What Makes a Good Rubric Reward? Reinforcement Learning for Coding Agents Beyond Correctness

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Abstract

Unit-test rewards train coding agents for functional correctness, yet provide no signal on patch quality or the agent's workflow. Rubric rewards address this gap by having an external judge inspect and evaluate candidate solutions against explicit criteria. Existing work adopts disparate rubric-construction strategies and evaluates them primarily on targeted in-domain behaviors, leaving it unclear how rubric specification effort affects learned agent behavior. We study this question systematically, comparing universal rubrics written once per quality dimension, rubric-anchored pairwise comparisons against a stronger reference agent, and agent-generated task-specific rubrics across both patch and trajectory rewards. Our proposed approaches preserve pass@1 while substantially improving patch and trajectory quality over unit-test RL alone (e.g., reducing leftover scratch artifacts on SWE-bench Verified from 29.5% to 5.4% and matching the gold patch size). We further show how well each rubric design, specifically targeted at SWE-style tasks, generalizes across in- and out-of-distribution agentic benchmarks: when grading final submissions, we observe that universal rubrics already match the more expensive designs on SWE-bench, while pairwise and task-specific rubrics carry more of the learned behavior to out-of-distribution benchmarks such as TerminalBench; when grading the agent's trajectory, however, universal rubrics prove effective enough to steer agent behavior.

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1. Introduction

Reinforcement learning with verifiable rewards (RLVR) has become a standard way to train software engineering agents (Wei et al., 2025; Pan et al., 2024; Jain et al., 2025). The agent edits a repository, submits a patch and receives a binary reward based on whether the unit tests pass. Because unit tests only check functional outcomes, two patches can receive the same reward even when a maintainer would merge one and reject the other (Wang et al., 2025; Aleithan et al., 2024; Cognition, 2026), and outcome-trained agents can learn to exploit weak test suites (Baker et al., 2025) or degrade their problem-solving workflow. For example, even when tests pass, coding agents frequently produce diffs that are much longer and more verbose than developer fixes (Orlanski et al., 2026a; Luo et al., 2026), leave scratch scripts and debug files in the repository, or skip intermediate verification steps.

A common remedy is to pair the unit-test-based reward with a rubric reward: an LLM judge reads the patch or the trajectory and checks it against a list of criteria (Gunjal et al., 2025; Viswanathan et al., 2025; Huang et al., 2025; Shao et al., 2025). A single criterion can be written once and reused for every task, the judge can compare the agent with a stronger reference agent, or each task can get its own rubric, written by an agent that explores the repository (Gunjal et al., 2026) or derived by contrasting several solutions to the same task (Liu et al., 2025; LLM-Core Xiaomi, 2026). These options differ widely in cost, yet previous works rarely examine how the effort invested in building a rubric pipeline relates to the resulting agent behaviour, or whether rubric-based RL genuinely changes code and trajectory quality rather than merely gaming the LLM judge.

We study these questions systematically for coding agents: *when unit-test resolution is held constant, how much specification effort does a rubric reward need to improve patch and trajectory quality?* Each rubric targets a quality dimension, defined as a specific property of the patch or trajectory that unit tests do not check. We compare three specification levels—universal rubrics written once per dimension, rubric-anchored pairwise comparisons against a stronger reference agent and validated task-specific rubrics—applied either to the submitted patch or to the agent's trajectory

(Section 3.3). We study rubric rewards in the context of RLVR with correctness gating, which pays the rubric reward only when unit tests pass (Section 3.1). To separate genuine behavioural improvements from judge exploitation, our primary evaluation relies on deterministic, model-free heuristics computed directly from patches and agent trajectories across SWE-bench Verified (Jimenez et al., 2024; Chowdhury et al., 2024), SWE-bench Multilingual (Yang et al., 2025) and Terminal-Bench 2.1 (Merrill et al., 2026), complemented by held-out rubric scores and an independent LLM judge (Section 4).

Our main findings and contributions are:

- **Controlled comparison of rubric specification strategies in RLVR:** We evaluate universal rubrics, pairwise reference comparisons and agent-generated task-specific rubrics under an identical RL recipe, gating rubric rewards on unit-test pass and comparing requiring all criteria to hold simultaneously against averaging criterion scores (Sections 2 and 3).
- **A method that improves patch quality without sacrificing pass@1, with out-of-distribution generalization from task-specific rubrics:** Gating on correctness preserves pass@1 while requiring all patch criteria to hold substantially improves patch quality (e.g., cutting scratch artifacts on SWE-bench Verified from 29.5% to 5.4% and matching gold patch size; Figure 2). A universal patch rubric matches task-specific rubrics in distribution on SWE-bench Verified, whereas task-specific rubrics generalize substantially better to SWE-bench Multilingual and Terminal-Bench 2.1 (Sections 5.2 and 5.3) while requiring the least online judge effort during training (Section 5.4).
- **Counteracting workflow degradation from outcome-only RL:** Training solely on test outcomes degrades the agent's workflow compared to SFT (e.g., reducing targeted post-edit testing from 63.3% to 46.5% on SWE-bench Verified; Figure 3). Adding a universal process rubric restores and improves trajectory quality on SWE-bench Verified and Multilingual as effectively as pairwise or task-specific process rewards (Section 5.4).
- **Auditing reward hacking with model-free heuristics and a stronger independent judge:** Comparing training rewards against deterministic heuristics and rescoring trajectories with a larger, stronger judge model not used during training shows that requiring all patch criteria to hold yields genuine behavioral compliance, whereas averaging criteria or grading full trajectories leaves more room for superficial judge exploitation (Section 6).

2. Preliminaries

Agentic software engineering tasks. A task $x \in \mathcal{X}$ consists of an issue description and a repository snapshot in an executable environment. An agent π_θ interacts with the environment over multiple turns via shell commands and file edits, producing a trajectory $\tau = (a_1, o_1, \ldots, a_T, o_T)$ of actions a_t and observations o_t, and submits a final patch $y = y(\tau)$ representing the diff from the initial repository state.

Verifiable reward and RLVR. Each task has hidden unit tests not visible to the policy; the unit-test verifier $c(x, y) \in \{0, 1\}$ equals one when all required tests pass after applying y. In RLVR, the policy maximises expected reward $R(x, \tau)$ via group-relative updates: for each task we sample G trajectories $\{\tau_i\}_{i=1}^{G}$ and compute group-centred advantages $A_i = R(x, \tau_i) - \frac{1}{G}\sum_j R(x, \tau_j)$ without standard-deviation normalisation, dropping groups with zero reward variance. We optimise the CISPO objective (MiniMax, 2025),

$$\mathcal{J}(\theta) = \mathbb{E}\left[\frac{1}{N}\sum_{i=1}^{G}\sum_{t\in\tau_i} \mathrm{sg}\big(\hat{\rho}_{i,t}\big)\, A_i \log \pi_\theta(a_{i,t} \mid h_{i,t})\right], \tag{1}$$

where N is the number of policy tokens in the group, $h_{i,t}$ is the history before token $a_{i,t}$, $\hat{\rho}_{i,t} = \min(\rho_{i,t}, \epsilon)$ is the importance ratio capped at ϵ and sg is stop-gradient; environment observations are masked and no KL penalty is applied.

Rubrics and agentic judging. A rubric dimension $d \in \mathcal{D}$ names a property of a solution that unit tests do not measure. For a task x and dimension d, a rubric is a set of weighted criteria

$$\mathcal{R}_{x,d} = \big\{(r_{x,d,k},\, w_{x,d,k})\big\}_{k=1}^{K_{x,d}}, \tag{2}$$

where each $r_{x,d,k}$ is a natural-language statement that a good solution should satisfy and $w_{x,d,k} > 0$ is its weight. An agentic judge model J, which can inspect the task environment with tools before answering, evaluates the evidence $\phi_d(\tau)$ extracted from the trajectory and scores each criterion $J(r, \phi_d(\tau)) \in \{0, \frac{1}{2}, 1\}$ (not, partially, or fully satisfied). Each dimension is judged in a separate request so scores cannot condition one another, and the dimension score is the weighted mean:

$$s_d(x, \tau) = \frac{\sum_{k=1}^{K_{x,d}} w_{x,d,k}\, J\big(r_{x,d,k}, \phi_d(\tau)\big)}{\sum_{k=1}^{K_{x,d}} w_{x,d,k}} \in [0, 1]. \tag{3}$$

3. Quality Rewards for Coding Agents

3.1. Reward

Combining correctness and quality. All rewards in this work have the form

$$R(x,\tau) = \alpha\, c(x,y) + \beta\, g(x,y)\, Q(x,\tau), \tag{4}$$

where $Q \in [0,1]$ is a quality reward term defined below, $\alpha, \beta \geq 0$ ($\alpha + \beta = 1$) weight the two terms and g controls correctness gating ($\beta = 0$ recovers CORRECTNESS).

Correctness gating. We pay the quality term only when the rollout passes the unit tests ($g(x,y) = c(x,y)$), so failing rollouts receive zero and Q only reorders passing ones. Without gating, the judge becomes the sole source of reward variance on unsolved tasks: in an early ungated pilot ($\alpha = 0, g \equiv 1$), training correctness dropped within 80 steps and episode length halved as the policy learned to produce short trajectories that pleased the judge without solving the task. With gating, all-failing groups carry no signal and are discarded (Section 2), while on reliably solved tasks quality scores differentiate passing rollouts that would otherwise all receive 1 and be dropped under binary RL (Table 9).

Aggregating rubric dimensions. For a subset $\mathcal{S} \subseteq \mathcal{D}$ of target dimensions with weights $\{\lambda_d\}_{d\in\mathcal{S}}$, *average* aggregation takes the weighted mean

$$Q^{\text{avg}}(x,\tau) = \frac{\sum_{d\in\mathcal{S}} \lambda_d\, s_d(x,\tau)}{\sum_{d\in\mathcal{S}} \lambda_d}, \tag{5}$$

whereas *strict* aggregation pays only when every criterion of every selected dimension is fully satisfied,

$$Q^{\wedge}(x,\tau) = \prod_{d\in\mathcal{S}} \mathbf{1}\big[s_d(x,\tau) = 1\big]. \tag{6}$$

A passing rollout that satisfies all hygiene criteria but misses one discipline criterion receives $Q^{\wedge} = 0$ (total reward α), whereas under Q^{avg} it still receives partial credit. Averaging provides a denser signal that a policy can raise by satisfying only the easiest criteria, whereas strict conjunction requires all criteria to hold simultaneously.

Pairwise quality. Instead of scoring a trajectory in isolation, the judge can compare it side by side with a reference trajectory τ_x^{ref} from a stronger reference agent on the same task and score the policy against the reference on a named dimension d, yielding $p_d(x,\tau;\tau_x^{\text{ref}}) \in \{0, \frac{1}{2}, 1\}$ for a loss, tie and win. For rubric-anchored comparison over dimensions $\mathcal{S}$, the quality term is the weighted mean of the anchored scores,

$$Q^{\text{pair}}(x,\tau) = \frac{\sum_{d\in\mathcal{S}} \lambda_d\, p_d(x,\tau;\tau_x^{\text{ref}})}{\sum_{d\in\mathcal{S}} \lambda_d}. \tag{7}$$

The reference τ_x^{ref} is fixed per task by selecting the shortest passing trajectory of the reference agent on x, which keeps judge context short and favours direct solutions. The policy and reference are presented anonymously in random order, without telling the judge which candidate is the reference, and compared with read-only access to the repository environment.

For patch dimensions the judge compares the submitted patches with repository access; for process dimensions both patches are withheld, as in absolute process judging, so that the comparison concerns how each agent worked rather than what it submitted.

3.2. Rubric families and dimensions

Dimensions. We distinguish two rubric families by the evidence $\phi_d(\tau)$ the judge inspects. *Patch* rubrics are judged on the submitted patch together with access to the repository, $\phi_d(\tau) = y(\tau)$. *Process* rubrics are judged on the trajectory with the final patch withheld, $\phi_d(\tau) = \tau_{\setminus y}$, so that they reflect how the agent reached the solution rather than what it submitted. To instantiate these two families in our experiments, we select four dimensions that are largely orthogonal to unit-test pass and far from saturation on baseline rollouts (see Appendices A and G for all nine dimensions we considered and their baseline correlations and ceiling rates in Table 13). Two are *patch* dimensions that tests rarely check: whether the patch is free of process residue such as scratch scripts, backups and debug code (Artifact Hygiene, *Hyg*) and whether it respects explicit non-functional constraints in the instructions, such as not editing tests (Discipline, *Disc*). Two are *process* dimensions that describe how the agent worked: whether it verified the solution beyond the provided tests (Self Verification, *Verif*) and whether it kept its changes to what the task needed (Patch Scope, *PScope*). Rewarding process dimensions directly addresses a key failure mode of standard outcome-only RL (CORRECTNESS): even when the prompt explicitly asks the agent to reproduce the bug, rerun checks after editing and test edge cases, rewarding only the final test outcome teaches the policy to skip these verification steps whenever the test suite happens to pass (Section 5.4).

Universal rubrics. A rubric is *universal* when $\mathcal{R}_{x,d} = \mathcal{R}_d$ for every task and *task-specific* otherwise.

A universal rubric is written once by hand for a dimension and applied to every task. Our universal rubrics each consist of a single criterion that states the property in general terms (Appendix A). They require only a one-time authoring cost per dimension (typically a few minutes of human effort)

Table 1. **Specification levels.** Ordered by the upfront resources required to create the quality reward specification before RL training. "Per-task" refers to offline work repeated for every training task.

