OSREWARD: INSTITUTING STANDARDIZED EVALUATION FOR CROSS-PLATFORM COMPUTER-USE REWARD MODELS

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ABSTRACT

Computer-using agents (CUAs) are advancing rapidly across the digital world. A CUA trajectory records the agent's states, reasoning, and actions. Verifying whether it fulfilled the task instruction is central to CUA evaluation, data curation, and reinforcement learning. Neither human-written verifiers nor human annotators can provide such verification at scale, so the field increasingly turns to vision-language models (VLMs) as judges of CUA trajectories. But a fundamental question has long gone unexamined: are these VLM judges reliable enough? To study it systematically, we introduce OSReward, a realistic, high-quality benchmark that evaluates VLM judges on CUA trajectories. The trajectories come from diverse agent backbones executing human-verified instructions across four platforms, and are then rigorously labeled with ground-truth verdicts through multi-stage human annotation. Building on it, we derive OSReward-Hard, a challenge subset concentrating genuinely hard cases, and OSReward-Multi for fine-grained efficiency and alignment scoring. The most comprehensive evaluation of VLM judges to date finds even state-of-the-art models fall short of an ideal judge, sharing a systematic leniency bias that mislabels failed runs as successes. A few reliable judges are too costly to scale, while affordable open models trail far behind. To close this gap, we construct and release OS-Shepherd-100K, an open corpus of reasoning-annotated trajectory judgments for the CUA community. Based on it, we train OS-Shepherd (9B and 35B), open reward models that supply low-cost, stable, and reliable reward signals, narrowing the gap to frontier judges with 30–60$\times$ lower inference cost. Extensive analyses further inform the design of reliable CUA reward at scale. Our code, benchmark, and data are available at this link.

1 INTRODUCTION

Computer-using agents (CUAs) are advancing rapidly across the digital world, operating the web, mobile apps, and desktop software (Xie et al., 2024; Zhou et al., 2024; Rawles et al., 2025). A *trajectory* is the interleaved sequence of the agent's states, reasoning, and actions. Scaling that progress, through evaluation, data curation, and reinforcement learning (Xue et al., 2026b), requires verifying whether each trajectory fulfilled its task instruction. However, human-written verifiers cover only a handful of curated tasks, and they do not apply to the static corpora and previously collected trajectories that have no live environment left to inspect. Human annotation cannot keep pace either. Typical methods use a VLM as the judge (Zheng et al., 2023a; Zhuge et al., 2025), whether as reward models (Pan et al., 2024; Li et al., 2026; Chae et al., 2025) or autoraters (Sun et al., 2025a).

Yet whether this judge is reliable remains largely untested. Unlike judging text (Zheng et al., 2023a; Zhou et al., 2025) or general multimodal agents (Chen et al., 2024), judging a CUA trajectory means reading a long, interleaved record of states, reasoning, and actions. The judge must decide whether the environment truly reached the instructed goal rather than whether the agent merely claims so. No prior study measures how reliably models make this judgment across platforms. Our analysis also finds even the best VLM judges disagree with benchmark verifiers on a quarter of desktop verdicts.

To study this systematically, we build OSReward, a benchmark for evaluating the judge itself. Reusing existing agent benchmarks' off-the-shelf trajectories (Lin et al., 2025; Li et al., 2026) would confound judge errors with flaws in the runs themselves, leaving failures unattributable to the judge. OSReward is instead built on dedicated cross-platform data infrastructure that we design and operate end to end.

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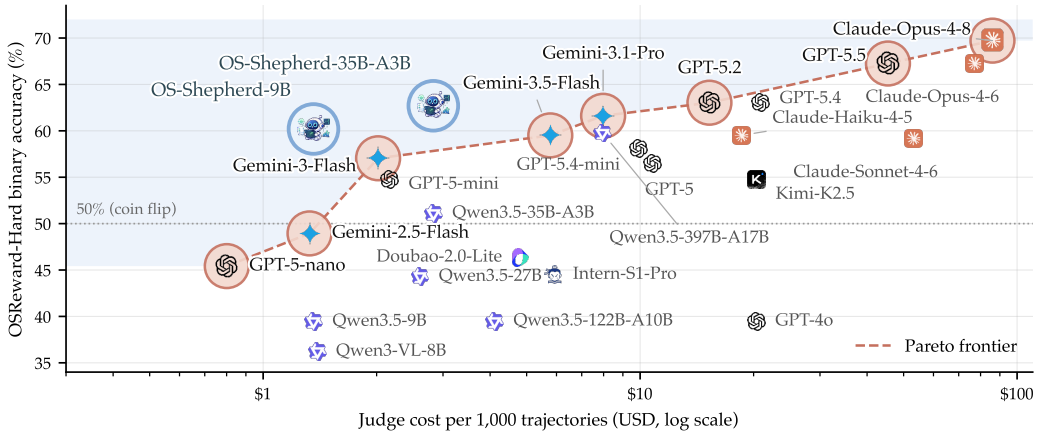


Figure 1: Cost against binary accuracy on OSReward-Hard: reliable judges are expensive, and OS-Shepherd comes nearest them at a fraction of the cost.

Its stock environments on web, mobile, Ubuntu, and Windows are extended with the common (Xie et al., 2024) and professional (Sun et al., 2026b) applications a real user has and realistic starting states. The collection spans everyday and professional applications, live websites, and both pure-GUI and GUI+CLI workflows. On these environments, annotators curate verified, environment-grounded instructions. Agents from four model families then execute them, and their varying capability yields both real successes and real failures. Each trajectory then passes rigorous multi-stage human labeling with strict screening. We obtain 1019 human-gold trajectories, long-horizon (up to 100 steps), organized into three views. The full set carries the breadth. OSReward-Hard concentrates hard cases, built from the trajectories the annotators themselves disagreed on, where current judges commonly fail, exposing error modes and remaining headroom. OSReward-Multi layers fine-grained efficiency and alignment labels on top of the binary verdicts. Grounded in careful human annotation, this labeled set offers a clean, standardized basis for studying VLM judges.

We then run the broadest evaluation of VLM judges yet, benchmarking 27 models. Frontier judges look adequate on the full set but fall sharply on OSReward-Hard, where the best judge drops below 70% and the mean judge falls to 52%. The errors share one signature: judges are easily fooled by *false successes*, where the executing agent claims completion despite failing the task, accepting such runs far more often than the reverse. The few judges accurate enough to trust, such as Claude-Opus-4-8 (Anthropic, 2026b) and GPT-5.5 (OpenAI, 2026b), are far too expensive for the millions of judgments that evaluation, curation, and training demand, while affordable open judges trail by a wide margin, leaving no judge both reliable and affordable, as shown in Figure 1.

To close this gap, we construct OS-Shepherd-100K, an open corpus of 100K reasoning-annotated trajectory judgments, and train open reward models on it. It combines the screened output of our own large-scale collection pipeline with filtered public corpora, spanning more trajectories, agent backbones, scenarios, and task types than reused corpora provide. The labeling pipeline builds on the findings of our judge study and needs no new human annotation. A trajectory enters the corpus only when strong judges independently agree on its verdict. We release the corpus in full, with its labels audited by a human study, so the community can study and train open CUA reward models.

Based on OS-Shepherd-100K, we train OS-Shepherd-9B and OS-Shepherd-35B with a recipe that directly targets the false success. As depicted in Figure 1, the OS-Shepherd models come nearest the reliable judges at 30–60$\times$ lower cost, putting a training-scale reward signal within an academic budget. Extensive analyses of what judges see and how their verdicts change across settings reveal when and where they remain unreliable. Evaluations on held-out benchmarks further confirm the generalization of the findings and the effectiveness of OS-Shepherd.

