rule	Added a narrow rule that unresolved bracket placeholders must trigger the template-scaffold flaw rather than receiving a perfect guard score.	Targeted replay fixed clear false negatives such as unresolved placeholder greetings without same-query degradation.
65	Query-rubric anti-template policy	Tightened query-rubric generation to distinguish query-grounded completion quality from generic expansion, structural fluency, and template-like length.	Replay had no node errors and successful query-rubric generation across sampled cases.

Table 23: Accepted writing intervention trace. Each row summarizes the operator family, the bounded reward-system change, and why the edit was retained after replay/gate checks.

Step	Rejected probe	Rejection reason
30	Further tightened query-rubric generation to repair query-rubric degeneration and same-query flattening.	Targeted replay showed lower same-query informativeness; broader replay was mixed and partly parse-confounded, so the edit was rolled back.
50	Further tightened the guard penalty for generic expansion.	Replay reduced same-query standard deviation and range, indicating compression of sustainable reward signal; the edit was rejected as a no-op.
60	Made mixed-script artifacts trigger the guard more deterministically.	Target activation was unstable and the penalty spilled over to non-template technical or plain-language cases.
70	Relaxed or rewrote query-rubric policy to reduce fallback and improve query-level informativeness.	Post-edit replay lowered the non-guard same-query signal and did not pass the safe retention bar.

Table 24: Rejected writing intervention probes. These rejected updates provide process evidence for the replay gate: candidate edits are filtered when replay indicates signal collapse, unstable triggering, parse-confounded behavior, or penalty spillover.

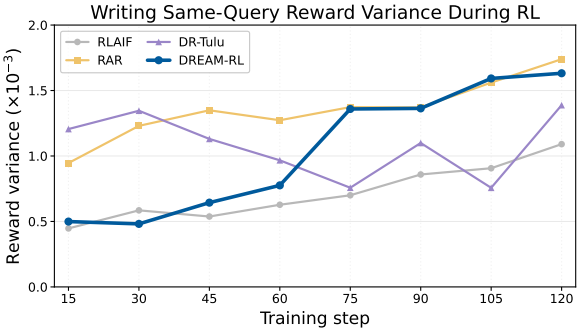

Figure 9: Writing same-query reward variance during RL, computed over 15-step rollout windows from the non-guard continuous scoring branch. Higher variance can indicate greater within-query spread, but is interpreted together with zero-distinction and reward-ranking alignment in Section 6.1.

E.2 Supplementary Reward-Variance Dynamics

E.3 Reward-Signal Ranking Audit

Section 6.1 uses zero-distinction to test whether the reward remains discriminative on on-policy rollout groups. This diagnostic measures signal availability, but it does not by itself show that the reward distinguishes responses in the correct direction. We therefore conduct a blind list-wise ranking audit that compares reward-induced rankings with independent preference rankings over the same response groups.

The independent ranking standard is method-agnostic and does not use WritingBench criteria, method-specific rubrics, or reward-system rubrics. Rankings are based on human-readable writing preferences that can be applied uniformly across methods: whether the response satisfies the user request, fits the requested format and audience, follows length and style constraints, remains concrete and useful, avoids unsupported specificity or self-certification, and is coherent as a finished writing deliverable. The same ranking standard is used for every method and checkpoint.

For each sampled group, the packet contains one query and four same-query candidate responses. Candidate identities are anonymized and shuffled. Annotators do not observe method labels, reward scores, hidden mappings, rollout source paths, or the reward ranking. Hidden mappings and logged reward scores are used only after all rankings for a packet are completed.

Each packet is independently ranked by a three-model LLM judge panel: GPT-5.4, DeepSeek-V4-Pro, and Kimi-K2.5. We aggregate the three rankings with Borda voting to obtain a consensus ranking, and we report inter-judge pairwise agreement as a stability diagnostic. This design reduces sensitivity to any single judge trajectory and lets us separate reward-alignment results from annotation instability. Human review is used for packet validation and calibration: human annotators provide an initial preference prior, inspect packet construction and blinding, and check a 20-group manually ranked subset against the LLM consensus ranking.

Reliability check	Groups	Pairwise agreement
Three-model LLM judge panel	480	0.8408
Human vs. LLM consensus	20	0.71

Table 25: Reliability checks for the blind list-wise ranking audit. The three-model value averages inter-judge pairwise agreement over all method/checkpoint groups. The human-vs-LLM row reports the manually checked 20-group subset.

The main metric is consensus pairwise ranking agreement. A four-response ranking induces six pairwise preferences. We compare the six preferences from the independent consensus ranking with the six preferences induced by reward scores, ignoring reward ties, and average the agreement over groups. We additionally report auxiliary diagnostics in Figure 10. Judge-vs-reward pairwise agreement averages each LLM judge's ranking against the reward ranking before consensus. Top-1 match measures whether the reward-selected best response is also ranked first by the independent judge. Reward-top mean rank measures where the reward-selected best response appears in the independent ranking; lower is better. Inter-judge agreement measures the intrinsic reliability of the list-wise annotation task.