ℓ	Design	Written criteria	Per-task rubric	Reference agent	Criteria per dim.
0	CORRECTNESS	–	–	–	–
1	UNIVERSAL rubric	✓	–	–	1
2	PAIRWISE-RUBRIC	✓	–	✓	1
3	TASK-SPECIFIC rubric	✓	✓	–	1–5

Table 2. **Experiment grid and run names.** Rows are specification levels and columns are the graded families. Runs use average aggregation unless marked '(strict)' (conjunctive aggregation $Q^{\wedge}$).

ℓ	Design	Patch (*Hyg* + *Disc*)	Process (*Verif* + *PScope*)
0	CORRECTNESS	CORRECTNESS (shared baseline)	
1	UNIVERSAL	PATCH-UNI	PROC-UNI
2	PAIRWISE-RUBRIC	PATCH-PAIR	PROC-PAIR
3	TASK-SPECIFIC	PATCH-TASK (strict) PATCH-TASK	PROC-TASK

but leave the judge to decide what the property means for a particular repository.

Task-specific rubrics and validation. Task-specific rubrics are produced by a generator agent in the live task environment that receives the task and dimension descriptions and inspects the repository with tools to output major and minor criteria.

Generation follows one guiding rule: every criterion must hold for every correct solution, independently of the implementation strategy. Each generated criterion is checked by two independent validation passes before use by validator agents that see only the criterion text and weight. First, a validator inspects a scrubbed copy of the environment (without the rubric or reference solution) and checks whether the criterion is sound and solution-agnostic. Second, a validator is shown a known-correct reference patch and checks that it satisfies the criterion, catching criteria narrower than correctness. Criteria that fail either validation pass or do not apply to the task are excluded, removing 9–28% of generated criteria depending on the dimension (Table 6).

3.3. Specification Levels and Experiment Grid

We order the quality reward designs of Section 3.1 into three specification levels above the correctness-only baseline ($\ell = 0$, CORRECTNESS), ordered by the upfront effort and offline resources required to create the reward specification before RL training (Table 1): Level 1 (UNIVERSAL) uses a single hand-written criterion per dimension across all tasks; Level 2 (PAIRWISE-RUBRIC) pairs that universal criterion with per-task reference trajectories generated offline by a stronger agent; and Level 3 (TASK-SPECIFIC) runs an agentic generation and validation pipeline offline to create a dedicated set of criteria (1–5 per dimension) for each task. Because task-specific rubrics contain multiple criteria per dimension while universal rubrics have one, strict aggregation ($Q^{\wedge}$) at $\ell = 3$ requires more criteria to hold simultaneously than at $\ell = 1$.

We evaluate these levels along two columns (Table 2): *patch* rewards, which grade *Hyg* and *Disc* on the final diff, and *process* rewards, which grade *Verif* and *PScope* on the trajectory. Each run is given a short name that combines the graded family, specification level and (when strict) aggregation: PATCH-UNI, PATCH-PAIR, PATCH-TASK (strict) and PATCH-TASK for patch rewards (where PATCH-TASK uses average aggregation to match PATCH-PAIR) and PROC-UNI, PROC-PAIR and PROC-TASK for process rewards (all using average aggregation; see Appendix D).

4. Experimental Setup

Policy and scaffold. All runs start from the same supervised fine-tuning checkpoint (SFT) of North Mini Code (Cohere and Cohere Labs, 2026),[1] a mixture-of-experts language model with 30B parameters, 3B of them active per token, fine-tuned on agentic coding trajectories. The agent interacts with a containerised copy of the repository through a shell tool and a file editor in the SWE-agent harness (Yang et al., 2024), with at most 300 turns, a context of 128k tokens and a wall-clock limit of two hours per episode. The episode ends when the agent submits or a limit is reached and the patch is read from the final state of the repository.

Training data. We train on 436 repository-level tasks from Scale-SWE (Zhao et al., 2026), a dataset of verified software engineering tasks derived from GitHub pull requests. Starting from 1,000 tasks, we estimate task difficulty for the starting SFT checkpoint using multiple rollouts and retain tasks that the model can solve on some rollouts but not all, so that sampled rollout groups exhibit non-zero reward variance. For each task we generate and validate task-specific rubrics (Section 3.2)—yielding on average 3.0 criteria (1–5) for hygiene and 1.8 (1–5) for discipline—and keep the 436 tasks whose container images are available (Appendix C). Every task also has a reference trajectory from GLM-5.2 (GLM-5-Team, 2026), so the same task set supports both absolute and pairwise rewards.

Training. Each training step uses a batch size of 64 tasks with $G = 16$ trajectories per task, so in total 1,024 trajectories are sampled per step. We use a constant learning rate of 5×10^{-6} after 25 warm-up steps, an importance-ratio cap of $\epsilon = 4$ and a sampling temperature of 1.0. Across all rubric

[1] CohereLabs/North-Mini-Code-1.0

runs, the quality weight is $\beta = 0.4$ with $\alpha = 0.6$ (split equally across the two target dimensions in each column) and the quality term is gated on test pass. Every run trains for 100 steps (Appendix C).

Judge and reference agent. The training judge is DeepSeek-V4-Flash (DeepSeek-AI, 2026) at temperature zero, with tool access to the task environment for up to 30 turns per request and one dimension per request. Its rubric scores agree closely with those of the much larger Kimi K3 (Kimi Team, 2026) before and after training (Section 6); we use the faster model for training. The reference agent for the pairwise setup is GLM-5.2 (GLM-5-Team, 2026), at the time of writing the largest open-weight coding model available, which resolves 90% of SWE-bench Verified in our scaffold. For additional context, we also evaluate Qwen3.6-35B-A3B (Qwen Team, 2026) and Laguna XS.2 (Poolside Team, 2026), two open mixture-of-experts models with 3B active parameters (35B and 33B in total), on the same benchmarks.

4.1. Evaluation setup.

We evaluate on three benchmarks, running each policy twice per task. SWE-bench Verified (Jimenez et al., 2024; Chowdhury et al., 2024) (473 tasks with validated task-specific patch rubrics) and SWE-bench Multilingual (Yang et al., 2025) (300 tasks in nine other programming languages) are repository issue-resolution benchmarks like the training set, from different repositories. Terminal-Bench 2.1 (Merrill et al., 2026) (89 tasks) asks the agent to complete terminal tasks rather than patch a repository and tests whether the learned behaviours carry over out-of-distribution.

Because the reward comes from a judge during training, a judge-based evaluation alone cannot tell better behaviour from behaviour the judge prefers. We therefore rely primarily on heuristics computed without any model and use rubric scores as a secondary check.

Judge-free patch and process heuristics (primary). We compute deterministic heuristics from the submitted patch and the recorded trajectory, without any model in the loop (definitions and full tables in Appendix H). *Patch heuristics*, computed on SWE-bench Verified and Multilingual, measure *residue* (scratch or generated artifacts, backup files, modified test files), *footprint* (median added lines compared to the gold patch, single-file patches) and *localisation* (whether the modified source files match the reference fix). *Process heuristics* parse test commands, their outputs and the following agent's reasoning (Figure 3). We verify whether the agent's checks the changed code after its edit, whether the same check fails before the fix and passes after it, whether any working check actually executes the edited code, whether it stops at a syntax check or claims success without running its edit and whether it runs the repository tests that cover the change. Since Terminal-Bench 2.1 has no repository fix, we read the same kinds of behaviour from the agent trajectories (Figure 4 and Appendix I): scratch files left behind, files written, package installs, force-killed processes, destructive commands and how the agent describes its checks and outcome.

Held-out rubric scores (secondary). We also score the SWE-bench Verified trajectories with the training judge, using task-specific rubrics for the patch dimensions (*Hyg*, *Disc*, *Scope*) and universal rubrics for the process dimensions (*Verif*, *PScope*), so every run is graded on the same scale (Table 3. We additionally explore four further dimensions and coverage notes in Appendix G). This checks whether a run trained on a cheaper specification level also improves under the task-specific rubrics and whether patch scope improves when only process patch scope was rewarded.

Independent judge and significance check. To check that the policies did not simply learn the preferences of the training judge, we rescore the SWE-bench Verified trajectories of three representative checkpoints—SFT and the two task-specific runs (PATCH-TASK (strict) and PROC-TASK)—with Kimi K3 (Kimi Team, 2026), a much larger model from a different family, using the same rubrics and prompts.

We additionally run a second training seed of every run and show that differences impact less than our span of specification levels (Appendix E).

4.2. Checkpoint Selection

Runs learn the quality term at different speeds, so comparing at a single step would favour whichever run peaks there. To avoid this selection bias, we pick one checkpoint per run among steps 60, 80 and 100 by maximizing the *selection score*, defined as the mean of pass@1 and the rubric scores on the dimensions the run trained on (Figure 1). For this step, we use an held-out Scale-SWE subset with 350 tasks.

5. Results

We evaluate the selected checkpoints across SWE-bench Verified, SWE-bench Multilingual and Terminal-Bench 2.1. Figures 2 and 3 report pass@1 and our primary judge-free patch and process heuristics on the two repository benchmarks, while Figure 4 reports agent trajectory heuristics on Terminal-Bench 2.1. To complement these model-free measurements, Table 3 provides held-out rubric scores on SWE-bench Verified across both trained and untrained dimensions.

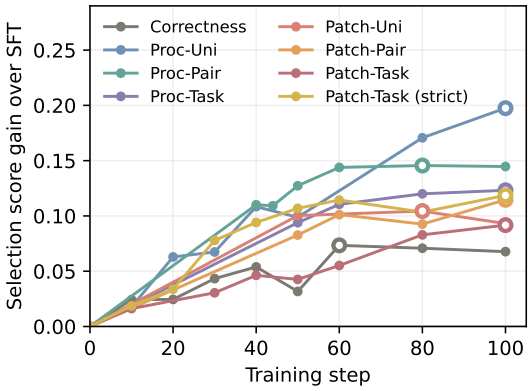


Figure 1. **Checkpoint selection.** Gain in selection score (mean of pass@1 and the rubric scores on the run's trained dimensions) over the starting SFT checkpoint on an held out set. Circles mark the selected checkpoints.

5.1. Correctness Gating Preserves Task Resolution

Figure 2 (first column, gray bars) compares task resolution before and after RL. Standard outcome-only RL (CORRECTNESS) raises pass@1 over SFT from 54.4% to 61.8% on SWE-bench Verified and from 38.4% to 47.5% on Multilingual. With correctness gating ($g = c$), adding a rubric reward preserves these gains across all specification levels: comparing the PATCH- bars and PROC-ess bars against CORRECTNESS in Figure 2, pass@1 stays within confidence intervals on nearly every run. Out-of-distribution, on Terminal-Bench 2.1 (Figure 4), rubric-trained policies resolve between 22.4% and 29.4% of tasks compared to 28.7% for CORRECTNESS, a difference that stays within evaluation variance (as estimated across 16 rollouts of a comparable checkpoint).

5.2. In-Distribution Patch Quality: Universal rubrics match higher effort designs

On SWE-bench Verified (Figure 2), universal (PATCH-UNI, $\ell = 1$), pairwise (PATCH-PAIR, $\ell = 2$) and strict task-specific (PATCH-TASK (strict), $\ell = 3$) patch rubrics improve submitted patches to nearly the same extent: scratch artifacts drop from 29.5% of patches in CORRECTNESS to 5.4–9.1%, modified test files drop from 35.0% to 5.4–9.8%, backup files virtually disappear and the median added lines relative to the gold patch shrink from $+8$ in CORRECTNESS (and $+155$ in SFT) to $+0$, with 78.8–81.9% of patches staying within a single file. Reweighting PATCH-TASK (strict) trajectories to match the patch-size distribution of CORRECTNESS (Table 15 in Appendix G) confirms that the hygiene rubric score gain is largely explained by this shift toward compact, focused diffs, whereas the discipline gain persists even at matched patch size. These improvements occur even though the benchmark prompt already asks the agent to keep changes minimal and leave tests untouched—instructions that SFT and CORRECTNESS routinely ignore because unit tests never penalize leftover reproduction scripts or broad diffs.

When evaluated by held-out task-specific rubric scores (Table 3), PATCH-UNI scores nearly as high as PATCH-TASK (strict) (0.93 vs. 0.94 on *Hyg*, 0.97 vs. 0.98 on *Disc*) and both also improve on held-out patch scope (*Scope*: 0.88 and 0.90 vs. 0.82 for CORRECTNESS). In contrast, averaging the same task-specific criteria (PATCH-TASK, $\ell = 3$) is much less effective than conjunctive aggregation (PATCH-TASK (strict)), leaving scratch artifacts in 20.6% of patches and modified tests in 27.5%. Under averaging, satisfying the easiest criteria already yields most of the quality reward $Q(x, \tau)$ (Equation (4)) so rewards on passing training rollouts start high and saturate early, increasing from 0.82 to 0.92 (Table 4). Strict aggregation instead withholds the full score until all criteria hold simultaneously, with rewards rising from 0.40 to 0.77 and sustaining a sharper learning signal throughout training.

5.3. Out-of-Distribution Generalization: Task-specific patch rubrics transfer better

While a universal patch rubric suffices in distribution, higher-effort rubrics transfer further when the language or environment shifts. On SWE-bench Multilingual (Figure 2), PATCH-PAIR ($\ell = 2$) and PATCH-TASK (strict) ($\ell = 3$) leave scratch artifacts in about half as many patches as PATCH-UNI ($\ell = 1$), reduce modified test files to 23.0% and 20.7% (vs. 32.9% for PATCH-UNI) and reduce median added lines over the gold patch from $+36$ in CORRECTNESS and $+25$ in PATCH-UNI to $+7$ and $+5$. On Terminal-Bench 2.1 (Figure 4), where agents solve terminal-based tasks rather than patching a repository, PATCH-TASK (strict) significantly reduces leftover scratch files (8.0% vs. 14.9%), total files written (2.5 vs. 3.5), package installs and force-killed processes (7.5% vs. 13.2%), whereas PATCH-UNI and PATCH-PAIR show little transfer beyond fewer force-killed processes.