2 Related Work

Computer-using agents perceive digital environments and take actions to complete user tasks (OpenAI, 2025a; Wu et al., 2024; Sun et al., 2024), and standardized environments across web, mobile, and desktop (Chen et al., 2025b; Zhou et al., 2024; Kong et al., 2026) give them reproducible tasks. That reproducibility rests on hand-written verifiers, one per task. Evaluation and training in these

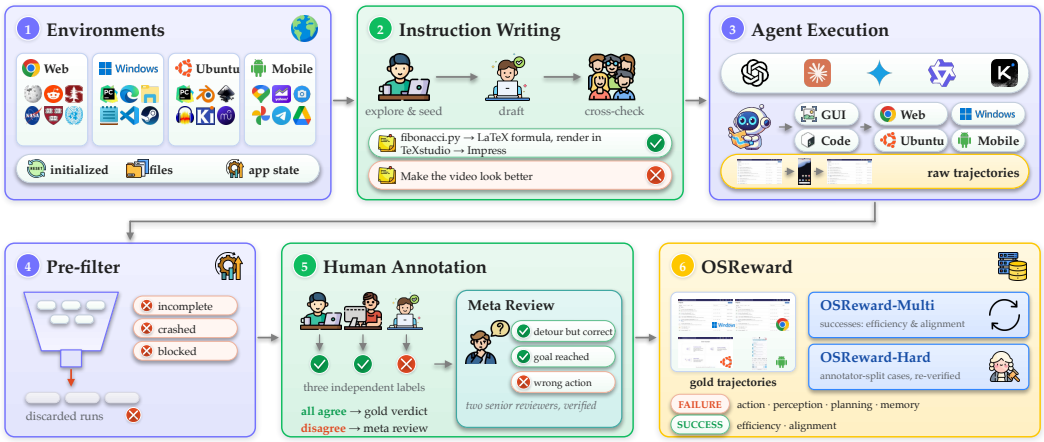


Figure 2: How OSReward is built: environments are prepared, instructions written and cross-checked, trajectories collected by agents, then labeled by three annotators with meta-review.

environments are outgrowing those verifiers: trajectory data is collected at scale (Qin et al., 2025; Xue et al., 2026b), policies are optimized with reinforcement learning over ever-longer interactions (Bai et al., 2024; Qi et al., 2024; Sun et al., 2025b), and agents are expected to self-evolve on synthetic experience (Zhang et al., 2026; Xue et al., 2026a; Jiang et al., 2026). Every stage of this pipeline consumes a reward signal. Judging a CUA trajectory is much more complex than judging text (Zheng et al., 2023a; Cobbe et al., 2021; Wang et al., 2024) or general multimodal responses (Chen et al., 2024; Li et al., 2025). An emerging line of work nevertheless puts a VLM judge in this role, as the reward model behind trajectory synthesis and data filtering (Sun et al., 2025a; Wang et al., 2026b; Zhang et al., 2025) and as the basis of trained reward models and critic-style autoraters (Chen et al., 2025a; Xiao et al., 2025; Li et al., 2026; Chae et al., 2025; Wu et al., 2026). Recent work has begun to examine the reliability of model-based reward (Lin et al., 2025; Lù et al., 2025), but these early efforts stay on single, isolated platforms and reuse off-the-shelf trajectories, although platforms differ in what a judge must read (Xue et al., 2025; Sun et al., 2026a). OSReward is, to our knowledge, the first to measure VLM-judge reliability across platforms on fresh, human-gold trajectories, and OS-Shepherd turns what it reveals into an open, low-cost reward model (extended discussion in § H).

3 OSReward

OSReward is a cross-platform benchmark for CUA trajectory judges, built from fresh trajectories collected on our infrastructure and labeled with human-annotated gold verdicts, as shown in Figure 2.

3.1 Data Infrastructure

The benchmark is only as good as the environments behind it. On desktop and mobile, we go well beyond stock benchmark images. Each machine carries the everyday applications a real user has. Every task starts from a rich state of user profiles, real files to edit, seeded app databases, and distractor content, so that success must change the environment rather than narrate completion. Our **Windows** environment is built out into a lived-in machine with some twenty everyday applications spanning IDEs, media editors, 3D and database tools, several with accounts already logged in, plus command-line utilities. Rollouts here stretch to a hundred steps. The **Ubuntu** machine comes fully initialized with about thirty daily and professional applications. A typed pool of real files, some twenty types with hundreds of files each, lets any task start from a rich state. The rollouts span both pure-GUI and GUI+CLI action spaces, with Python and shell tooling preinstalled. The **mobile** environment is an Android emulator initialized to the same depth, with signed-in accounts. **Web** tasks instead run on live websites through a pool of isolated Chromium sessions hardened against websites that resist automation, with purely vision-driven observation and action. Collecting everything on one infrastructure keeps judge scores comparable across platforms and gives a reward model one consistent trajectory format. More infrastructure details are provided in § A.

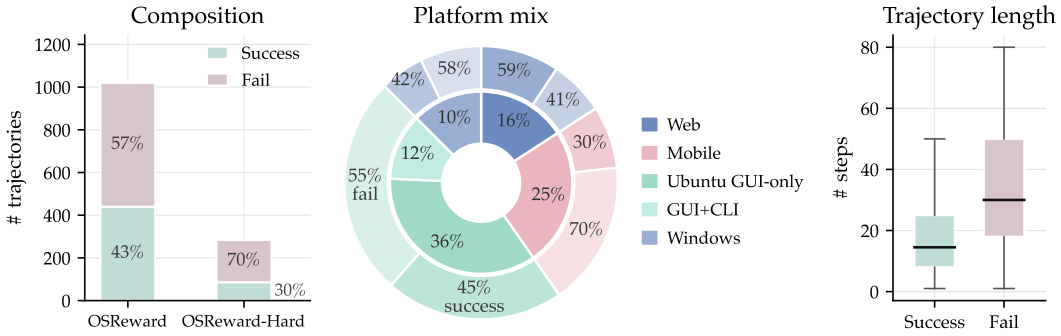


Figure 3: OSReward overview: outcome composition, platform mix, and trajectory length.

3.2 Task Instructions

An instruction must be grounded in what the environment offers and executable there, and the pool deliberately includes open-ended tasks that are difficult to verify with task-specific rules. Annotators write instructions after exploring the applications and environment states, ensuring that each task is grounded in a concrete and executable setting. Every draft passes a human validity check and a peer cross-check by annotators other than its author. Roughly 1500 candidates are considered, and about 800 survive into the next stage; only instructions that pass both checks enter the benchmark.

3.3 Trajectory Collection and Gold Annotation

Trajectories from Diverse Agent Backbones. A judge should be measured on trajectories from many agents. Each surviving instruction is rolled out by one to three agents from the Claude, Gemini, Kimi, and Qwen families, and the capability spread yields real successes and real failures. An automatic pre-filter discards runs with severe collection problems (persistent anti-bot blocks, network failures, frozen executions), so a FAIL in the benchmark reflects the agent failing the task.

Human Annotation. Every surviving trajectory is labeled on an in-house annotation website that replays its full multimodal context, every screenshot, thought, and action. We apply one deliberately strict standard. An answer the agent did not obtain or verify through the environment is a FAIL even when it happens to be correct, and the judging prompt carries the same rule. The target is therefore grounded task completion, including evidence of verification, rather than answer correctness alone. A trajectory judged SUCCESS is then scored on the two OSReward-Multi axes, (1) *alignment*, how well the actions matched the task intent (Sun et al., 2026a), and (2) *efficiency*, how free the run was of wasted steps. A trajectory judged FAIL is instead tagged with the errors that caused it, from a failure taxonomy spanning reasoning-and-planning, action, perception, and memory errors.

Consensus and Meta-Review. Every trajectory that passes the pre-filter is labeled independently by three annotators. Where they agree unanimously, the verdict is final. The trajectories they disagree on escalate to a *meta-review*, in which two senior reviewers each re-examine the trajectory and settle the final judgment, so no gold verdict rests on a single reader. The pass also discards trajectories with residual quality problems rather than force a label. Three-way annotation, meta-review, and the hard-set re-verification cost roughly 800 human hours.

3.4 OSReward and Its Variants

OSReward comes in three views. The full set is built for breadth and diversity across platforms, agents, and tasks. OSReward-Hard is derived from it as a compact challenge subset, and OSReward-Multi adds fine-grained ratings to its successful trajectories.

OSReward holds 1019 trajectories spanning all four platforms, roughly balanced between successes (43%) and failures (57%), as summarized in Figure 3. They are generated by agents from four model families across GUI-only and GUI+CLI action spaces, with trajectories ranging from roughly a dozen to 100 steps. Reasoning-and-planning errors dominate the failures, tagged on 86% of failed runs. Failed runs are also markedly longer than successful ones, potentially making them harder to verify.