E.4 Case Studies

Writing guard-style penalty repair. This case supports the main-text hack-rate analysis. The post-hoc Hack taxonomy in Appendix D.5 was not exposed to the meta-judge agent. The agent instead inspected on-policy rollout evidence and reward traces, then diagnosed overlapping failure modes in its own terms. In the writing run used in Figure 5(a), the step-20 update promoted a structural guard-style aggregation around a penalty signal. Before the update, the live graph contained a con-

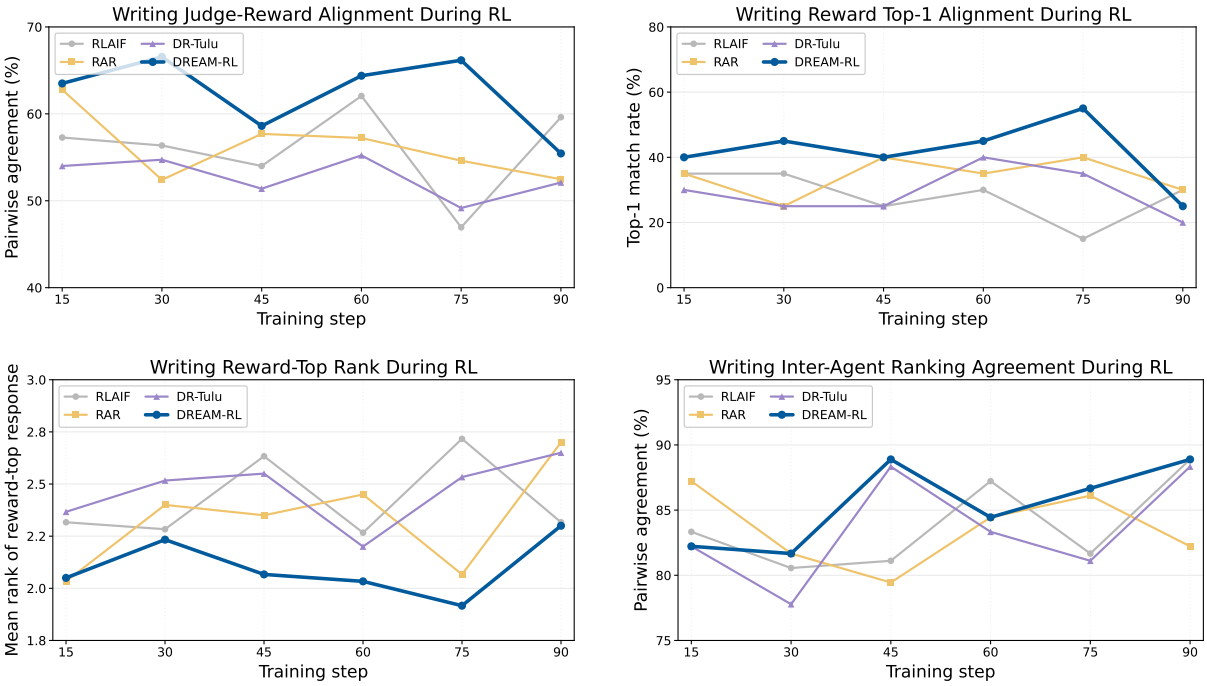

Figure 10: Supplementary diagnostics for the blind reward-ranking audit. These curves complement the main consensus pairwise ranking agreement curve in Figure 5(d).

tinuous Global Rubric Node, a Query-Level Rubric Node, and a terminal weighted-sum Composition Operator:

> `writing_global_judge` → `writing_query_judge` → `final_reward`, where `final_reward` was a weighted sum over the global and query-level scores.

The meta-judge diagnosed concrete reward-hacking evidence: many rollout responses contained word-count tags, placeholders, or template residue, and several artifact-heavy responses still received high rewards. These observations overlap with the evaluation-time families of fabricated authority, self-certification, and one-dimension over-optimization, but were derived from rollout diagnostics rather than from the external auditor labels. Instead of only editing the main rubric again, the agent added a bounded integrity side node after the query judge and marked it as `role=guard` in the final aggregator. The side node covers artifact-free output, specificity/authenticity, and anti-template behavior. The final reward can be viewed as

$$r_{\text{final}} = h_{\text{base}} \cdot h_{\text{guard}},$$

where h_{base} is the weighted positive score from the global and query-level nodes, and $h_{\text{guard}} \leq 1$ can only reduce rewards for detected artifacts.

Later updates refined the same guard-style path rather than introducing the post-hoc Hack labels. A step-90 probe attempted to switch the side-node scoring mode to `flaw_penalty`, but replay revealed an operator-specific failure: empty flaw extraction mapped to an always-pass score, so this probe was treated as diagnostic evidence rather than a successful repair. Subsequent retained edits at steps 95–115 made bounded local updates to the guard-role node and grounding items, targeting mixed-script glitches, placeholders, explicit word-count tags, and dense unsupported numeric/entity specificity. Replay evidence showed activation on targeted bad cases while preserving strong clean examples in sampled checks. This case therefore shows a structure-level guard-style penalty repair and later calibration, not merely a criteria-only dynamic rubric rewrite.

Roleplay coverage repair. This case supports the main-text on-policy coverage analysis. We use a representative roleplay macro update at step 55. Before the edit, the meta-judge diagnosed that the query-side roleplay reward under-covered latest-turn consequence tied to visible scene-state changes. Several high-scoring responses were long and polished, but relied on decorative `<role-think>` padding, transplantable taunts, or unsupported specifics instead of concrete scene movement. A sampled same-query Morgan group was nearly flat, with score range about 0.01,

indicating that the reward did not separate materially different continuations.

The agent updated only `roleplay_query_rubric`. The edit strengthened criteria for latest-turn consequence, substantive content inside required roleplay blocks rather than tag compliance alone, and grounded progression with economy. It also demoted long private planning, decorative inner monologue, catchphrase or persona-name stuffing, and unsupported invented specifics. This is a positive-side coverage/calibration edit rather than a hack-only guard. Replay validation accepted the candidate graph: mean score changed from 0.6313 to 0.6390, within-group standard deviation from 0.0765 to 0.0844, and within-group range from 0.1969 to 0.2177. The case supports the main-text claim that the meta-judge can repair missing on-policy quality dimensions, not only penalize obvious hacking artifacts.