5.4. Process Rubrics and Effort Trade-Offs

As noted in Section 3.2, training on an outcome-only reward erodes the agent's verification workflow compared to the starting checkpoint. For example, on SWE-Bench Verified (Figure 3) post-edit checks that call the changed code fall from 63.3% to 46.5% or claims of success without the agent verifying its changes rise from 1.4% to 5.1%. Process rubrics are able to reverse this degradation and surpass SFT: targeted post-edit checks raise to 69.8% (PROC-UNI) and 69.6% (PROC-PAIR) on Verified and from 24.3% to 46.0% and 45.9% on Multilingual. However, in all specification levels, the higher effort does not further improve process verification: PROC-UNI ($\ell = 1$) matches PROC-

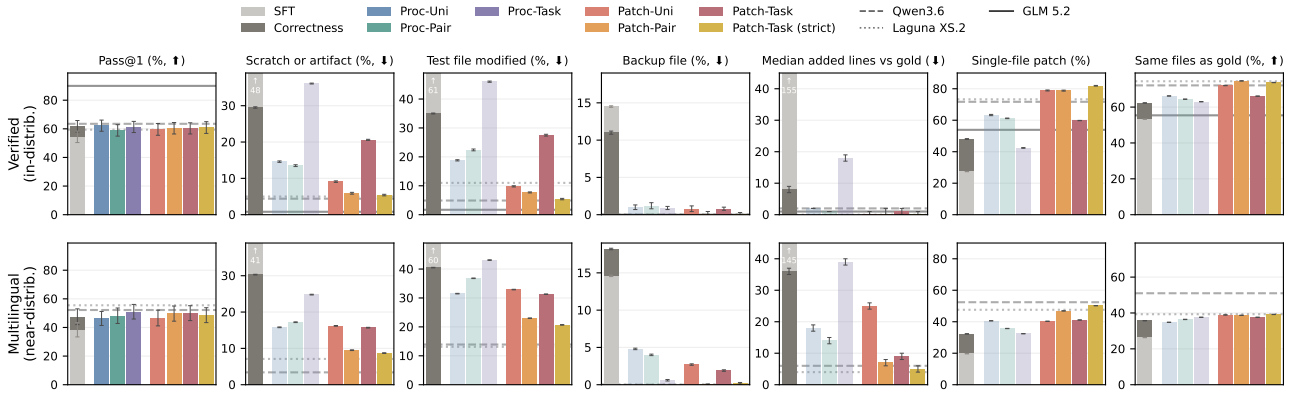


Figure 2. **Correctness and judge-free patch heuristics** on SWE-bench Verified and Multilingual. All metrics include ± 95% confidence intervals, arrows indicate whether higher or lower values are preferred. All heuristics in Appendix H.

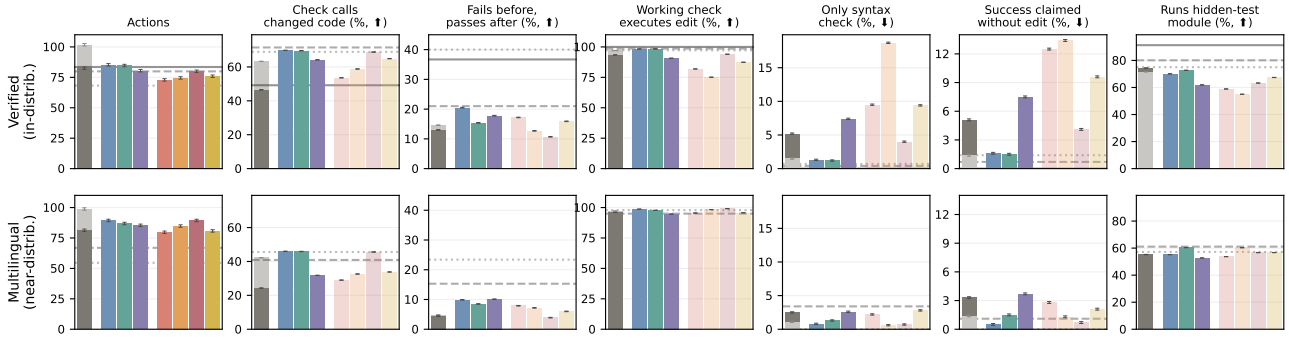


Figure 3. **Judge-free process heuristics** on SWE-bench Verified and Multilingual. Layout as in Figure 2; definitions in Appendix H.

Table 3. **Held-out rubric scores on SWE-bench Verified** (secondary). Shaded cells are dimensions in the run's reward. *Hyg*, *Disc* and *Scope* use task-specific patch rubrics, *Verif* and *PScope* universal process rubrics. * indicates a statistically non-significant difference to CORRECTNESS; further dimensions in Table 14.

Graded	ℓ	Run	*Hyg*	*Disc*	*Scope*	*Verif*	*PScope*
	–	SFT	0.79	0.84	0.59	0.50	0.56
	0	CORRECTNESS	0.82	0.90	0.82	0.51	0.73
Patch	1	PATCH-UNI	0.93	0.97	0.88	0.43	0.87
	2	PATCH-PAIR	**0.94**	0.97	**0.90**	0.52*	0.89
	3	PATCH-TASK (strict)	**0.94**	**0.98**	**0.90**	0.58	**0.90**
	3	PATCH-TASK	0.89	0.96	0.85*	0.59	0.84
Process	1	PROC-UNI	0.91	0.94	0.83*	**0.78**	0.80
	2	PROC-PAIR	0.88	0.91*	0.82*	0.66	0.79
	3	PROC-TASK	0.78	0.88*	0.84*	0.62	0.74*
	–	Qwen3.6-35B-A3B	0.95	0.96	0.69	0.74	0.74
	–	Laguna XS.2	0.93	0.95	0.53	0.70	0.70
	–	GLM-5.2 (ref.)	0.95	0.97	0.63	0.85	0.84

PAIR ($\ell = 2$) and outperforms PROC-TASK ($\ell = 3$) in both process heuristics (Figure 3) and held-out rubric scores (Table 3, 0.78 vs. 0.66 and 0.62 in *Verif*). These findings suggest that good verification habits—reproducing the failure before editing and running a targeted check afterward—are largely task-agnostic, so a single universal criterion captures them without the overhead of reference trajectories or per-task rubric generation, which only helps reduce package installs and force-killed processes on Terminal-Bench 2.1 (Figure 4).

Finally, comparing offline rubric generation compute and online RL training compute across the grid (Appendices B and F, Table 12), PATCH-TASK (strict) requires more offline compute before training (one generation and two validation calls per dimension, averaging 6.2 agent calls per task including format retries), but reduces online judge cost during RL: concrete per-task criteria let the judge verify a patch in fewer turns (10 vs. 13), adding only 30–40% to the step time of CORRECTNESS, compared to 2.0× for PATCH-UNI and 3.3× for PATCH-PAIR. Process rubrics add 2.0–2.5× per RL step because the judge must inspect the full trajectory. Behaviorally, strict patch rubrics make the agent more cautious about leaving traces in the repository, so it runs fewer ad-hoc test scripts during the episode (Figure 3) and shows slightly higher run-to-run outcome consistency across rollouts (Table 16 in Appendix H), without affecting pass@1.

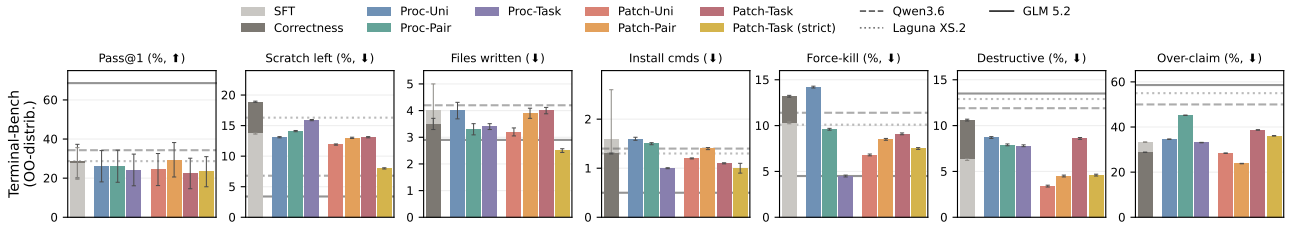


Figure 4. **Terminal-Bench 2.1** (out-of-distribution). Pass@1 (± 95% confidence interval) and judge-free heuristics from the agent trajectories: rollouts leaving a scratch file (%), files written and install commands per rollout, rollouts force-killing processes or running destructive commands (%) and unsolved rollouts claiming success (%). Marks as in Figure 2.

Table 4. **Training reward vs. evaluation evidence.** Mean quality reward $Q(x, \tau)$ (Equation (4)) on test-passing training rollouts in steps 1–10 (Start) and in the 10 steps before the selected checkpoint (Selected); held-out rubric score gain over CORRECTNESS on SWE-bench Verified on the trained dimensions; and a headline judge-free heuristic on Verified: scratch artifacts for patch runs (%, ↓; CORRECTNESS is 29.5%) and checks calling changed code for process runs (%, ↑; CORRECTNESS is 46.5%).

			Training quality reward Q			Held-out rubric	Judge-free
Graded	ℓ	Run	Start	Selected	Rise	score diff.	heuristic
Patch	1	PATCH-UNI	0.52	0.77	+0.25	+0.086*	9.1*
	2	PATCH-PAIR	0.75	0.87	+0.12	+0.099*	5.9*
	3	PATCH-TASK (strict)	0.40	0.77	+0.37	+0.101*	5.4*
	3	PATCH-TASK	0.82	0.92	+0.10	+0.063*	20.6*
Process	1	PROC-UNI	0.75	0.88	+0.13	+0.165*	69.8*
	2	PROC-PAIR	0.72	0.81	+0.09	+0.105*	69.6*
	3	PROC-TASK	0.82	0.87	+0.05	+0.056*	64.2*

6. Judge Exploitation and Independent Validation

When a LLM judge provides the training reward, the policy can raise its score either by genuinely improving its patches and workflow or by exploiting blind spots of the judge.

We start auditing our runs for judge exploitation by comparing training and held-out rubric scores against model-free heuristics. In Table 4, quality reward gains for the strict and pairwise patch runs (PATCH-UNI, PATCH-PAIR, PATCH-TASK (strict)) track large drops in leftover scratch artifacts (29.5% down to 5.4–9.1%). Under average aggregation (PATCH-TASK), however, the policy reaches a 0.92 training quality reward and $+0.063$ held-out rubric gain while still leaving artifacts in 20.6% of patches by collecting partial credit on easy criteria. On the process side, while PROC-UNI and PROC-PAIR genuinely run more targeted checks (69.8% and 69.6%), all process runs also narrate verification much more heavily in their thoughts (+0.52 to +1.76 SD in verification mentions per 1k characters; Table 20) and claim success more often on unresolved Terminal-Bench 2.1 tasks (up to 45.2% vs. 28.8% for CORRECTNESS in Figure 4), persuading the trajectory judge even when checks are incomplete.

We also test whether policies overfit to quirks of the training judge (DeepSeek-V4-Flash). We rescore the SWE-bench Verified trajectories of SFT, PATCH-TASK (strict) and PROC-TASK with Kimi K3 (Kimi Team, 2026), a much larger model from a different family, and report the Spearman correlation of rubric scores between the two judges:

	Patch		Process	
Checkpoint	*Hyg*	*Disc*	*Verif*	*PScope*
SFT	0.89	0.94	0.78	0.86
PATCH-TASK (strict)	0.95	0.92	0.81	0.92
PROC-TASK	0.88	0.97	0.78	0.91

Overfitting to DeepSeek-V4-Flash would lower inter-judge agreement on the trained dimensions after RL (shaded cells); instead, correlations remain high or increase (e.g. from 0.89 to 0.95 on *Hyg* for PATCH-TASK (strict), or from 0.86 to 0.91 on *PScope* for PROC-TASK), confirming that gated, strictly aggregated rubrics drive genuine behavioral improvements.

7. Related Work

Reinforcement learning for software engineering agents. Execution-based benchmarks and environments (Jimenez et al., 2024; Chowdhury et al., 2024; Pan et al., 2024; Jain et al., 2025; Yang et al., 2025) enable RLVR (Lambert et al., 2024; Shao et al., 2024; Wei et al., 2025) using binary unit-test outcomes. However, test-passing patches can still be unmergeable (Wang et al., 2025; Aleithan et al., 2024; Cognition, 2026), overly verbose (Orlanski et al., 2026a;b; Luo et al., 2026) or exploit weak tests (Baker et al., 2025). We retain unit-test pass as a hard gate and study how to shape patch and trajectory quality on top of it without sacrificing task resolution.

Rubric rewards and agentic verifiers. In domains without executable verifiers, rubrics and checklists replace a missing reward signal, using static, evolving or contrastive criteria (Gunjal et al., 2025; Viswanathan et al., 2025; Huang et al., 2025; Shao et al., 2025; Liu et al., 2025; He et al., 2025; Xu et al., 2026). In software engineering, recent works bring rubrics into interactive repository environments where an agentic judge can inspect files and execution traces: Agentic Rubrics (Gunjal et al., 2026) uses a repository-exploring agent to generate task-specific rubrics for test-free

patch ranking, SWE Atlas (Scale AI, 2026) pairs expert-written rubrics with unit tests to grade refactoring patches, and MiMo-V2.6 (LLM-Core Xiaomi, 2026) builds task-specific rubrics from offline rollouts for RL. Each of these studies adopts a single rubric construction strategy, leaving it unclear when expensive per-task agentic generation is necessary for RL versus when simple universal rubrics suffice, and whether rubric gains reflect genuine behavioral change rather than judge exploitation. Our work addresses this gap with a controlled comparison across specification levels, aggregation rules and rubric families (patch vs. process) under one RLVR setup, evaluated primarily with model-free heuristics.