OSReward-Hard is a challenge subset of 284 trajectories concentrating the hardest cases, drawn mainly from annotator disagreements and re-verified in an additional review pass. These trajectories often look successful from their records or involve convoluted execution paths, making the final outcome difficult to determine. The selection deliberately raises the share of failures (a 30/70 SUCCESS/FAIL split) to expose how easily existing judges are fooled by false successes.

Table 1: Judges on OSReward and OSReward-Hard under the main setting, sorted by full-set accuracy.

Judge	Access	OSReward				OSReward-Hard			
		Acc	sRec	fRec	BalAcc	Acc	sRec	fRec	BalAcc
Claude-Opus-4-8	closed	**89.7**	91.1	88.9	90.0	**69.7**	69.8	69.7	**69.7**
GPT-5.5	closed	89.5	91.8	87.8	89.8	67.3	66.3	67.7	67.0
Claude-Opus-4-6	closed	89.5	92.7	87.7	**90.2**	67.3	72.1	65.2	68.6
Gemini-3.1-Pro	closed	87.9	90.2	86.2	88.2	61.6	61.6	61.6	61.6
Gemini-3.5-Flash	closed	87.8	95.7	81.8	88.8	59.5	81.4	50.0	65.7
Claude-Sonnet-4-6	closed	87.7	97.5	80.3	88.9	59.2	90.7	45.5	68.1
GPT-5	closed	87.4	86.8	87.9	87.4	58.1	43.0	64.6	53.8
GPT-5.4	closed	87.1	87.3	87.0	87.1	63.0	62.8	63.1	63.0
Gemini-3-Flash	closed	87.0	96.6	79.8	88.2	57.0	86.0	44.4	65.2
GPT-5-mini	closed	86.1	93.8	80.2	87.0	56.3	79.1	46.5	62.8
Kimi-K2.5	open weights	85.9	95.5	79.2	87.3	54.8	83.7	42.1	62.9
Qwen3.5-397B-A17B	open weights	85.8	95.2	78.6	86.9	58.5	91.9	43.9	67.9
Claude-Haiku-4-5	closed	84.5	80.9	87.2	84.0	59.5	47.7	64.6	56.2
GPT-5.2	closed	83.9	73.0	**92.2**	82.6	63.0	30.2	**77.3**	53.8
Doubao-2.0-Lite	closed	83.3	98.5	72.1	85.3	45.5	96.1	24.3	60.2
GPT-5-nano	closed	82.3	97.0	71.1	84.1	45.4	95.3	23.7	59.5
Intern-S1-Pro	open weights	82.3	92.3	74.7	83.5	43.7	70.9	31.8	51.4
Qwen3.5-35B-A3B	open weights	82.2	92.4	74.5	83.5	51.1	83.7	36.9	60.3
GPT-4o	closed	81.0	96.8	69.0	82.9	39.4	90.7	17.2	53.9
Qwen3.5-122B-A10B	open weights	79.6	96.8	66.4	81.6	39.4	89.5	17.7	53.6
Qwen3.5-9B	open weights	76.7	**98.9**	59.9	79.4	39.4	**97.7**	14.1	55.9
OS-Shepherd-9B (ours)	open weights + data	86.1	86.6	86.0	86.3	60.2	66.3	57.6	61.9
OS-Shepherd-35B-A3B (ours)	open weights + data	85.6	85.0	86.2	85.6	62.7	68.6	60.1	64.3

OSReward-Multi. Beyond the binary verdict, the 440 successful trajectories carry human alignment and efficiency sub-labels that grade how well a successful run did its job, which no existing CUA-judge benchmark measures. Alignment and efficiency each use a three-level rubric. On both axes we report macro-recall, which the label skew cannot inflate. We release it as an exploratory track. More annotation details, the failure taxonomy, and the rubric are provided in § B.

4 Benchmarking VLMs as Judges

4.1 Experimental Setup

Models. The 27 judges span model series from GPT (Hurst et al., 2024; OpenAI, 2025b; 2026a;b), Claude (Anthropic, 2025; 2026a;b;c), Gemini (Comanici et al., 2025; Gemini Team, 2025), Qwen (Bai et al., 2025; Qwen Team, 2026), Doubao (ByteDance Seed Team, 2026), Kimi (Kimi Team et al., 2026), and Intern (Zou et al., 2026). The roster runs from closed frontier judges to small open VL models, and several models are additionally run in a thinking variant.

Protocol. Each judge receives the task instruction, the last N screenshots ($N = 5$ by default), and the full history of the executing agent's reasoning and actions. We use five trailing screenshots rather than the full visual history to keep evaluation costs manageable across judges. For click-like actions, the action location is highlighted with a red marker on the corresponding screenshot. Each judge returns a SUCCESS/FAIL verdict and, on OSReward-Multi trajectories, alignment and efficiency ratings. Our analyses further vary the screenshot selection and count, the action marker, and decoding. We report binary accuracy, success recall, failure recall, and balanced accuracy, defined as the mean of the two recalls. The model and evaluation details are in § C.

4.2 The Accuracy Ceiling

On OSReward, the strongest judges cluster around 90% binary accuracy. As shown in Table 1, Claude-Opus-4-8 reaches 89.7%, with GPT-5.5 and Claude-Opus-4-6 close behind. Their ordering changes under balanced accuracy, placing the three models in a similar performance range. Closed judges generally outperform open-weight models, with the largest gaps appearing among smaller open VLMs. Larger open-weight judges, *e.g.*, Kimi-K2.5 and Qwen3.5-397B, come within 4 pp of the best binary accuracy but still trail the leading closed judges. Open-versus-closed comparisons and complete results for all 27 judges are provided in § D.

4.3 The Leniency Bias

The Strict–Lenient Plane. Binary accuracy hides *how* a judge errs. Plotting each judge at its (fRec, sRec) makes the direction of error visible, as shown for OSReward-Hard in Figure 4a, and two

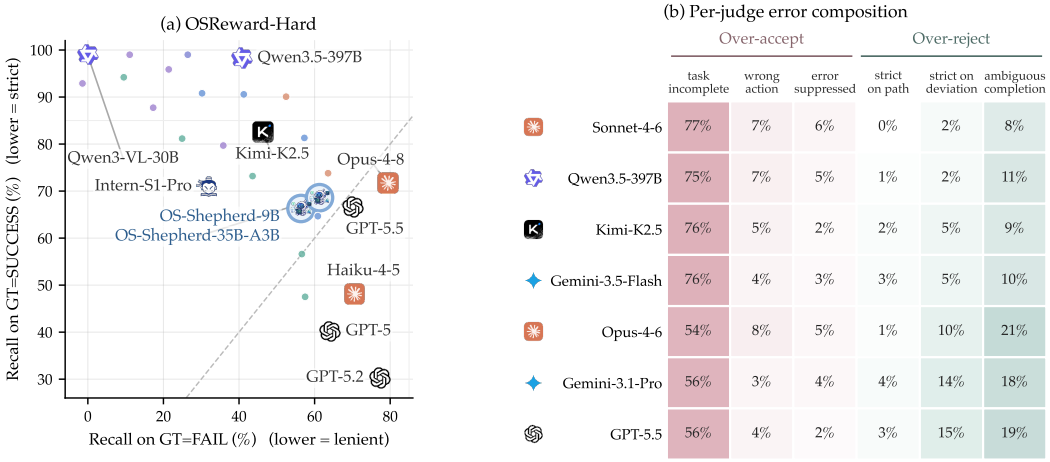


Figure 4: (a) Success and failure recall on OSReward-Hard and (b) the composition of judge errors: the field skews lenient, and over-accepting an incomplete task dominates every family.

clusters emerge. A large *lenient* cluster has high sRec but low fRec, accepting almost everything, while a smaller *strict* one (GPT-5.2, Claude-Haiku-4-5) trades success recall to catch more failures. The top judges sit near the diagonal (sRec = fRec), but they are few, and the field skews lenient.

The Dominant Error. We sort every incorrect verdict into *over-accepts* and *over-rejects*, as summarized in Figure 4b. One mode dominates: over-accepting an incomplete task makes up two-thirds of all errors and leads for every judge. Pooled across judges, over-accepts outnumber over-rejects three to one, and two to one among the strongest. Verdicts lean on the agent's narrative, as shown in § 5, so a failed run that ends with a success claim is what judges miss. De-biasing this one lenient mode is the highest-value intervention; the full-set plane is in § D.

4.4 OSReward-Hard: The Challenge Set

The Performance Collapse. OSReward-Hard drops every judge by 20–43 pp, as shown in Table 1. Even the best judge loses a full twenty points and lands at 69.7%, level with a constant always-FAIL judge. The mean judge falls to 52%. Raw accuracy is a trap here. The hard-set columns of Table 1 carry the recalls and balanced accuracy, where such a constant predictor falls to 50%. The collapse is also *structured*. Windows is the hardest platform to judge and mobile the easiest. The failure types that hinge on reading the screen, perception and then action, are markedly harder to catch than planning-and-reasoning failures, which are legible in the thought and action text.

Leniency Widens. The strict–lenient spread grows on the hard set, as shown in Figure 4a. Fail recall now runs from near zero to 77%. The lenient cluster, *e.g.*, Qwen3-VL-30B and Intern-S1-Pro, accepts almost every hard failure. The best judges, Claude-Opus-4-8 and GPT-5.5, stay balanced but only at ∼70% recall on each side, and a few cross into the strict half. Only Claude-Opus-4-8 and GPT-5.5 remain balanced and accurate; the few other judges near the diagonal keep their balance by giving up accuracy. An accurate judge that is neither too strict nor too lenient barely exists yet.

4.5 OSReward-Multi: Fine-Grained Grading

On OSReward-Multi, a judge additionally rates alignment and efficiency when it predicts SUCCESS; a predicted FAIL yields no rating on either axis. We report macro-recall to measure whether the emitted levels are usable as-is, and threshold-free AUC to measure whether the judge can rank the levels. Quality grading is far weaker than outcome judging, as shown in Table 2: the best judge falls from ∼90% on the binary verdict to the low sixties. Judges rank the levels better than they assign the exact ratings, suggesting that they preserve relative ordering information even when fine-grained level assignment remains difficult, especially on *alignment*. Our OS-Shepherd models inherit this weakness, the 35B recovering part of

Table 2: OSReward-Multi (%): macro-recall and AUC.

Judge	Macro-recall			AUC
	Align	Effic	Multi	
GPT-5.5	**58.7**	68.2	**63.5**	**66.7**
Claude-Opus-4-8	52.9	68.7	60.8	65.6
Claude-Sonnet-4-6	53.2	62.6	57.9	61.9
Gemini-3.5-Flash	47.6	**71.4**	59.5	60.8
OS-Shepherd-35B-A3B (ours)	47.7	65.8	56.8	60.7
OS-Shepherd-9B (ours)	44.1	54.0	49.0	58.5
Gemini-3-Flash	50.6	61.5	56.0	55.8

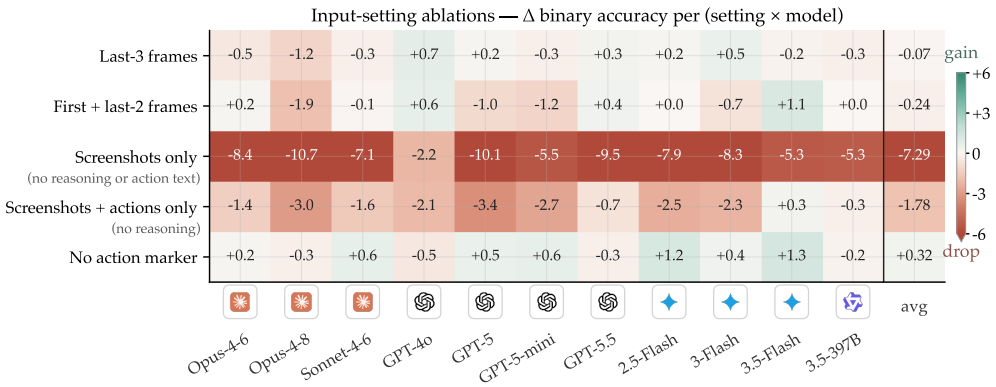


Figure 5: Input ablations: change in binary accuracy per setting and model against the main setting.

the gap. The binary verdict stays our primary metric; hard-set breakdown and scoring details are in § D, and case studies in § G.

5 Analysis: What Drives a Verdict

Text History Has the Largest Effect. One ablation dominates the rest, as shown in Figure 5. Dropping the per-step thought and action text costs 7.3 pp on average and several times that on the web, where typed strings carry intent the screenshots cannot encode. It also flips 22.7% of verdicts, three times what any visual change does. Dropping only the chain-of-thought is far milder (1.8 pp), so within the text the agent's actions carry more signal than its stated reasoning. This reliance on text history may help explain the leniency bias in § 4.3: judges may be misled by the executing agent's confident but unsupported completion claims.

Screenshots Still Matter. Visual evidence remains useful even when the full text history is available. With text history alone, mean full-set accuracy across the 11 tested judges is about 6.0 pp lower than under the main setting, as reported in § D.6. By contrast, Figure 5 shows that replacing the default last five screenshots with the last three or the first screenshot plus the last two changes mean binary accuracy by less than 0.5 pp, while removing action markers has similarly little effect. The sweep in Figure 15 further shows no consistent improvement beyond five trailing screenshots across the tested judges. The ablations also suggest a recipe for corpus annotation: retain the full text history, omit action markers, and use a small set of screenshots.

Inference-Time Scaling Offers Limited Gains. We conduct inference time scaling experiments, including increasing reasoning effort and repeated sampling. Increasing reasoning effort improves judging accuracy, but the gains are marginal for frontier models. A SOTA judge like GPT-5.5 sees a marginal accuracy improvement, moving from 88.99% with medium reasoning effort to 89.50% with high reasoning effort. In addition, combining repeated sampling also brings limited accuracy gain. A majority vote among the top three judges improves accuracy by only about one percentage point over the best single judge, at several times the cost. Although the result pool contains a correct verdict for nearly every case, majority voting often misses it because several judges agree on the wrong answer.

The Cost of a Reliable Verdict. The remaining option is to pay for a stronger judge. Accuracy and cost are in direct tension, sharpest on OSReward-Hard as depicted in Figure 1. Claude-Opus-4-8 holds 69.7% there at ∼$100 to judge the full set[1], while the best sub-$3 judge drops to 57.0%. On the full set the same trade-off looks benign, about 3 pp for a 42× price cut. At the millions of calls an RL run issues, even the frontier judges are out of reach: no input or inference setting buys reliability, and the judges that have it cost $45–100 per pass. We explore both the visual-input and the judge-setting effects further in § D, with per-model results and the full sweeps.

6 OS-Shepherd: An Open Reward Model

Reliable judging is unaffordable at the scale training demands, and the affordable judges stay lenient under every input and inference setting tested. We turn these findings into OS-Shepherd, an open-weight, open-data reward model aimed at the false-success problem and cheap to run at that scale.

[1]Costs use official API list prices where available; open-weight models without official pricing are priced at market rates (May 2026) for similar-size models.

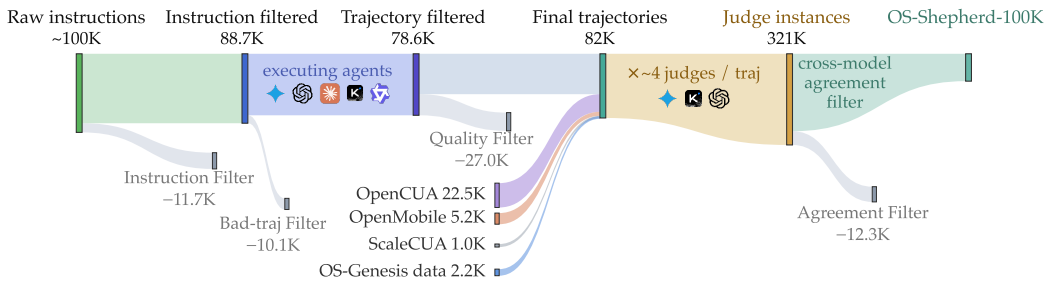


Figure 6: The OS-Shepherd-100K pipeline, from raw instructions to the agreement-filtered training set.