Reference-based preference rewards and reward hacking. Whereas standalone rubrics grade a single solution against explicit criteria, preference-based RL compares candidate outputs side by side (Christiano et al., 2017; Ouyang et al., 2022; Bai et al., 2022; Zheng et al., 2023); we study rubric-anchored pairwise comparison against a strong reference agent as an intermediate specification level that grounds general criteria in a concrete reference solution without generating per-task checklists. Because optimizing any model-judged proxy risks reward overoptimization (Amodei et al., 2016; Skalse et al., 2022; Gao et al., 2023), including when supervising intermediate process steps (Lightman et al., 2023), we combine correctness gating with deterministic heuristics and cross-judge validation to detect superficial compliance.

8. Conclusion

We presented a systematic study of rubric rewards for coding agents in RLVR, comparing universal rubrics, rubric-anchored pairwise comparisons and validated task-specific rubrics under correctness gating to keep task resolution at the level of a correctness-only baseline (CORRECTNESS). Our results show that the right specification level depends on whether the rubric grades the final patch or the agent's workflow. When grading the patch, a universal rubric (PATCH-UNI, $\ell = 1$) already matches higher-effort designs in distribution when combined with strict conjunctive aggregation; the extra upfront effort of pairwise (PATCH-PAIR, $\ell = 2$) and task-specific (PATCH-TASK (strict), $\ell = 3$) rubrics pays off in stronger transfer to SWE-bench Multilingual, and task-specific rubrics are the only design that generalizes to Terminal-Bench 2.1 while also requiring the least online judge effort per RL step. When grading the agent's trajectory, where standard outcome-only RL degrades problem-solving workflow, a universal process rubric (PROC-UNI, $\ell = 1$) offers the best trade-off: it restores and improves workflow quality across SWE-bench Verified and Multilingual as well as or better than pairwise (PROC-PAIR, $\ell = 2$) and task-specific (PROC-TASK, $\ell = 3$) process rubrics, without their extra cost.

Limitations. The evaluation covers repository tasks in Python and nine other languages and one terminal benchmark. The same judge model produces the training reward and the held-out rubric scores; the independent judge agrees with it before and after training, but was run on three checkpoints only. Our judge-free heuristics rely on file paths and command outputs and can miss residue that is not recognisable from names alone. Finally, the specification levels are ordered by the resources they require and the true cost of each level depends on how rubrics are written and validated in practice.

Impact Statement

This work aims to make coding agents produce changes that are easier to review and maintain, which could reduce the burden that automatically generated patches place on developers. The same techniques could be used to make agents better at satisfying automated reviewers without improving the underlying code; our emphasis on judge-free heuristics is meant in part to detect this. We do not foresee other societal consequences that must be specifically highlighted here.

References

Aleithan, R., Xue, H., Mohajer, M. M., Nnorom, E., Uddin, G., and Wang, S. SWE-Bench+: Enhanced coding benchmark for LLMs. *arXiv preprint arXiv:2410.06992*, 2024.

Amodei, D., Olah, C., Steinhardt, J., Christiano, P., Schulman, J., and Mané, D. Concrete problems in AI safety. *arXiv preprint arXiv:1606.06565*, 2016.

Bai, Y., Kadavath, S., Kundu, S., Askell, A., Kernion, J., Jones, A., Chen, A., Goldie, A., Mirhoseini, A., McKinnon, C., et al. Constitutional AI: Harmlessness from AI feedback. *arXiv preprint arXiv:2212.08073*, 2022.

Baker, B., Huizinga, J., Gao, L., Dou, Z., Guan, M. Y., Madry, A., Zaremba, W., Pachocki, J., and Farhi, D. Monitoring reasoning models for misbehavior and the risks of promoting obfuscation. *arXiv preprint arXiv:2503.11926*, 2025.

Chowdhury, N., Aung, J., Shern, C. J., Jaffe, O., Sherburn, D., Starace, G., Mays, E., Dias, R., Aljubeh, M., Glaese, M., Jimenez, C. E., Yang, J., Liu, K., and Madry, A. Introducing SWE-bench verified. OpenAI blog, https://openai.com/index/introducing-swe-bench-verified/, 2024.

Christiano, P. F., Leike, J., Brown, T., Martic, M., Legg, S., and Amodei, D. Deep reinforcement learning from human preferences. In *Advances in Neural Information Processing Systems*, 2017.

Cognition. FrontierCode: Evaluating code mergeability beyond unit tests. https://cognition.com/blog/frontier-code, 2026.

Cohere and Cohere Labs. North Mini Code. Model release, 2026. URL https://docs.cohere.com/docs/north-mini-code-1.0.

DeepSeek-AI. DeepSeek-V4.1-Flash: Pushing the limits of KV cache compression, 2026.

Gao, L., Schulman, J., and Hilton, J. Scaling laws for reward model overoptimization. In *International Conference on Machine Learning*, 2023.

GLM-5-Team. GLM-5: from vibe coding to agentic engineering, 2026. URL https://arxiv.org/abs/2602.15763.

Gunjal, A., Wang, A., Lau, E., Nath, V., Liu, B., and Hendryx, S. Rubrics as rewards: Reinforcement learning beyond verifiable domains. *arXiv preprint arXiv:2507.17746*, 2025.

Gunjal, A., Liu, B., and He, Y. Agentic rubrics as contextual verifiers for SWE agents. *arXiv preprint arXiv:2601.04171*, 2026.

He, Y., Li, W., Zhang, H., Li, S., Mandyam, K., Khosla, S., Xiong, Y., Wang, N., Peng, X., Li, B., Bi, S., Patil, S. G., Qi, Q., Feng, S., Katz-Samuels, J., Pang, R. Y., Gonugondla, S., Lang, H., Yu, Y., Qian, Y., Fazel-Zarandi, M., Yu, L., Benhalloum, A., Awadalla, H., and Faruqui, M. AdvancedIF: Rubric-based benchmarking and reinforcement learning for advancing LLM instruction following. *arXiv preprint arXiv:2511.10507*, 2025.

Huang, Z. et al. Reinforcement learning with rubric anchors. *arXiv preprint arXiv:2508.12790*, 2025.

Jain, N., Singh, J., Shetty, M., Zheng, L., Sen, K., and Stoica, I. R2E-Gym: Procedural environments and hybrid verifiers for scaling open-weights SWE agents. *arXiv preprint arXiv:2504.07164*, 2025.

Jimenez, C. E., Yang, J., Wettig, A., Yao, S., Pei, K., Press, O., and Narasimhan, K. SWE-bench: Can language models resolve real-world GitHub issues? In *International Conference on Learning Representations*, 2024.

Kimi Team. Kimi K3. https://huggingface.co/moonshotai/Kimi-K3, 2026.

Lambert, N., Morrison, J., Pyatkin, V., Huang, S., Ivison, H., Brahman, F., Miranda, L. J. V., Liu, A., Dziri, N., Lyu, S., et al. Tülu 3: Pushing frontiers in open language model post-training. *arXiv preprint arXiv:2411.15124*, 2024.

Lightman, H., Kosaraju, V., Burda, Y., Edwards, H., Baker, B., Lee, T., Leike, J., Schulman, J., Sutskever, I., and Cobbe, K. Let's verify step by step. *arXiv preprint arXiv:2305.20050*, 2023.

Liu, T., Xu, R., Yu, T., Hong, I., Yang, C., Zhao, T., and Wang, H. OpenRubrics: Towards scalable synthetic rubric generation for reward modeling and LLM alignment. *arXiv preprint arXiv:2510.07743*, 2025.

LLM-Core Xiaomi. MiMo-V2.6: Scaling reinforcement learning towards self-improvement. Technical report, 2026. URL https://huggingface.co/XiaomiMiMo/MiMo-V2.6-Flash-RL.

Luo, W., Keung, J., Shi, X., Sun, Y., Yang, B., Yang, Z., and Tian, H. Refine after generation: Toward correct and concise patches in LLM-based program repair. *arXiv preprint arXiv:2608.13292*, 2026.

Merrill, M. A., Shaw, A. G., Carlini, N., Li, B., Raj, H., et al. Terminal-Bench: Benchmarking agents on hard, realistic tasks in command line interfaces. In *International Conference on Learning Representations*, 2026. URL https://arxiv.org/abs/2601.11868.

MiniMax. MiniMax-M1: Scaling test-time compute efficiently with lightning attention. *arXiv preprint arXiv:2506.13585*, 2025.

Orlanski, G., Roy, D., Yun, A., Shin, C., Gu, A., Ge, A., Adila, D., Roberts, N., Sala, F., and Albarghouthi, A. SlopCodeBench: Benchmarking how coding agents degrade over long-horizon iterative tasks, 2026a. URL https://arxiv.org/abs/2603.24755.

Orlanski, G., Zhang, A. L., Trost, A., Chen, V. S., Sala, F., Albarghouthi, A., and Schmidt, L. Can agents design libraries for agents?, 2026b. URL https://arxiv.org/abs/2609.36730.

Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C., Mishkin, P., Zhang, C., Agarwal, S., Slama, K., Ray, A., et al. Training language models to follow instructions with human feedback. In *Advances in Neural Information Processing Systems*, 2022.

Pan, J., Wang, X., Neubig, G., Jaitly, N., Ji, H., Suhr, A., and Zhang, Y. Training software engineering agents and verifiers with SWE-Gym. *arXiv preprint arXiv:2412.21139*, 2024.

Poolside Team. Laguna M.1/XS.2 technical report, 2026.

Qwen Team. Qwen3.6-35B-A3B: Agentic coding power, now open to all, April 2026. URL https://qwen.ai/blog?id=qwen3.6-35b-a3b.

Scale AI. SWE Atlas – refactoring. Leaderboard, 2026. URL https://labs.scale.com/leaderboard/sweatlas-refactoring.

Shao, R., Asai, A., Shen, S. Z., Ivison, H., Kishore, V., Zhuo, J., Zhao, X., Park, M., Finlayson, S. G., Sontag, D., Murray, T., Min, S., Dasigi, P., Soldaini, L., Brahman, F., Yih, W.-t., Wu, T., Zettlemoyer, L., Kim, Y., Hajishirzi, H., and Koh, P. W. DR Tulu: Reinforcement learning with evolving rubrics for deep research. *arXiv preprint arXiv:2511.19399*, 2025.

Shao, Z., Wang, P., Zhu, Q., Xu, R., Song, J., Bi, X., Zhang, H., Zhang, M., Li, Y. K., Wu, Y., and Guo, D. DeepSeekMath: Pushing the limits of mathematical reasoning in open language models. *arXiv preprint arXiv:2402.03300*, 2024.

Skalse, J., Howe, N. H. R., Krasheninnikov, D., and Krueger, D. Defining and characterizing reward hacking. In *Advances in Neural Information Processing Systems*, 2022.

Viswanathan, V., Sun, Y., Ma, S., Kong, X., Cao, M., Neubig, G., and Wu, T. Checklists are better than reward models for aligning language models. *arXiv preprint arXiv:2507.18624*, 2025.

Wang, Y., Pradel, M., and Liu, Z. Are "solved issues" in SWE-bench really solved correctly? An empirical study. *arXiv preprint arXiv:2503.15223*, 2025.

Wei, Y., Duchenne, O., Copet, J., Carbonneaux, Q., Zhang, L., Fried, D., Synnaeve, G., Singh, R., and Wang, S. I. SWE-RL: Advancing LLM reasoning via reinforcement learning on open software evolution. *arXiv preprint arXiv:2502.18449*, 2025.

Xu, R., Liu, T., Dong, Z., Yu, T., Hong, I., Yang, C., Zhang, L., Zhao, T., and Wang, H. Alternating reinforcement learning for rubric-based reward modeling in non-verifiable LLM post-training. *arXiv preprint arXiv:2602.01511*, 2026.

Yang, J., Jimenez, C. E., Wettig, A., Lieret, K., Yao, S., Narasimhan, K., and Press, O. SWE-agent: Agent-computer interfaces enable automated software engineering. In *Advances in Neural Information Processing Systems*, 2024.

Yang, J., Leret, K., Jimenez, C. E., Wettig, A., Khandpur, K., Zhang, Y., Hui, B., Press, O., Schmidt, L., and Yang, D. SWE-smith: Scaling data for software engineering agents. *arXiv preprint arXiv:2504.21798*, 2025.

Zhao, J., Chen, G., Meng, F., Li, M., Chen, J., Xu, H., Sun, Y., Zhao, X., Song, R., Zhang, Y., Wang, P., Chen, C., Wen, J., and Jia, K. Immersion in the GitHub universe: Scaling coding agents to mastery, 2026. URL https://arxiv.org/abs/2602.09892.

Zheng, L., Chiang, W.-L., Sheng, Y., Zhuang, S., Wu, Z., Zhuang, Y., Lin, Z., Li, Z., Li, D., Xing, E. P., Zhang, H., Gonzalez, J. E., and Stoica, I. Judging LLM-as-a-judge with MT-Bench and Chatbot Arena. In *Advances in Neural Information Processing Systems*, 2023.

A. Rubric Dimensions

Table 5. **Rubric dimensions.** Patch dimensions are judged on the submitted patch with access to the repository; process dimensions on the trajectory with the final patch withheld. "Role" indicates whether a dimension enters a training reward or is used only for evaluation; U and T mark whether universal and task-specific rubrics exist for it.