6.1 OS-SHEPHERD-100K

Training needs far more labels than human annotation can supply, so VLM judges label the corpus. Because judges herd, as shown in § 5, voting cannot sharpen a verdict; we instead select by agreement and discard the rest, so a trajectory enters OS-Shepherd-100K only when diverse strong judges independently reach the same verdict.

From Instructions to Annotated Trajectories. The pipeline, as illustrated in Figure 6, filters the self-collected instructions, executes them via agents within our infrastructure, and joins the surviving trajectories with selected open-source CUA trajectories (Sun et al., 2025a; Wang et al., 2026a; Cheng et al., 2026; Liu et al., 2026). The rollouts span five model families (Claude, Gemini, GPT, Kimi, Qwen) under varying harnesses, action spaces, screen resolutions, and step budgets, to reduce reliance on any single agent's execution style. The corpus covers web, Windows, macOS, Ubuntu, and Android, and about 46% of the Ubuntu data interleaves GUI actions with command-line steps. These trajectories are annotated by an ensemble of strong VLM judges using the screenshot configurations listed in Table 14. Agreement filtering retains about 85% of the judged trajectories, with per-stage counts shown in Figure 6.

Label Provenance and Negatives. Every sample carries a judge's *reasoning* alongside the verdict, which makes OS-Shepherd-100K the first large-scale reasoning-annotated judge corpus for cross-platform CUA trajectories. The retained reasoning is taken from a strong judge whose verdict agrees with the final label, keeping the rationale consistent with that label. Grounded FAIL trajectories, which a reward model must learn to reject, are scarce in open data, so we over-collect them. Corpus statistics, contamination check, and label-quality study are in § E.1.

6.2 TRAINING

OS-Shepherd is trained in two stages on OS-Shepherd-100K and judges under the same protocol as the reference judges, starting from Qwen3.5 (Qwen Team, 2026).

SFT Stage. We fine-tune the base VLM on the 96.6K agreement-filtered samples to judge under the main setting. SFT alone lifts OS-Shepherd-9B far above its Qwen3.5-9B base, primarily by correcting the base model's near-total leniency.

RL Stage. What SFT leaves behind is the *false success*, the judge study's dominant error and the harmful one for a reward signal, since it reinforces incorrect behavior. We mine approximately 3.1K trajectories, primarily ensemble-labeled failures for which the SFT judge disagrees with the label under greedy decoding but agrees with it in some sampled responses, for a short GRPO (Shao et al., 2024) pass. Rewards are computed against the ensemble-agreed labels: 1.0 for a correct verdict in the required format, 0.1 for an incorrect but correctly formatted verdict, and 0 for a format violation. RL primarily shifts the operating point rather than improving overall discrimination, sacrificing some success recall to better reject false successes. Training details are in § E.

6.3 EVALUATING OS-SHEPHERD

Both trained models appear in Table 1 beside the reference judges and the 9B's base.

Where OS-Shepherd-9B Lands. Trained end to end, the 9B moves from the bottom third of the field into the commercial band on the full set (86.1%). On OSReward-Hard it achieves 57.6% failure recall, which the cheap and lenient field misses almost entirely, while staying on the balanced diagonal; the only judges that match this are frontier models at many times its cost. At $1.36 to judge the full set, no other sub-$2 judge comes near it, and it leads the closest-priced commercial judge on OSReward-Hard at a third less cost, as shown in Figure 1. OS-Shepherd-35B-A3B follows the

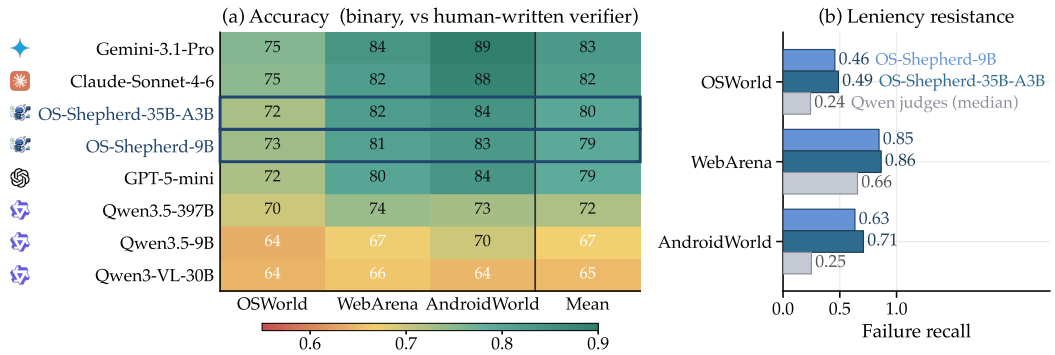


Figure 7: Judges on three existing benchmarks: (a) agreement with benchmark verifiers and (b) failure recall.

identical recipe and lands beside the 9B. Four times the parameters buy 2.4 pp of hard-set balanced accuracy and nothing on the full set, so what transfers is the recipe.

Cost at Training Scale. A reward model is queried throughout a training run, so even a small cost accumulates. For illustration, a training run with 200 updates, batch size 16, and 16 rollouts per example requires 51K judge calls. At OSReward's average trajectory cost that is about $4,000 with Claude-Opus-4-8 or $2,300 with GPT-5.5, against about $68 with OS-Shepherd-9B, priced at the market rate for a 9B model. That is a 30–60× reduction. With our data and recipe, a small open judge reaches the performance range of commercial judges on the full set, leads similarly priced judges on OSReward-Hard, and closes most of its base model's gap to the frontier. The full-set cost view is in § D.

7 Generalization to Existing Benchmarks

We run the same judges on AndroidWorld, WebArena, and OSWorld, three existing benchmarks held out from OS-Shepherd's training and OSReward, each against its human-written verifier.

Judges vs. Human-Written Verifiers. Agreement with human-written verifiers varies substantially across benchmarks, as shown in Figure 7a. The strongest judges approach ∼90% agreement on mobile, while performance is lower on web and desktop across judges. The verifiers are imperfect (Xie et al., 2025), and the desktop shortfall is the leniency bias described in § 4.3 appearing outside OSReward: judges accept failed runs as successes, mostly on long, complex tasks.

OS-Shepherd Transfers Across Benchmarks. The OS-Shepherd models are the best open judges on OSWorld and AndroidWorld and sit in the frontier cluster on WebArena, beating every general open model up to Qwen3.5-397B on all three, as shown in Figure 7a. What transfers is the de-biasing itself, as depicted in Figure 7b. Where successes dominate, on OSWorld and AndroidWorld, OS-Shepherd-9B catches far more true failures than any general Qwen judge, whose median sits near "always SUCCESS." WebArena inverts the base rate, so an over-lenient judge scores *below* the trivial all-FAIL baseline. The resistance comes from training, since general Qwen judges stay lenient from 30B to 397B while the 35B model on the identical recipe lands beside the 9B. A single 9B trained on none of these benchmarks thus carries its de-biasing across all three at training-time cost. The held-out provenance and the OSWorld analysis are in § F.

8 Conclusion

We introduce OSReward, a cross-platform benchmark built from freshly collected, human-annotated computer-use trajectories, with hard and fine-grained evaluation tracks. Our evaluation reveals systematic over-acceptance of failed trajectories across model families, particularly on challenging cases. Guided by these findings, we construct the reasoning-annotated OS-Shepherd-100K corpus and train OS-Shepherd through SFT and targeted RL, including 9B and 35B models. The resulting models narrow the accuracy gap to frontier judges at substantially lower inference cost, with reduced leniency transferring to held-out benchmarks. By releasing the benchmark, corpus, and models, we provide both a standardized basis for studying judge failures and practical resources for building more reliable, affordable computer-use reward models.

Ethics Statement

OSReward releases trajectories that include screenshots of live websites and of logged-in accounts. Every trajectory admitted to the benchmark was checked for personally identifiable information during the human annotation passes, and none enters the release, as described in § B.2. Gold labels were produced by computer-science graduate students and experienced CUA researchers working on the in-house annotation platform described in § B.1. Trajectory collection ran in isolated virtual machines and browser sessions, so agent actions could not affect real user accounts beyond the accounts we created for collection; live-website collection followed per-domain pacing and dropped sites that persistently refuse automation, as described in § A.1. A reward model that is systematically lenient can reinforce incorrect agent behavior at training time; OS-Shepherd is released with its training corpus and evaluation so that this failure mode can be measured rather than assumed away. All annotators and meta-reviewers were fairly compensated for their work.