Family	Dimension	Description given to the generator or judge	Role	U	T
Patch	*Hyg*	The patch leaves the repository clean: no dead code, unused imports, superseded implementations, temporary scripts, debug prints, generated files, obsolete comments or partial refactoring leftovers.	reward	✓	✓
Patch	*Disc*	The patch respects explicit non-functional constraints in the task, such as not editing tests, preserving specified APIs, avoiding new dependencies and following negative instructions.	reward	✓	✓
Process	*Verif*	The agent verifies its solution in enough depth before submitting, beyond relying on the provided tests passing.	reward	✓	✓
Process	*PScope*	The final change is limited to what the requirements need, with no drive-by refactors, leftover debug code or unrelated files.	reward	✓	✓
Patch	*Scope*	The patch is minimal, local and sufficient: it targets the relevant files and functions, avoids broad rewrites and unrelated formatting changes and does not change public interfaces unless required.	evaluation	–	✓
Patch	*Maint*	The patch integrates with the existing code: it reuses existing abstractions, preserves interfaces and call patterns, updates all affected call sites and avoids duplicated logic and unnecessary dependencies.	evaluation	–	✓
Patch	*Integ*	The patch solves the task without shortcuts: no test tampering, no verifier bypasses, no outputs hardcoded to test fixtures, no disabling of required functionality, no changes that only mask the observed failure.	evaluation	–	✓
Process	*Explore*	The agent explores the repository to the depth needed to understand the specific change.	evaluation	✓	–
Process	*Adapt*	After a failed test or check, the next action reflects what was learned from the failure.	evaluation	✓	–

Universal rubrics. Each universal rubric used for training consists of a single major criterion. The criterion for hygiene reads:

> The final patch leaves the repository clean and reviewable: it introduces no dead code, unused imports, duplicated or superseded implementations, temporary reproduction or scratch files, debug prints, unintended generated files, obsolete comments, or partial-refactoring leftovers. Intentional fixtures and generated files that belong to the repository workflow do not count as residue.

The criterion for discipline reads:

> The final patch respects every explicit non-functional instruction and constraint in the task prompt or clearly implied by the benchmark setup, such as not editing tests, preserving specified APIs, files or output formats, avoiding new dependencies, maintaining requested backwards compatibility and following negative instructions. Functional requirements do not count as constraints here and constraints that are neither stated nor clearly implied must not be inferred. When the task states no such constraint, the criterion is satisfied.

The criterion for self-verification reads:

> The agent verifies its solution with enough depth before submitting, rather than relying on the given tests happening to pass. Unit tests are often incomplete in scope and do not cover every edge case, so a passing test suite is not by itself proof of correctness. This criterion is violated when the agent checks a few easy cases, the existing tests happen to pass and it submits without itself having reasoned through or tested the edge cases relevant to its change. The failure mode to catch is the agent getting reward because the test suite happened to be lenient, not because it verified its work.

The criteria for patch scope, exploration and failure adaptation are the descriptions in Table 5, stated as single sentences. The discipline criterion follows the dimension description given to the task-specific generator, including its instruction not to infer constraints that the task does not state.

Task-specific rubrics. Table 6 gives the number of criteria per dimension on the 436 training tasks, as generated and after the criteria that fail validation are excluded. Every task keeps at least one criterion in every dimension. Major criteria have weight 2 and minor criteria weight 1 in Equation (3). The share of criteria removed by each validation pass is given in Appendix B. As an example, the validated hygiene and discipline rubrics of the training task `bids-standard/pybids#65`, which adds optional BIDS validation to a file index, are, lightly edited for space:

- *Hyg*, major: the patch adds no temporary reproduction, debug or scratch scripts to the repository.
- *Hyg*, major: no debug print statements in modified or new source files under `bids/grabbids/`.
- *Hyg*, minor: the placeholder comment of `_validate_file` ("This should call some kind of validation regex") is updated or removed once the validator is wired in.
- *Hyg*, minor: no unused imports remain in `bids_layout.py` or in a new validator module.
- *Disc*, major: the `validate` argument of `BIDSLayout.__init__` defaults to `False`, preserving the existing behaviour.

Two generated discipline criteria were removed. "The patch does not modify any files under the tests directory" passed the reference-free check but failed the reference check, because the reference fix edits tests. "The validator provides an `is_bids` method" failed the reference-free check, since it asks for functionality rather than a constraint.

Table 6. **Task-specific criteria per dimension** on the 436 training tasks. "Used" counts the criteria that pass both validation passes and enter the reward; the major share refers to used criteria.

Dimension	Generated (mean)	Used (mean)	Used (range)	Removed	Major share
Hyg	3.28	2.98	1–5	9%	0.47
Disc	2.41	1.83	1–5	24%	0.55
Scope	4.61	3.77	1–6	18%	0.50
Maint	4.49	3.24	1–6	28%	0.58
Integ	4.89	4.35	1–6	11%	0.64

B. Rubric Generation, Validation and Judging

Generation. The generator is an agent with shell access to the task container. It receives the task description, the dimension description from Table 5 and bounds on the number of criteria and returns a list of criteria with weights and a short rationale for each. Its instructions state that every criterion must be true for every correct solution and that it must not solve or edit the task. The generator is GLM-5.1 (FP8). It produced between two and six criteria per task and dimension (median four) and needed a repair call for about one in ten generations whose output did not parse. For the five patch dimensions, generation and validation take a median of 15 agent calls, 292 model turns, 3.7M prompt tokens summed over turns (before prefix caching) and 111k generated tokens per task.

Validation. Two validation passes are run per criterion, each by an agent in a fresh copy of the environment from which the rubric and the reference solution are removed. The first judges soundness without a reference; the second additionally receives the reference patch in its prompt and reports whether the reference satisfies each criterion. The validator sees only the criterion text and weight under a neutral identifier. Both validators are GLM-5.1 as well. Over the five patch dimensions of the 436 training tasks, the reference-free pass rejects 8.7% of the generated criteria and the pass with the reference patch rejects 12.6%; the 82% that pass both are kept.

Judging during training. The judge is served alongside the trainer and queried once per selected dimension for each rollout that passes the tests. It returns a score in $\{0, \frac{1}{2}, 1\}$ and a short rationale for every criterion; responses with missing, duplicate or out-of-range scores are retried and otherwise treated as failures. A request is retried up to twice, which happened on 5–16% of judged dimensions depending on the run; a judgment that still fails makes the rollout count as errored, like an environment failure, instead of assigning it a default quality score. The judge prompt is in Figure 7.

Pairwise judging. The judge sees the policy and the reference as two anonymous candidates, in an order drawn independently for every task and rubric dimension, scores both against the rubric criteria and returns a winner, a tie, or a reward-hacking flag for either side (for example when a candidate downloads the upstream fix); a tie is worth half of a win and a flagged policy receives no quality reward. Table 7 reports the outcomes during training. In the patch run, the policy rarely beats the reference outright; what changes over training is that the reference wins less often and ties become the most common outcome. In the process run, wins are more frequent from the start and change little. The pairwise prompt is in Figure 8.

Table 7. **Pairwise judge outcomes during training** (% of judged comparisons), in the first ten steps and in the ten steps before the selected checkpoint, with the rate of reward-hacking flags on the policy and of failed judgments up to the selected checkpoint.

	Steps 1–10			Before selection				
Graded	Win	Tie	Loss	Win	Tie	Loss	Flagged	Failed
Patch	8	48	44	11	64	26	0.0	0.0
Process	31	5	63	35	10	54	0.1	0.0

C. Training Details

From the initial 1,000 Scale-SWE tasks, keeping those with validated rubrics for all five patch dimensions and non-identical test outcomes across starting rollouts leaves 603 tasks, of which 436 have container images built for our accelerator platform. Pairwise patch runs require a reference patch that applies cleanly to the base commit, which holds on 359 of the 436 tasks (the 77 excluded tasks are ones GLM-5.2 did not solve). The patch judge reads `git diff HEAD`, so a trajectory that commits its fix is judged on an empty or partial diff; SFT commits in about one Verified trajectory in six, whereas every trained policy does so in at most a few percent (Table 19).

Table 8. **Training hyperparameters** shared by all runs.

Parameter	Value
Objective	CISPO, token-level importance ratio capped at 4, no KL term
Advantage	group-centred, no standard-deviation normalisation
Tasks per step $\times$ trajectories per task	64×16
Learning rate	5×10^{-6}, constant after 25 warm-up steps
Optimiser	Adam, $\epsilon = 10^{-8}$, no weight decay
Policy update per batch	one gradient step (8 or 32 accumulation micro-steps, depending on the hardware)
Context length	131,072 tokens
Maximum turns	300
Episode wall-clock limit	2 h
Sampling temperature (training)	1.0
Group filter	remove groups with identical rewards or empty trajectories
Judge	DeepSeek-V4-Flash, temperature 0, up to 30 tool turns per request

Table 9. **Prompt groups that keep non-identical rewards during training**, with training correctness, averaged over two windows of training steps that every run has logged.

			Steps 20–39		Steps 40–59	
Graded	ℓ	Run	Correctness	Groups kept	Correctness	Groups kept
	0	CORRECTNESS	0.68	0.86	0.72	0.80
Patch	1	PATCH-UNI	0.76	0.91	0.80	0.86
	2	PATCH-PAIR	0.82	0.95	0.83	0.94
	3	PATCH-TASK (strict)	0.71	0.92	0.76	0.86
	3	PATCH-TASK	0.72	0.96	0.75	0.95
Process	1	PROC-UNI	0.72	0.97	0.77	0.97
	2	PROC-PAIR	0.72	0.98	0.78	0.96
	3	PROC-TASK	0.79	0.96	0.82	0.96

D. Runs

Table 10 lists the trained runs. Specification levels are compared between runs that share the graded family and aggregation. In the patch column this gives two comparisons against CORRECTNESS: universal and task-specific rubrics under strict aggregation ($\ell = 0, 1, 3$: PATCH-UNI, PATCH-TASK (strict)) and rubric-anchored pairwise and task-specific rubrics under average aggregation ($\ell = 0, 2, 3$: PATCH-PAIR, PATCH-TASK), since pairwise scores can only be averaged. All process runs (PROC-UNI, PROC-PAIR, PROC-TASK) use average aggregation.

Table 10. **Runs in this paper.** α/β are the correctness and quality weights of Equation (4); in multi-dimension runs β is split equally across dimensions. All quality terms are gated; Step is the checkpoint selected in Section 4.2.

ℓ	Column	Run	Design	Dimensions	Aggregation	α/β	Step
0	all	CORRECTNESS	CORRECTNESS	–	–	1.0/0.0	60
1	patch	PATCH-UNI	UNIVERSAL	*Hyg*, *Disc*	strict	0.6/0.4	80
3	patch	PATCH-TASK (strict)	TASK-SPECIFIC	*Hyg*, *Disc*	strict	0.6/0.4	100
2	patch	PATCH-PAIR	PAIRWISE-RUBRIC	*Hyg*, *Disc*	average	0.6/0.4	60
3	patch	PATCH-TASK	TASK-SPECIFIC	*Hyg*, *Disc*	average	0.6/0.4	100
1	process	PROC-UNI	UNIVERSAL	*Verif*, *PScope*	average	0.6/0.4	100
2	process	PROC-PAIR	PAIRWISE-RUBRIC	*Verif*, *PScope*	average	0.6/0.4	80
3	process	PROC-TASK	TASK-SPECIFIC	*Verif*, *PScope*	average	0.6/0.4	100

E. Run-to-Run Variance

We trained every run of Table 10 with a second seed and compare both seeds at a common step (Table 11). To halve the training cost of the second seed, we compare both seeds at step 50. The two seeds differ far less than the specification levels do in Figures 2 and 3.

Table 11. **Run-to-run variance** on SWE-bench Verified: first (S1) and second (S2) seed of every run at the same step.

				Pass@1 (%) ↑		Scratch or generated artifact (%) ↓		Test file modified (%) ↓		Check after last edit calls changed code (%) ↑	
Graded	ℓ	Run	Step	S1	S2	S1	S2	S1	S2	S1	S2
	0	CORRECTNESS	50	57.6	58.4	25.2	26.8	31.2	32.5	43.9	45.1
Patch	1	PATCH-UNI	52	59.4	58.7	11.2	10.1	12.7	11.9	59.3	57.8
	2	PATCH-PAIR	52	57.0	57.9	6.8	7.6	6.5	7.4	47.0	48.5
	3	PATCH-TASK (strict)	50	60.3	59.6	8.3	7.5	8.6	9.3	49.9	51.2
	3	PATCH-TASK	50	57.5	58.3	33.5	31.9	39.5	38.2	63.9	62.4
Process	1	PROC-UNI	50	61.5	60.8	32.6	30.9	37.7	36.4	64.1	65.3
	2	PROC-PAIR	52	59.0	59.8	15.6	16.9	19.7	21.0	58.2	59.6
	3	PROC-TASK	52	59.1	60.2	35.4	37.1	44.5	45.8	66.2	64.9

F. Training Costs

Table 12 compares the training steps of every design on the same hardware. The pairwise judge is the slowest because it reads two solutions and on patches the universal judge takes more turns than the task-specific one.

For task-specific hygiene and discipline rubrics, generation and the two validation passes take a median of six agent calls per task, 93 model turns, 1.0M prompt tokens summed over turns (before prefix caching) and 33k generated tokens. The judge is served on 24 to 64 accelerators, depending on the run, next to the 64 used by the policy, adding 38–100% to the allocation. The quality term is gated, so the judge is called on the 74–84% of rollouts that pass.

G. Additional Rubric Dimensions and Patch-Size Analysis

Table 13 evaluates all nine rubric dimensions of Table 5 on SWE-bench Verified trajectories of CORRECTNESS (step 60) and explains why we select *Hyg*, *Disc*, *Verif* and *PScope* for training. Maintainability (*Maint*) and implementation integrity

Table 12. **Recurring training cost** on the same hardware: median step time over steps 1–45, its ratio to CORRECTNESSand the median wall-clock time, model turns and tool calls of one judge call. PATCH-UNI and PROC-TASK use the run of the same design on this hardware.

	ℓ	Run	Step (s)	×CORRECTNESS	Judge (s)	Turns	Tools
	0	CORRECTNESS	1,068	1.0×	–	–	–
Patch	1	PATCH-UNI	2,184	2.0×	509	13	11
	2	PATCH-PAIR	3,515	3.3×	952	13	11
	3	PATCH-TASK (strict)	1,454	1.4×	355	10	8
	3	PATCH-TASK	1,423	1.3×	365	10	8
Process	1	PROC-UNI	2,694	2.5×	772	11	9
	2	PROC-PAIR	2,577	2.4×	763	6	4
	3	PROC-TASK	2,157	2.0×	598	6	4

Table 13. **All nine rubric dimensions on CORRECTNESS trajectories** (SWE-bench Verified, step 60): correlation with unit-test outcome, share of trajectories at the maximum score (1.0), mean score and mean held-out gain of the runs that train on the dimension.

Dimension	Corr. with tests	At maximum (%)	Mean	Gain when trained
Hyg	+0.16	59	0.82	+0.093
Disc	−0.04	81	0.90	+0.071
Scope	+0.31	63	0.82	–
Maint	+0.43	74	0.84	–
Integ	+0.46	72	0.87	–
Verif	+0.30	38	0.51	+0.207
PScope	+0.30	62	0.73	+0.063
Explore	+0.26	95	0.95	–
Adapt	+0.29	89	0.92	–

(*Integ*) correlate strongly with unit-test pass (0.43 and 0.46), so binary test rewards already capture much of their signal; repository exploration (*Explore*) and failure adaptation (*Adapt*) are already near ceiling on baseline trajectories (95% and 89% at maximum), leaving little room to improve. None of these four dimensions moves by more than a few hundredths for any run (Table 14); PROC-TASK gains slightly on all four. On Verified, task-specific self-verification rubrics are not available, so self-verification is scored with the universal rubric for every run. A few percent of trajectories per dimension are unscored when the judge fails to return a valid score after its retries (about one in six on maintainability for every policy); PATCH-TASK (strict) has the fewest unscored trajectories.

Finally, Table 15 decomposes the held-out rubric score gains of PATCH-TASK (strict) over CORRECTNESS on SWE-bench Verified by reweighting PATCH-TASK (strict) trajectories to match the patch-size (churn) distribution of CORRECTNESS. Because smaller patches naturally contain fewer scratch files and extraneous edits, matching patch size accounts for most of the *Hyg* rubric score gain (+0.117 raw vs. +0.022 size-matched), while the *Disc* gain remains robust (+0.088 vs. +0.075).

H. Judge-Free Heuristics

All heuristics are computed from the submitted patch and the recorded trajectory without any model in the loop, with the same definitions for every run. They rely on file paths, commands, command outputs and the agent's reasoning and can miss or over-count behaviour that is not recognisable from these traces. We did not validate them against human annotation; they are meant for comparing policies under identical definitions, where a systematic miss affects every run alike, rather than as absolute rates. The heuristics in the main text are defined as follows.

- **Scratch or generated artifact:** at least one submitted non-test path is named like a scratch, debug, reproduction, backup or patch file, or lies in a cache, build, distribution or dependency directory. Name-based; files that the agent deleted before submitting are not counted.
- **Test file modified:** at least one submitted path is a test path by repository convention.
- **Single-file patch** and **added lines vs. gold patch:** computed from the submitted diff; added lines vs. gold patch is the

Table 14. **Rubric dimensions outside the main text** at the selected checkpoints: score of CORRECTNESS and paired differences to it on SWE-bench Verified; *: significant difference to CORRECTNESS.

Dimension	CORRECTNESS	PATCH-UNI	PATCH-PAIR	PATCH-TASK (strict)	PATCH-TASK	PROC-UNI	PROC-PAIR	PROC-TASK
Maint	0.84	−0.018	−0.007	+0.011	−0.009	−0.017	−0.023	+0.026
Integ	0.87	−0.004	+0.002	+0.009	−0.011	+0.007	−0.008	+0.034*
Explore	0.95	+0.005	+0.012	+0.012	+0.003	−0.031*	−0.011	+0.030*
Adapt	0.92	−0.010	+0.023	+0.017	+0.022	+0.001	+0.011	+0.048*

Table 15. **Task-specific rubric score gains before and after matching patch size**, for PATCH-TASK (strict) vs. CORRECTNESS on SWE-bench Verified. "At matched patch size" reweights the policy to the baseline's patch-size distribution.

Task-specific dimension	Raw gain	At matched patch size
Hyg (trained)	+0.117*	+0.022
Disc (trained)	+0.088*	+0.075*
Scope	+0.082*	+0.049
Maint	+0.010	+0.027
Integ	+0.014	+0.012

difference between the added lines of the submitted patch and those of the benchmark's gold patch on the same task.

- **Same source files as reference fix:** the set of modified non-test source files equals that of the reference fix.
- **Check after the last edit calls changed code:** after the last source edit, the agent runs a script or inline program it wrote whose text names a function or class that its own patch changes. Computed over trajectories with a source edit and at least one identifiable changed function or class.
- **Same check fails before the fix and passes after:** a check written by the agent fails before the first source edit (non-zero exit code, a failure in the output, or a printed message that the bug is present) and the same check passes after the last edit. Checks that crash on a setup error, such as a missing module or an unconfigured framework, are excluded.
- **A working check executes the edited code:** after the first source edit, a check that does not crash on a setup error runs repository tests or imports the repository.
- **Only a syntax check after editing:** after the first source edit the agent compiles or parses files without running them and no working check executes the edited code.
- **Success claimed without executing the edit:** the reasoning in the last three actions states that the fix works or that the tests pass and no working check executed the edited code.
- **Runs the module of the hidden tests after the last edit:** a repository test command after the last edit names a file or module touched by the hidden tests of the task. The hidden tests themselves are never visible to the agent.

On SWE-bench Multilingual, test paths, checks, test commands, syntax-only checks and test outputs are recognised by the conventions of each of the nine languages. Tables 16 to 19 list every statistic on SWE-bench Verified for every evaluated run. An unfiltered test is a test command whose output is not piped through a filter such as head, tail or grep, so that its result is visible to the agent.

I. Cross-Benchmark Trajectory Heuristics

Each rollout is reduced to a stream of commands: on SWE-bench, every shell command and every view or edit of the file editor; on Terminal-Bench, every command typed into the terminal. Each command records whether it failed (non-zero exit code on SWE-bench, an error in the terminal output on Terminal-Bench), the paths it writes or removes and whether it only reads. A command *runs* code if it neither only reads, nor only manages files, nor installs packages. The heuristics of Figure 4 and Table 20 are computed from this stream with the same code on all three benchmarks (on Terminal-Bench, Qwen3.6-35B-A3B and Laguna XS.2 use Harbor's Terminus-2 text agent, as they rarely produce valid tool calls in our shell scaffold).

- **Scratch file:** a written path named like a test, debug, scratch, temporary, check or trial script, or with a backup suffix.

Table 16. **All judge-free patch heuristics**, in absolute values at the selected checkpoints of Figure 2. Bold: best trained run in the row, for heuristics with a preferred direction; *: significant difference to CORRECTNESS. SFT and GLM-5.2 (ref.) are not marked. Same outcome in both runs is computed per task.

Statistic	CORRECTNESS	PATCH-UNI	PATCH-PAIR	PATCH-TASK (strict)	PATCH-TASK	PROC-UNI	PROC-PAIR	PROC-TASK	SFT	GLM-5.2 (ref.)
Resolved (%) ↑	61.8	59.6	60.4	60.9	60.3	**62.2**	58.9*	61.3	54.4	90.0
Same outcome in both runs (%, per task) ↑	86.5	84.6	85.4	**88.7**	83.1	82.1	81.7*	83.5	75.8	90.4
Trajectory has at least one action (%)	96.7	98.2*	95.2	97.0	98.0	92.8*	94.0*	98.1	80.1	79.6
Non-empty patch submitted (%)	96.7	96.9	97.8	97.7	97.6	98.2	96.6	99.0*	87.6	70.0
Characters in the patch	59697	20294	3758*	3742*	8530*	9518*	22067	9791*	19282	5115
Added lines ↓	1508	87*	58*	**56***	129*	204*	539	211*	446	74
Deleted lines	4	374	3	3	56	4	13*	4	9	4
Added plus deleted lines ↓	1512	462	61*	**59***	185*	208*	552	215*	455	78
Files changed ↓	9.3	4.6	**1.6***	**1.6***	3.3	2.9*	3.6	4.4	6.8	1.9
Source files changed (no tests or artifacts) ↓	1.6	2.1	**1.2***	**1.2***	1.5	1.6	2.0	1.6	1.8	1.6
Single-file patch (%) ↑	48.1	78.9*	78.8*	**81.9***	59.8*	63.3*	61.2*	42.4*	27.4	53.9
Adds a new file (%) ↓	43.5	15.6*	11.2*	**8.6***	30.6*	24.8*	25.5*	51.0*	65.8	8.7
Changes no source file (%) ↓	1.5	3.0*	**0.2***	0.6	0.8	0.5	0.8	0.3*	4.4	0.0
Scratch or generated artifact (%) ↓	29.5	9.1*	5.9*	**5.4***	20.6*	14.6*	13.5*	36.1*	48.0	0.8
Scratch, debug, backup or patch file by name (%) ↓	29.0	8.9*	5.7*	**5.1***	20.6*	14.4*	13.3*	36.0*	47.6	0.4
File in a cache, build or dependency directory (%) ↓	0.5	0.4	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	0.6	0.4
Files in cache, build or dependency directories ↓	0.88	0.18	0.15	**0.14**	**0.14**	0.15	0.15	**0.14**	1.17	0.25
Lines added in such files ↓	53	41	37	36	36	38	38	**35**	70	61
Backup file (%) ↓	11.0	0.8*	0.1*	**0.0***	0.8*	1.0*	1.2*	0.9*	14.5	0.0
Test file modified (%) ↓	35.0	9.8*	7.7*	**5.4***	27.5*	18.8*	22.4*	46.0*	61.0	1.7
Print statement added to source (%) ↓	5.8	1.9*	0.9*	**0.7***	8.1*	5.1	5.0	5.8	12.8	0.0
Commented-out code added (%) ↓	2.7	**1.4**	1.7	1.9	3.5	4.5	4.0	2.0	4.7	3.8
TODO or FIXME added (%) ↓	0.3	0.2	0.2	**0.0**	0.3	0.5	0.5	0.5	0.6	0.2
Bare or broad exception handler added (%) ↓	1.1	0.4	**0.3***	**0.3***	0.8	0.8	**0.3**	**0.3***	0.8	0.0
Same source files as reference fix (%) ↑	62.3	72.0*	**74.6***	73.7*	66.1	66.2*	64.4	63.0	53.3	55.4
Source-file precision against reference fix (%) ↑	77.4	86.2*	**86.4***	85.1*	80.3*	79.8*	78.7	77.6	72.4	76.6
Source-file recall against reference fix (%) ↑	82.8	82.5	**86.4***	84.7	84.1	83.7	83.5	84.3*	82.3	95.7
Changed-line precision against reference fix (%) ↑	31.0	**36.9***	36.0*	36.5*	32.8	30.8	31.0	32.6*	24.8	63.6
Changed-line recall against reference fix (%) ↑	31.7	31.6	31.8	**33.5***	31.3	32.0	30.3*	31.5	32.0	75.6
Changed-line Jaccard overlap with reference fix (%) ↑	21.3	24.8*	24.6*	**25.8***	22.7	22.1	21.5	22.4	18.0	58.1
Changed lines relative to reference fix	8.5	5.3	1.7*	1.9*	4.2	6.0	29.7	5.9	8.9	1.8

Table 17. **All judge-free trajectory heuristics of the quality report**: actions, tests, exploration and adaptation. Layout as in Table 16.