Reproducibility Statement

The benchmark construction is described in § 3 with the per-stage funnel, agreement statistics, and annotation rubric in § B; the collection infrastructure and action spaces are in § A. The judging protocol, the exact prompt, and every evaluated model with its API identifier and thinking setting are in § C. OS-Shepherd's corpus statistics, contamination check, and the full SFT and RL configuration (data sizes, learning rate, rollouts, KL coefficient, frameworks, hardware) are in § E. The benchmark, the OS-Shepherd-100K corpus, the model checkpoints, and the evaluation code will be released; an anonymous copy is available at https://anonymous.4open.science/r/OSReward/.

AI Use Statement

In this work, we used generative AI tools for refining the writing, including grammar and spelling corrections. Additionally, we used generative AI tools for coding assistance. We also used VLMs for instruction synthesis and automated trajectory annotation, as described in the methodology. The authors reviewed and take responsibility for the research design, experiments, analysis, claims, and final presentation.

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A Data-Collection Infrastructure

This appendix expands § 3.1. Collection on every platform runs through the same course (realistic environment, grounded instructions, rollout by executing agents, and automatic verification); here we give each platform's environment back-end and its concrete instruction and verification implementation. An *executing agent* is the agent that operates the environment and produces a trajectory: a model backbone driving that platform's action space through the platform's own harness, with the action spaces listed in Tables 3, 4 and 6; the backbones used are listed per platform below. The executing agents follow the ReAct-style loop and its variants (Yang et al., 2026; Cheng et al., 2026), which we adopt to collect the longer-horizon and more complex trajectories the judge study needs. The same infrastructure produces two disjoint datasets: the human-verified OSReward evaluation trajectories described in § 3 and the larger, ensemble-labeled OS-Shepherd training corpus introduced in § 6. For each platform we give the environment and software coverage, the instruction method, the trajectory collection, and how the two datasets are drawn from it.

Why Own Infrastructure. Building the environments ourselves affords coverage far beyond reused trajectories: more applications, websites, and scenarios, spanning both pure-GUI and GUI+CLI workflows. Platforms differ in what a judge must read: action spaces, the applications and websites in play, and run lengths from around a dozen steps on mobile to a hundred on desktop. Rich initialization is what makes a trajectory worth judging: realistic state to fail from, success that must change the environment rather than narrate completion, and concrete state for a machine-checkable verifier to inspect. Collecting everything on one infrastructure also keeps the output uniform, so judge scores stay comparable across platforms and a reward model sees one consistent trajectory format.

A.1 Web

Environment. The web environment is a Playwright browser service with one isolated, headless-Chromium session per rollout. We collect at a 1920×1080 viewport, while the configurable backend also supports higher resolutions such as 2560×1440; a stealth plugin helps reduce automation blocking. Observation and action are screenshot- and coordinate-driven rather than DOM-id-driven. The agent receives a screenshot and emits visual coordinates, which we normalize and map to viewport pixels through model-specific adapters (Gemini uses 0–1000 relative boxes, Qwen uses relative points, and Claude and Kimi use screenshot-pixel coordinates). The action space spans pure-GUI primitives, browser primitives, and a terminal `stop` action, as listed in Table 3; `max_actions` defaults to 15 and rises to 30 for harder tasks. Rollouts split between pure-GUI actions and GUI plus browser primitives, so the reward model sees visual agents and API-mixing agents alike. Unlike the desktop and mobile platforms, the web side needs no environment initialization: collection runs on the live, open internet, whose realism no snapshot reproduces, and sites that persistently block automation are dropped by the pre-filter. A pool of Chromium-based browser workers hosts many isolated sessions in parallel, one per web rollout; browser-level hardening and per-domain pacing mitigate blocking by websites that resist automation, and low-quality runs are screened out afterward, supporting reliable collection at scale. To collect data for tasks requiring user logins, we also use several self-hosted local mirror websites.

Collection and Robustness. Instructions are drawn, with pre-filtering, from existing large-scale web-task pools (Trabucco et al., 2025), plus an *OS-Genesis data* split: following the OS-Genesis setup (Sun et al., 2025a), we re-collect trajectories with Gemini-3-Flash on its self-hostable sites (Zhou et al., 2024). Across a pool of browser workers, collection executes many rollouts in parallel, each in an isolated session with no browsing state shared across trajectories. No instruction or trajectory is taken from any existing benchmark's test set; those test sets serve purely as held-out evaluation in § 7. The source of an instruction does not determine its inclusion in the benchmark. Every instruction in the OSReward web split undergoes the human vetting and peer cross-checking described in § 3.2. The remaining machine-generated instructions feed exclusively into the OS-Shepherd training corpus. Furthermore, because the platform installs no applications, its coverage is defined by the diversity of its tasks rather than an application roster (see Table 5 for the other three platforms). Figure 8 profiles the roughly 32K filtered instructions submitted for collection: the twenty most frequent task types, about 65% of the pool, span article reading, fact lookups (cost, availability, contacts, dates, opening hours), academic-paper, shopping, and library tasks. Task types follow InSTA's

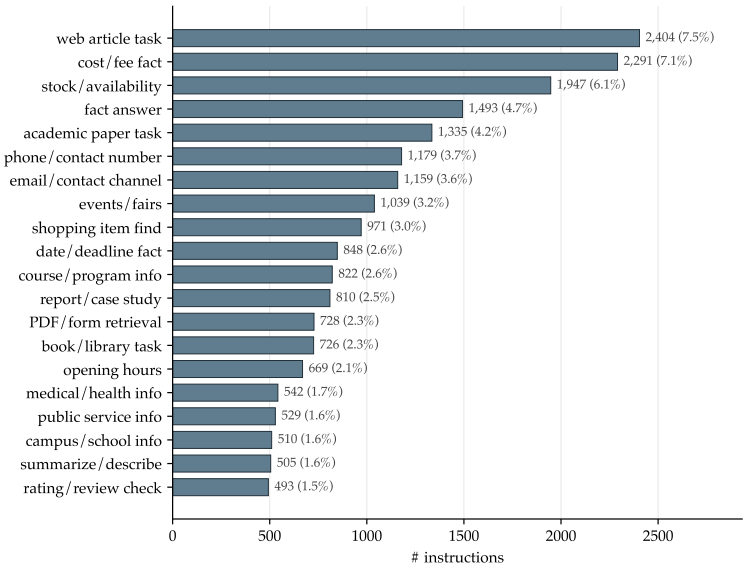


Figure 8: The twenty most frequent task types among the roughly 32K web instructions sampled for collection, together about 65% of the pool. Fact-finding lookups dominate, followed by article, academic-paper, and shopping tasks.

automatic categorization procedure with light post-processing. For large-scale online collection, rule-based safeguards inspect the initial page and every subsequent step for CAPTCHAs, bot-challenge interstitials (including those associated with Cloudflare, Akamai, and DataDome), access-denied pages, login walls, and rate limits. A blocked search engine triggers a fallback to another search engine. A target-site block encountered after a rollout begins triggers backtracking; the task is marked as blocked only when no recovery path remains. Per-domain concurrency limits and cooldowns reduce repeated blocking, while screenshot retries and page-stability checks guard against incomplete or stale observations. After collection, we bucket each trajectory (`valid_candidate`, `blocked`, `env_error`, and others), assign it a rule-based quality score, and remove near-duplicates.

A.2 WINDOWS

Environment. Our Windows environment extends existing works' virtual machine setting (Bonatti et al., 2024) with about twenty everyday applications and common command-line tools such as `ffmpeg`, toward a machine a real user would recognize. The collected data exercises twenty-three applications, from browsers and meeting clients to IDEs and media tools, with the full coverage listed in Table 5. To enhance sample diversity, we switch between 2K and 4K resolutions during the data collection process.