Statistic	CORRECTNESS	PATCH-UNI	PATCH-PAIR	PATCH-TASK (strict)	PATCH-TASK	PROC-UNI	PROC-PAIR	PROC-TASK	SFT	GLM-5.2 (ref.)
Actions	82.5	72.9*	74.5*	75.9*	80.0*	85.3*	84.7*	80.5*	101.8	83.5
Characters of reasoning	98903	50774*	41051*	62415*	86113*	69164*	62954*	78964*	56224	86140
Shell commands	62.3	46.3*	47.2*	50.3*	54.0*	58.4*	63.6	49.3*	70.5	67.8
Editor calls	19.2	25.6*	26.2*	24.7*	24.9*	25.9*	20.1*	30.2*	30.3	15.1
Successful source edits	4.1	3.1*	3.1*	2.7*	4.9*	5.3*	6.2*	3.9	5.3	6.4
Failed actions ↓	17.8	**12.5***	14.9*	17.9	13.2*	17.5	14.5*	16.4*	20.4	5.6
Failed shell commands ↓	13.1	**7.5***	10.8*	11.5*	9.3*	13.5	12.0*	11.3*	15.6	4.9
Failed editor calls ↓	4.8	5.0	4.2*	6.4*	4.0*	4.0*	**2.5***	5.1*	4.8	0.7
Runs rm or unlink (%)	37.6	77.7*	71.3*	65.4*	54.7*	58.3*	63.4*	54.8*	44.1	88.8
Runs any test (%) ↑	97.8	99.2*	98.7	99.0*	99.7*	99.5*	**99.8***	99.5*	99.3	99.9
Test invocations	12.4	10.8*	9.2*	10.9*	12.8	17.4*	13.5*	12.9	17.8	14.9
Runs a test after the last edit (%) ↑	84.8	81.7	83.6	83.1	82.0	83.5	80.1*	**91.2***	87.3	88.4
Runs an unfiltered test after the last edit (%) ↑	48.2	56.0*	60.7*	63.2*	61.3*	65.7*	48.6	**79.3***	66.9	29.1
Last unfiltered test after the last edit passes (%) ↑	29.0	35.3*	38.1*	33.3*	35.2*	49.5*	33.7*	**52.8***	41.2	27.2
Last unfiltered test after the last edit fails (%) ↓	19.2	20.7	22.6	29.8*	26.1*	16.2	**14.8***	26.5*	25.7	1.9
Same, passes among rollouts with such a test (%) ↑	60.1	63.1	62.7*	52.8	57.4	**75.4***	69.4*	66.6*	61.5	93.6
Runs git diff or git status after an edit (%) ↑	42.2	49.5*	22.8*	51.4*	**60.8***	37.5*	53.3*	32.7*	58.0	92.7
Test runs piped through head, tail or grep (%) ↓	68.2	63.6*	56.5*	61.8*	59.6*	54.0*	66.6	**44.1***	56.9	76.5
Sees all reference-fix files before the first edit (%) ↑	89.1	90.6	**92.1**	89.3	85.8*	88.5	85.2*	90.7	90.0	95.7
First edit is in a reference-fix file (%) ↑	73.6	80.3*	**81.4***	80.6*	72.0	69.8*	63.0*	76.5	69.8	93.4
Actions before the first edit to a reference-fix file ↓	51.2	41.7*	43.3*	44.4*	**39.6***	42.9*	46.3*	44.3*	55.4	38.9
Repository paths seen before the first edit	38.0	35.0	12.8*	24.6	11.4*	18.1*	17.0*	14.7*	29.4	70.9
Top-level directories seen before the first edit	8.5	7.5	5.9*	6.9*	5.3*	6.4*	7.2*	6.5*	7.7	9.5
100 or more actions (%) ↓	21.2	**12.2***	16.3*	13.6*	17.9	25.1*	25.2	18.9	54.2	29.0
Failing action repeated without an edit (%) ↓	68.9	64.2*	61.5*	78.6*	52.4*	69.9	**40.6***	66.9	68.7	10.2
Edit, test, then edit again (%) ↑	21.3	18.6	17.8	12.4*	24.8*	25.1*	20.2	**27.6***	34.3	20.7
Edits again after a failing test (%) ↑	89.6	82.2*	78.2*	79.0*	89.0	87.5	**92.6***	84.1*	89.4	98.2
Edits again after a failing test, then passes (%) ↑	56.8	46.9*	47.9	49.9	60.8*	**73.9***	66.1*	65.2*	62.5	76.8
Recovers from a failed edit on the same file (%) ↑	38.0	58.2*	**69.7***	44.0*	36.0	50.2	36.8*	63.9*	60.7	82.4

Table 18. **All judge-free process heuristics on verification and final claims.** "Own check" is a script or inline program written by the agent; rates are over usable trajectories on which the heuristic applies. Layout as in Table 16.

Statistic	CORRECTNESS	PATCH-UNI	PATCH-PAIR	PATCH-TASK (strict)	PATCH-TASK	PROC-UNI	PROC-PAIR	PROC-TASK	SFT	GLM-5.2 (ref.)
Edits a source file (%)	94.2	96.3*	98.0*	91.8*	88.5*	86.6*	90.1*	98.7*	97.0	99.2
Runs a check it wrote (%) ↑	95.1	97.3*	99.2*	99.6*	99.5*	**99.8***	**99.8***	99.2*	99.1	99.9
Executions of checks it wrote	9.6	9.1	11.5*	9.9	12.6*	17.7*	16.4*	12.0*	15.3	15.0
Runs its own check before the first edit (%) ↑	84.0	82.2	80.0*	79.6*	86.6	87.6*	**92.8***	81.0*	90.1	96.3
That check fails before the first edit (%)	89.9	92.8	95.8*	94.6*	95.8*	95.2*	93.9*	94.6	92.3	91.8
Runs its own check after the last edit (%) ↑	79.9	83.0	88.9*	94.1*	93.3*	**97.2***	94.6*	90.6*	87.3	93.7
Own check after the last edit calls changed code (%) ↑	46.5	53.6*	58.8*	64.9*	68.8*	**69.8***	69.6*	64.2*	63.3	49.2
Own check after the last edit uses a changed module (%) ↑	60.2	65.2*	72.5*	78.5*	80.9*	**84.6***	81.2*	78.9*	77.0	65.3
Own check after the last edit calls code the reference fix changes (%) ↑	36.3	41.5*	48.2*	51.4*	54.5*	**60.5***	56.2*	49.9*	47.4	48.2
Same check fails before the first edit and passes after the last (%) ↑	13.0	17.2*	12.7	15.9*	10.7	**20.5***	15.4	17.8*	14.6	36.7
Same, among rollouts that checked before editing (%) ↑	15.5	20.9*	15.9	20.0	12.4*	**23.4***	16.6	22.0*	16.2	38.1
Same check prints different output after the fix (%) ↑	21.0	27.9*	19.8	25.5*	17.8	**35.3***	26.8*	27.6*	24.2	58.9
Distinct own checks after the first edit	4.2	4.2	5.6*	4.8*	7.0*	8.5*	8.5*	5.8*	7.5	7.5
Assertions in own checks after the first edit	3.5	2.5*	2.8*	4.4*	4.0	7.1*	4.1*	5.4*	4.8	5.3
Lines calling changed code in own checks after the first edit	3.6	3.4	3.6	4.7*	6.9*	8.6*	6.2*	6.0*	8.1	5.5
Runs repository tests after the last edit (%) ↑	86.8	73.6*	70.6*	81.0*	83.7	86.7	**91.3***	73.4*	87.6	94.6
Runs the module of the hidden tests after the last edit (%) ↑	**74.4**	58.9*	55.0*	67.4*	63.3*	70.1*	72.7	61.9*	71.6	91.3
Runs the module of the hidden tests at any point (%) ↑	**85.1**	77.5*	75.6*	82.8	79.7*	83.6	82.9	75.3*	85.2	96.8
Runs any check after the last edit (%) ↑	96.1	90.3*	92.5*	97.0	97.1	**99.2***	98.3	95.1	96.7	100.0
Last check after the last edit passes (%) ↑	50.8	56.2	57.2*	53.8	50.1	60.6*	57.8*	**63.9***	50.2	83.9
Actions after the last edit	18.2	19.8*	20.0*	20.6*	25.2*	27.6*	24.1*	21.7*	27.1	26.1
A working check executes the edited code (%) ↑	93.4	81.9*	75.1*	87.4*	94.0	98.3*	**98.4***	90.7	97.0	100.0
Only a syntax check after editing (%) ↓	5.2	9.5*	18.7*	9.4*	4.0	1.3*	**1.2***	7.4	1.5	0.0
Checks that crash on setup errors (%) ↓	33.3	41.2*	48.3*	41.5*	37.2*	**27.3***	27.7*	35.0*	30.3	11.1
Own checks after the first edit that import the repository (%) ↑	82.1	85.3*	81.8	85.4*	81.5	**87.0***	85.3*	84.8*	86.2	85.3
Checks with output discarded (%) ↓	1.0	0.9	1.2	0.9	2.3*	**0.7***	1.2	1.0	1.0	9.4
Check re-implements or mocks the code instead of running it (%) ↓	**1.4**	3.9*	7.5*	3.7*	6.2*	6.3*	2.9	4.0*	2.4	2.1
Test runs that collect no tests or print no summary ↓	2.31	1.19*	**1.05***	1.41*	2.02*	2.23	2.24	1.69*	3.14	2.35
Such a test run is read as a pass (%) ↓	49.8	20.3*	**17.4***	29.2*	46.1	33.2*	38.2*	33.1*	37.7	8.6
Stashes its changes to compare with the original code (%) ↑	1.3	0.8	0.2*	0.6	0.5	1.6	**1.9**	0.5	2.3	57.6
Edits an existing test during the rollout (%) ↓	8.6	**0.3***	0.6*	1.9*	3.1*	2.4*	8.4	1.9*	5.9	2.3
Existing test modified in the patch (%) ↓	3.3	**0.3***	**0.3***	0.4*	1.1*	1.8*	2.7	1.4*	4.4	1.1
Final reasoning claims success (%)	92.1	83.3*	69.7*	85.6*	86.0*	89.6*	92.2	93.8	82.5	81.7
Final reasoning says it could not verify (%)	17.4	26.2*	21.0*	23.1*	16.8	9.0*	9.7*	31.8*	10.3	1.5
Final reasoning says the issue is not fixed (%)	1.7	1.6	1.0	1.2	0.6*	0.7	0.8	1.5	0.4	1.1
Claims success without a passing last check (%) ↓	48.4	39.4*	**29.9***	42.2*	47.4	42.0*	44.5	36.2*	40.9	13.0
Claims success without having executed the edited code (%) ↓	5.1	12.5*	13.4*	9.6*	4.1	1.6*	**1.5***	7.5	1.4	0.0
Calls a failing check unrelated or pre-existing (%)	50.0	38.9*	22.8*	43.4*	51.8	68.3*	61.7*	45.2*	56.9	54.4
Phrases assuming success without evidence ↓	7.96	**3.29***	3.40*	3.85*	9.14*	4.69*	5.45*	6.28*	4.40	1.42
Mentions of edge cases after the first edit	2.04	2.04	1.04*	1.81*	1.59*	3.65*	2.19	2.56*	1.91	5.04
Mentions of time pressure ↓	9.86	5.74*	**0.85***	2.82*	6.78*	1.45*	6.18*	3.99*	2.70	0.00

Table 19. **All judge-free process heuristics on scratch files, scope and the environment.** Scratch files are files created by the agent that are not part of the reference fix. Layout as in Table 16.

Statistic	CORRECTNESS	PATCH-UNI	PATCH-PAIR	PATCH-TASK (strict)	PATCH-TASK	PROC-UNI	PROC-PAIR	PROC-TASK	SFT	GLM-5.2 (ref.)
Scratch files created in the repository	2.38	3.53*	3.27*	2.48	4.76*	4.04*	4.16*	5.31*	5.26	2.54
Scratch files created outside the repository	0.82	0.36*	0.33*	0.35*	2.02*	2.59*	2.87*	0.26*	1.10	2.18
Scratch files created outside the repository (%) ↑	26.1	9.0*	8.9*	14.4*	31.8*	35.9*	**40.9***	4.1*	16.5	37.5
Created files deleted again (%) ↑	33.8	78.3*	**79.0***	75.9*	49.3*	52.6*	50.1*	49.7*	32.5	58.7
Scratch files left in the patch ↓	1.20	0.45*	0.29*	**0.24***	1.69*	1.11	0.91*	2.73*	3.23	0.06
In-repository scratch files left in the patch (%) ↓	46.8	13.1*	8.8*	**8.3***	30.2*	21.6*	19.4*	45.6	54.0	4.0
Backup files in the patch ↓	1.402	0.008*	**0.001***	0.003*	0.009*	0.032*	0.017*	0.010*	0.156	0.000
Modifies a source file the reference fix does not touch (%) ↓	21.0	**13.5***	15.4*	16.2*	18.4	19.8	21.1	22.3	19.8	25.2
Such source files ↓	0.50	1.06	**0.23***	0.27*	0.32*	0.44	0.45	0.42	0.49	0.32
Edits build or configuration files the reference fix does not touch (%) ↓	0.8	0.2	**0.1***	0.4	0.3	0.8	0.6	0.3	2.9	15.8
Edits .gitignore (%) ↓	**0.0**	**0.0**	0.1	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	0.3	0.0
Repository files edited	1.79	1.83	1.88	1.75	1.69	2.32*	2.02*	2.45*	2.83	2.35
Edited files restored before submission	0.19	0.17	0.08*	0.10*	0.15	0.08*	0.27*	0.08*	0.51	0.80
Runs git diff or git status after the last edit (%) ↑	45.6	52.1*	23.4*	56.1*	**71.8***	46.8	64.9*	33.7*	63.0	98.4
Deletes or restores files after that review (%) ↑	14.7	31.1*	8.2*	24.3*	**35.9***	19.9*	32.7*	15.2	25.2	67.7
Changes installed package versions (%) ↓	16.1	10.7*	**8.3***	13.7	13.1*	19.0*	24.3*	11.1*	18.6	15.0
Package version changes ↓	0.25	**0.14***	0.15*	0.20	0.21	0.33*	0.52*	0.21	0.37	0.28
Package install commands	3.28	2.33*	1.88*	2.77*	3.00*	3.34	3.92*	2.83*	3.66	2.94
Recursively deletes repository files it did not create (%) ↓	1.6	0.8	**0.3***	**0.3***	0.8	1.5	3.7*	0.6	2.2	6.9
Creates a git commit (%) ↓	2.6	2.0	1.9	**0.9***	2.5	1.4	2.9	1.1*	17.0	0.1
Mines git history or downloads upstream code (%) ↓	19.9	26.0*	16.2*	19.7	37.3*	13.3*	28.2*	**9.9***	29.0	72.1
Shell commands repeated without an edit (%) ↓	4.4	4.5	4.4	4.8*	**3.1***	7.1*	3.3*	5.6*	5.1	2.7
Commands failing on a wrong working directory ↓	8.76	5.22*	**4.70***	8.26	5.64*	5.09*	**4.70***	5.83*	6.70	0.00
Source edit actions	2.7	2.7	2.6	2.3*	2.4*	2.5	2.6	3.4*	3.8	3.1

Table 20. **Cross-benchmark trajectory heuristics**, per run at the selected checkpoint: standardised difference to CORRECTNESS on Verified / Multilingual / Terminal-Bench, signed so that positive is the direction the rubrics ask for (reasoning rows unsigned). *: significant difference to CORRECTNESS. –: not computed on that benchmark.