Instructions and Collection. Instructions come from a *data flywheel*. We initialize each application with human-written seed instructions, which are screened for completability and a balanced difficulty distribution, and collect their corresponding trajectories. Each later round samples two or three consecutive prompt–screenshot steps from the collected trajectories, has Gemini-3.1-Pro write two or three new instructions grounded only in what those steps show, embeds and clusters the instruction pool to drop near-duplicates, and collects again until a target count is reached. Trajectories are rolled out by four agents based on the WindowsAgentArena and OSWorld harnesses, under a mainly GUI action space with text entry and a 50/100-step cap. In numbers, 5,000 initial instructions filter to 2,192 high-quality ones; rolling these out collects 2,007 trajectories (187 runs fail), and post-processing keeps 1,511 for training. Step counts are long-tailed (a large share run to the 100-step cap), and the action stream is dominated by mouse moves and keyboard input. This flywheel operates at training scale; its trajectories feed the OS-Shepherd Windows split. The OSReward Windows benchmark's 105 human-verified trajectories instead follow the annotator-written, peer-checked route of § 3.2. The Windows action space is listed in Table 4.

Table 3: Action spaces of the executing agents on web (left) and mobile (right). On web, the second block lists the browser primitives and the third the terminal action.

Action	Description
`click [coord]`	Clicks at the specified screen location.
`double_click [coord]`	Double-clicks at the specified screen location.
`hover [coord]`	Moves the pointer to the specified screen location.
`scroll [up/down]`	Scrolls the screen in the specified direction.
`drag [coord] [coord]`	Drags from the first coordinate to the second.
`type [text]`	Types text at the current cursor location.
`fill [coord] [text]`	Clicks at a location, clears its content, and types text.
`clear [coord]`	Clicks at a location and clears the current text input.
`hotkey [keys]`	Presses the specified key or key combination.
`wait [seconds]`	Waits for the page to load.
`goto [url]`	Navigates directly to a URL.
`go_back`	Navigates to the previous page in browser history.
`go_forward`	Navigates to the next page in browser history.
`select_option [coord] [text]`	Selects text from the dropdown at a screen location.
`set_checked [coord] [bool]`	Sets the control state at a screen location.
`stop [answer]`	Terminates the episode and returns the final answer.

Action	Description
`click`	Clicks at the target elements.
`long_press`	Presses and holds on the target element.
`type`	Types the specified text at the current cursor location.
`scroll`	Scrolls in a specified direction on the screen.
`navigate_home`	Navigates to the device's home screen.
`navigate_back`	Returns to the previous screen or page.
`open_app`	Launches the specified application.
`wait`	Agent decides it should wait.
`terminate`	Agent decides the task is finished.
`keyboard_enter`	Presses the Enter key.

A.3 UBUNTU

Environment. Building upon existing virtual machine and application setups (Xie et al., 2024; Sun et al., 2026b), our Ubuntu environment incorporates about thirty everyday and professional applications across multiple domains, including development, documentation, graphics, media, scientific research, and personal tools, as listed in Table 5. It also integrates common CLI and Python tooling such as `python-docx`, `python-pptx`, and `ffmpeg`. To provide tasks with realistic starting states, we construct a categorized file pool covering roughly twenty common file types associated with the installed applications (`.docx`, `.pptx`, `.xlsx`, `.mp3`, `.png`, `.mp4`, `.pdf`, `.tex`, `.svg`, `.blend`, `.dxf`, code repositories, and more). For each type, we sample 100–500 real files from established public benchmarks and corpora, including TableBench for spreadsheets, DocVQA-derived PDFs, WorldVQA images, MMAU audio, SWE-Bench repositories, arXiv LaTeX sources, and PolyHaven / BlenderBench 3D scenes, and organize them by type under a shared root directory.

Generate-as-Verify Instructions (Training Scale). To reach training scale beyond the annotator-written benchmark pool described in § 3.2, Ubuntu instructions are also generated automatically. Each generation initializes an application (and, when needed, a file) from the pool, then gives Gemini-3.1-Pro the initialized screenshot, a short per-app tutorial, and a constrained prompt that requires absolute file paths, a spread of estimated-step difficulties, and a machine-checkable verifier per task.

Table 4: Action space of the executing agents on Windows, with each action's parameter format.

Action	Parameter specification
`computer.mouse.move_abs`	**Format:** `[x,y]` **Details:** Move the mouse to a normalized screen position; `x`, `y` are floats.
`computer.mouse.single_click`	**Format:** `[]` **Details:** Single-click at the current mouse position.
`computer.mouse.double_click`	**Format:** `[]` **Details:** Double-click at the current mouse position.
`computer.mouse.right_click`	**Format:** `[]` **Details:** Right-click at the current mouse position.
`computer.mouse.scroll`	**Format:** `[direction]` **Details:** Scroll the screen up or down; `direction` is a string.
`computer.mouse.drag`	**Format:** `[x1,y1,x2,y2]` **Details:** Drag from the current mouse position to the target normalized position; coordinates are floats.
`computer.keyboard.write`	**Format:** `[text]` **Details:** Type the given text.
`computer.keyboard.press`	**Format:** `[key]` **Details:** Press a keyboard key such as Enter or Delete.
`computer.os.open_program`	**Format:** `[program_name]` **Details:** Open the specified application.
`computer.window_manager.switch_to_application`	**Format:** `[window_name]` **Details:** Switch to the specified open window or application.
`computer.wait`	**Format:** `[time]` **Details:** Wait for the given number of milliseconds (`time` is an integer).
`COMMAND`	**Format:** `[]` **Details:** Output and execute a Python code block for the current step.
`ANSWER`	**Format:** `[answer]` **Details:** Return the specific answer text for the given prompt.
`DONE`	**Format:** `[]` **Details:** The task is finished; end the episode.
`FAIL`	**Format:** `[]` **Details:** The task cannot be completed; end the episode.

The model emits three to five structured task files, each with an `instruction`, an environment `config`, and an `evaluator`. A verifier is either rule-based (an OSWorld-style Python function that reads VM files via `vm_file` or command output via `vm_command_line` and returns a score in $[0, 1]$) or VLM-based (a flag plus a textual hint of what the judge should inspect) for states that no file exposes; the two can be combined. We then filter each batch in four stages: a second-model quality check, embedding-based deduplication (cosine similarity above 0.8), a static compile check of every rule function, and a runtime check that executes it. These synthesized instructions, including the reverse-synthesized share of § 6.1, are additionally screened with strict checks against the benchmark's instruction set, ruling out training-data contamination toward OSReward, as verified in § E.1.

Collection. Trajectories are rolled out by Claude-Sonnet-4-6, Claude-Opus-4-6, Qwen3-VL-235B, and Gemini-3.1-Pro (the first three via their official computer-use agents, Gemini via one built to its public spec), under a 50–80-step cap and a GUI+CLI (Python or Bash) action space (Yang et al., 2026); pure-GUI Ubuntu trajectories in the training mix are sourced from the open-source datasets listed in Table 13, exposing the reward model to both purely visual and code-assisted executions. With Python and shell tooling preinstalled, rollouts split between a pure-GUI and a GUI+CLI action space, making Ubuntu the platform where visual and code-mixed agent styles meet. This generate-as-verify collection feeds the OS-Shepherd Ubuntu training split, alongside the open-source sets

Table 5: Application coverage of the collection infrastructure on Ubuntu, Windows, and Android, grouped by function; applications marked with * require a signed-in account. The web platform runs on live websites rather than installed applications, as described in § A.1.