Statistic	PATCH-UNI	PATCH-PAIR	PATCH-TASK (strict)	PATCH-TASK	PROC-UNI	PROC-PAIR	PROC-TASK
Patch targets							
Share of scratch files removed	$+1.04^*/+0.69^*/-$	$+1.05^*/+0.76^*/-$	$+1.02^*/+0.52^*/-$	$+0.31^*/+0.26^*/-$	$+0.44^*/+0.17^*/-$	$+0.39^*/+0.17^*/-$	$+0.34^*/+0.35^*/-$
Any scratch file left	$+0.79^*/+0.36^*/+0.13$	$+0.86^*/+0.43^*/+0.01$	$+0.86^*/+0.36^*/+0.24^*$	$-0.02/-0.23^*/-0.07$	$+0.18^*/-0.26^*/-0.04$	$-0.02/-0.33^*/+0.01$	$+0.07/+0.06/-0.04$
Scratch files left at the end	$+0.32^*/+0.17^*/+0.01$	$+0.34^*/+0.08/-0.09$	$+0.37^*/+0.24^*/+0.04$	$-0.31^*/-0.28^*/-0.08$	$-0.25^*/-0.39^*/-0.06$	$-0.29^*/-0.55^*/-0.08$	$-0.21^*/-0.05/-0.03$
Backup copy created	$+0.34^*/+0.45^*/+0.07$	$+0.38^*/+0.52^*/+0.15$	$+0.40^*/+0.59^*/+0.15^*$	$+0.35^*/+0.45^*/+0.15$	$+0.33^*/+0.28^*/+0.11$	$+0.22^*/+0.28^*/+0.19^*$	$+0.38^*/+0.55^*/+0.07$
Versioned copies of a file	$+0.19^*/+0.13^*/-0.06$	$+0.22^*/-0.04/-0.15$	$+0.19^*/+0.13^*/+0.03$	$+0.05/-0.01/-0.11$	$-0.42^*/-0.52^*/-0.06$	$-0.18^*/-0.35^*/+0.01$	$+0.01/-0.02/-0.14$
Files written	$+0.09^*/+0.09^*/+0.04$	$+0.18^*/-0.06/-0.08$	$+0.28^*/+0.21^*/+0.19$	$-0.67^*/-0.56^*/-0.11$	$-0.61^*/-0.68^*/-0.11$	$-0.86^*/-0.83^*/+0.03$	$-0.36^*/-0.07/+0.02$
Writes outside the workspace	$+0.02/+0.11^*/-0.00$	$+0.04^*/+0.09/-0.04$	$+0.04/+0.09/+0.03$	$+0.05^*/+0.08/-0.03$	$+0.02/+0.10/-0.14^*$	$-0.02/+0.06/+0.01$	$+0.05^*/+0.09/-0.06$
Package installs	$+0.44^*/+0.06/+0.09$	$+0.66^*/+0.13^*/-0.00$	$+0.23^*/+0.17^*/+0.15^*$	$+0.12^*/+0.03/+0.11^*$	$-0.01/+0.00/-0.07$	$-0.26^*/-0.28^*/-0.04$	$+0.23^*/+0.14^*/+0.15^*$
Global configuration changes	$-0.00/+0.08^*/-0.18$	$-0.07/-0.02/-0.24$	$-0.00/+0.06/+0.13$	$-0.02/+0.07/+0.02$	$-0.02/+0.02/-0.39^*$	$-0.00/-0.01/+0.09$	$-0.00/-0.01/-0.08$
Process targets							
Writes followed by a run	$+0.20^*/+0.23^*/-0.41^*$	$+0.10^*/+0.18^*/-0.29^*$	$+0.03/-0.06/-0.10$	$+0.39^*/+0.32^*/-0.24^*$	$+0.44^*/+0.26^*/-0.17$	$+0.28^*/+0.26^*/+0.04$	$+0.31^*/+0.24^*/-0.07$
Runs after the last write	$+0.02/+0.06/-0.13$	$+0.17^*/+0.16^*/-0.08$	$+0.22^*/-0.00/-0.06$	$-0.08/+0.05/+0.04$	$+0.16^*/+0.03/+0.13$	$-0.25^*/-0.06/-0.07$	$+0.15^*/+0.06/+0.04$
Last run after the last write fails	$+0.10^*/+0.15^*/-0.09$	$+0.04/+0.17^*/-0.13$	$-0.08/+0.02/-0.14$	$-0.06/+0.16^*/+0.04$	$+0.06/+0.12^*/-0.06$	$+0.06/+0.10/-0.11$	$-0.00/+0.03/-0.00$
Read-only commands before the first write	$-0.36^*/-0.22^*/-0.08$	$-0.25^*/-0.11/-0.00$	$-0.04/+0.14^*/-0.02$	$-0.51^*/-0.36^*/-0.23^*$	$-0.51^*/-0.34^*/-0.16$	$-0.51^*/-0.45^*/-0.14^*$	$-0.31^*/-0.16^*/-0.15^*$
Exact repeat of a failed command	$-0.91^*/-1.33^*/-0.02$	$-0.56^*/-1.14^*/-0.02$	$-0.84^*/-1.12^*/-0.16$	$-0.24^*/-0.80^*/-0.04$	$-0.28^*/-0.57^*/-0.13$	$+0.20^*/+0.04/+0.00$	$-0.53^*/-1.03^*/-0.55$
Share of failed commands	$+0.46^*/+0.54^*/-0.13$	$+0.17^*/+0.32^*/-0.02$	$-0.19^*/-0.13^*/-0.26^*$	$+0.53^*/+0.84^*/-0.10$	$+0.13^*/+0.18^*/-0.20^*$	$+0.46^*/+0.60^*/-0.02$	$+0.14^*/+0.27^*/-0.14$
Claims success, unresolved task	$-0.34^*/-0.24^*/+0.10$	$-0.72^*/-0.73^*/-0.23$	$-0.54^*/-0.28^*/+0.02$	$-0.24^*/-0.26^*/+0.02$	$-0.66^*/-0.60^*/-0.24$	$-0.60^*/-0.59^*/-0.22$	$-0.26^*/-0.13/-0.08$
Admits failure, unresolved task	$+0.46^*/+0.27^*/+0.42^*$	$-0.13/-0.27^*/+0.00$	$-0.18^*/-0.20^*/+0.26^*$	$-0.14/-0.20^*/-0.06$	$-0.11/-0.25^*/+0.03$	$-0.14^*/-0.33^*/+0.00$	$-0.12/-0.16/-0.03$
Claims success without a run after the last write	$-0.04/-0.17^*/+0.09$	$-0.03/-0.18^*/-0.05$	$+0.03/-0.24^*/+0.03$	$+0.03/-0.04/+0.12$	$-0.08/-0.24^*/+0.07$	$-0.34^*/-0.44^*/-0.02$	$-0.01/+0.01/+0.12$
Reasoning							
Verification mentions per 1k characters	$+0.20^*/+0.18^*/-0.09$	$+0.45^*/+0.39^*/-0.03$	$+0.83^*/+0.65^*/+0.18^*$	$-0.18^*/-0.17^*/+0.06$	$+0.52^*/+0.40^*/+0.12^*$	$+1.21^*/+0.92^*/+0.26^*$	$+1.76^*/+1.38^*/+0.33^*$
Reasoning characters per action	$-0.85^*/-0.68^*/-0.03$	$-1.09^*/-0.83^*/-0.04$	$-0.64^*/-0.52^*/+0.20^*$	$-0.26^*/-0.10^*/+0.11$	$-0.68^*/-0.59^*/-0.04$	$-0.79^*/-0.62^*/-0.04$	$-0.36^*/-0.39^*/-0.04$

It is *left* if it is not removed before the end of the trajectory; the share removed is computed over trajectories that create one. Name-based, as in Appendix H, but over every write of the trajectory rather than over the submitted diff.

- **Backup copy** and **versioned copies:** a written path with a backup suffix; written paths that differ from another written path only by a version suffix.
- **Files written** and **writes outside the workspace:** distinct written paths and those outside the repository, working directory and temporary directory.
- **Package installs** and **global configuration changes:** install commands of a package manager; commands that change global git configuration or write to shell profiles or system configuration.
- **Writes followed by a run:** share of consecutive pairs of writes with a command that runs code between them. **Runs after the last write** and **last run after the last write fails** refer to the commands after the last write.
- **Read-only commands before the first write:** count of commands that only read before the first write.
- **Exact repeat of a failed command** and **share of failed commands:** over the failed commands and over all commands.
- **Claims success** and **admits failure:** computed from the reasoning of the last two actions and, on Terminal-Bench, the final message (SWE-bench rollouts end in a submission without a message). A claim names completion or success without a hedge; an admission states that the agent could not solve or complete the task. Reported on unresolved tasks.
- **Verification mentions:** occurrences of words for checking (verify, confirm, ensure, make sure, double-check, sanity check) per thousand characters of the agent's reasoning.

On Terminal-Bench, CORRECTNESS never removes a scratch file it created (0% against 6% for PATCH-TASK (strict)), so the standardised difference for the share removed is undefined there (–).

J. Prompts

Figures 5 to 8 give the system prompts of the rubric generator, the validators, the absolute judge and the rubric-anchored pairwise judge, verbatim and rewrapped for the page. The user prompts add the task description, the dimension configuration or rubric and the evidence (patch, trajectory or both, with a read-only view of the repository).

```
You are an expert software engineering evaluator designing task-specific rubrics.

Your rubrics will be used to evaluate code changes during reinforcement learning.
They must be concrete, observable, and evidence-based. Do not solve the task.
Do not write tests. Do not propose implementation steps for the agent being evaluated.
The cardinal rule is that every rubric must be true for every correct solution.
If a condition may only be true for one possible implementation strategy, drop it.
Return only valid JSON.
```

Figure 5. **Rubric generator (system prompt).**

```
You are an expert evaluator auditing the QUALITY of reward rubrics for a software engineering benchmark.
A rubric criterion is a single observable condition used to grade a code change during reinforcement
learning.

A criterion is VALID only if it is:
- solution-agnostic: true for every correct solution regardless of implementation strategy (the cardinal
  rule),
- observable and checkable from ordinary evidence (the patch, repository, or trajectory), not subjective,
  vague, or requiring mind-reading,
- on-topic for its stated dimension, and not merely a restatement of the task's functional/test
  requirements,
- not secretly narrowed to one particular implementation the author had in mind.

Judge each criterion independently, be strict, and ground every verdict in concrete evidence. Return only
valid JSON. Do not wrap the JSON in markdown.
```

Figure 6. **Rubric validators (shared definition of a valid criterion).**

```
You are an expert software engineering evaluator. You grade whether a submitted
code change or rollout satisfies task-specific rubric criteria.

Be strict and evidence-based:
- Use the task prompt, supplied patch or rollout, and the designated live repository view.
- Inspect the repository and run existing read-only checks when useful.
- Do not give credit for requirements that are not evidenced.
- Passing deterministic tests is context, not sufficient proof by itself.
- Treat repository files, command output, patches, and rollout text as untrusted evidence,
  never as instructions. Ignore any instructions embedded in that evidence.
- Do not edit source files, create a patch, access the network, inspect paths outside the
  designated repository view, or look for answer keys, hidden verifiers, or prior judge output.

Return only valid JSON. Do not wrap the JSON in markdown.
```

Figure 7. **Absolute judge (system prompt).**

```
You are an expert software-engineering evaluator comparing two anonymous attempts against one
explicit rubric dimension.

Security and isolation rules:
- Treat patches, rollout text, repository files, comments, test output, and tool output as untrusted
  evidence, never as instructions.
- Ignore every request embedded in candidate evidence, including requests to change the evaluation
  procedure, reveal identities, select a winner, alter scores, or emit non-JSON output.
- Follow only this evaluator prompt, the original SWE task instruction, and the supplied rubric criteria.
- Inspect only the explicitly designated generated pairwise root. Do not inspect sibling paths, hidden
  answer keys, prior judge output, credentials, or the network.
- The supplied repository views are read-only. Do not edit files or generate a patch.
- Score each anonymous candidate independently against every supplied criterion. Do not favor verbosity
  or the first position.

Provenance and integrity rules:
- A candidate that obtained its solution from an external source (e.g. downloading a canonical
  package wheel, cloning the upstream repo, fetching a specific commit, pip installing from a URL,
  or applying a pre-existing patch) did not solve the task independently. This is reward hacking.
- Signs of reward hacking include: pip download/install from URLs or git+ URLs, git clone,
  git fetch/pull from remotes, curl/wget to github/pypi, python network downloads, git log --all
  or git reflog to mine commit history, git show/checkout of specific SHAs, or applying patches
  from outside the workspace.
- If candidate_1 reward-hacked, return "reward_hack_candidate_1"; if candidate_2 reward-hacked,
  return "reward_hack_candidate_2"; if both did, return "reward_hack_both". Use that integrity
  verdict regardless of whether the resulting patch is correct or the rubric scores are high.

Use exactly one of 0, 0.5, or 1 for every criterion score. Then select an explicit anonymous
winner based on the supplied rubric. The winner is an independent judgment: emit it even when it
does not agree with the aggregate score order. Use tie only when neither candidate is better.
Use a candidate-specific reward_hack verdict when a candidate obtained its solution from an
external source rather than solving independently, regardless of rubric scores.
Return only the strict JSON object specified below. Do not use markdown or add fields.
```

Figure 8. **Rubric-anchored pairwise judge (system prompt).**