Platform	Group	Applications
Ubuntu	Web & communication	Chrome, Thunderbird, Zoom*
	Development	VS Code, PyCharm, GitKraken, DBeaver, Wireshark, Meld, terminal
	Documents	LibreOffice Writer / Calc / Impress, TeXstudio, PDF Arranger, Zotero, Calendar
	Graphics & design	GIMP, Blender, Inkscape, Krita, Darktable, LibreCAD, KiCad, draw.io
	Media	VLC, Audacity, Mixxx, HandBrake, Shotcut, OBS Studio, MuseScore, Spotify*
	Scientific	Scilab, KAlgebra, GRASS GIS, Google Earth Pro, ChimeraX, Celestia
	Personal	HomeBank
Windows	Web & communication	Chrome, Microsoft Edge, Thunderbird, Feishu*, Discord*, Zoom*, Tencent Meeting*
	Development	VS Code, PyCharm, DBeaver
	Documents	Notepad, PDF Arranger, Zotero
	Graphics & design	Blender, Krita, draw.io
	Media	VLC, Shotcut, HandBrake, Spotify
	Utilities	File Explorer, Calculator
	Personal	Steam*
Android	Web & communication	Browser, Firefox, Gmail*, SMS, Contacts
	Documents	Markor, Google Keep*, Calendar
	Graphics & design	Draw
	Media	Camera, Gallery, Google Photos*, Audio Recorder, VLC, Retro Music
	Maps & navigation	OsmAnd, Google Maps
	Personal	Expense, Recipe, Yahoo Finance
	Utilities	Files, Clock, Calculator, and system tasks

listed in Table 13; about 46% of that split (its entire self-collected share) interleaves GUI actions with command-line steps, as shown in Table 12. The OSReward Ubuntu benchmark trajectories, the largest platform split, instead trace to the annotator-written, peer-checked instructions introduced in § 3.2, rolled out and human-verified as gold, as described in § 3.3. The Ubuntu action space is listed in Table 6.

A.4 ANDROID

Environment. The Android environment we built extends AndroidWorld's (Rawles et al., 2025) default applications in Pixel 6a with more everyday apps (Firefox, Gmail, Google Maps, Google Keep, Google Photos, Yahoo Finance, and a calculator; Table 5 lists the full coverage), each with a scripted initial state that seeds databases, files, and synced accounts (a registered account operated under human supervision) together with distractor content to ensure non-trivial task difficulty. Within our collection environment, we initialize the files, usage records, and databases of every application; this initialization includes randomly seeded records, browsing history, and photos, along with distractor content (noise events, decoy messages, look-alike files) to expand the exploration space further, and login-required applications come signed in with synced content.

OSReward Benchmark Data. The benchmark mobile trajectories are collected in our own Android virtual machine. Instructions comprise four categories: native-app tasks with human annotations and auto-verifiers, single-app and multi-app tasks on newly added applications, and a specialized subset with explicit negative constraints. An initial pool of 415 raw instructions is filtered down to 226 high-quality prompts. Executing these instructions with Gemini-3-Pro, Gemini-3.1-Pro, Gemini-3-Flash, and Qwen3-VL-235B yields 321 raw trajectories, from which the final human-verified mobile benchmark is curated. Incomplete rollouts caused by environment freezes, lost ADB connections, or host memory limits are discarded prior to human annotation.

Table 6: Action space of the executing agents on Ubuntu, with each action's parameter format.

Action	Parameter specification
`click`	**Format:** `[desc,num_clicks,button,hold_keys]` **Details:** Target element description; clicks number; button to click; keys to hold.
`type`	**Format:** `[desc,text,overwrite,enter,terminal]` **Details:** Target element description; text content; overwrite flag (bool); press enter after typing (bool); terminal flag (bool).
`scroll`	**Format:** `[desc,clicks,shift]` **Details:** Target element description; clicks (+up/−down); shift for horizontal scroll (bool).
`drag_and_drop`	**Format:** `[start_desc,end_desc,hold_keys]` **Details:** Descriptions for start/end locations; keys to hold during drag.
`hotkey`	**Format:** `[keys]` **Details:** List of keys to press in combination (e.g., ['ctrl', 'c']).
`hold_and_press`	**Format:** `[hold_keys,press_keys]` **Details:** Keys to hold down while pressing a sequence of other keys.
`open`	**Format:** `[app_or_filename]` **Details:** Name of the application or file to open.
`call_code_agent`	**Format:** `[task]` **Details:** A self-contained goal executable via code (e.g., data analysis, file processing).
`wait`	**Format:** `[time]` **Details:** Time to wait in seconds.
`done`	**Format:** `[]` **Details:** Signals successful completion of the entire task.
`fail`	**Format:** `[]` **Details:** Signals that the task is impossible to complete.

OS-Shepherd Training Data. Unlike the other three platforms, the mobile *training* data is not collected through our pipeline. It reuses the open-source OpenMobile collection (Cheng et al., 2026), built around the AndroidWorld infrastructure: environments are initialized from random seeds, instructions are synthesized by exploring that environment and composing long-horizon tasks, and each instruction is rolled out by a deliberately mismatched agent pair, Gemini-3.1-Pro as the strong model and Qwen2.5-VL as the weaker open one. The capability gap is intentional: the pairing yields roughly 1,000 of the false-success samples that the RL stage described in § E.2 feeds on, with a ∼6:4 SUCCESS:FAIL split at an average of about 13 steps. The mobile action space is listed in Table 3.

B OSReward Details

This appendix expands §§ 3.3 and 3.4: who labeled the data, the construction funnel in numbers, the failure-type taxonomy, and the OSReward-Multi rubric.

B.1 Annotators

The gold verdicts are produced by six annotators, all computer-science graduate students with working familiarity with computer-using agents, together with three meta-reviewers who are experienced CUA researchers. Before labeling commenced, annotators partitioned the platforms and directly interacted with the environments, ensuring all verdicts are firmly grounded in first-hand knowledge of application capabilities. Labeling was conducted on a custom-built platform that replays trajectories step-by-step, requiring annotators to both select a verdict *and* explicitly write their underlying reasoning. Recording the reasoning both discourages snap judgments and gives the meta-reviewers something concrete to adjudicate when annotators disagree. Every trajectory that clears the pre-filter is labeled independently by three annotators, with disagreements escalated to the meta-review described in § 3.3; annotation, meta-review, and the hard-set re-verification together cost roughly 800 human hours.

B.2 Annotation Pipeline and Statistics

Stages 4–6 of Figure 2 illustrate the annotation pipeline of § 3.3 and Figure 3 in the main text summarizes the resulting gold set; we detail the quantitative statistics of the construction funnel here. Annotators may brainstorm instructions with AI tools or software manuals, but every draft, whatever its origin, passes a human validity check and the peer cross-check of § 3.2. This pipeline has no exceptions: the long cross-application tasks, the hardest to specify because one instruction must stay grounded in several applications at once, are authored and screened like every other candidate rather than synthesized. Approximately 1500 candidate instructions are authored and cross-checked, with about 800 passing peer screening for machine collection. Only instructions that pass both checks enter the benchmark: an evaluation item must be individually trustworthy, a bar training data need not meet. Each instruction is then rolled out by one to three executing agents detailed in § A; backbones differ in action idiom, thought verbosity, and failure modes, so spreading the rollouts across the pool keeps the benchmark from reducing to one agent's interface style, and the capability spread yields the labeled failures that judge evaluation otherwise lacks. Gold labels bound what the study can conclude, so every surviving trajectory is labeled by human effort. Collection at this scale is noisy in ways that have nothing to do with agent ability: live websites are unstable and throttle or block automation behind anti-bot checks and reCAPTCHA, and an agent's own actions can crash an application or leave the collection system unresponsive. The automatic pre-filter described in § 3.3 eliminates these corrupted runs, ensuring that the remaining 1128 trajectories rigorously evaluate agent performance rather than infrastructural stability. Only persistently blocked runs are discarded. Trajectories where the agent successfully overcomes an initial block via retries are retained as valid; accordingly, the judging prompt in § C.2 retains a specific evaluation rule for persistent blocks. In the initial independent annotation pass, the three annotators agree unanimously on 75.0% of the 1,128 trajectories, with 83.3% pairwise agreement. The remaining 282 trajectories (25.0%) are escalated to meta-review. These statistics describe the initial annotations, before meta-review and the subsequent OSReward-Hard re-verification. The pass discards 109 trajectories (about 10% of the annotated pool) for residual quality problems rather than force a label, leaving the 1019-trajectory gold set (440 SUCCESS / 579 FAIL).

The OSReward-Hard selection runs an additional review pass over a broader candidate pool. Of 373 candidates re-examined in this pass, 284 are retained and 89 are returned to the full set based on the review outcome and the desired platform and SUCCESS/FAIL composition of the challenge subset. The pass also corrects the SUCCESS/FAIL label on 18 trajectories that had simply been labeled wrong. This additional review corrects identified labeling errors and retains cases assessed by senior reviewers as genuinely challenging. Every candidate is re-verified under this further review process, especially the fail cases. The subset's role is diagnostic: these runs briefly fooled even trained annotators, and together they expose the error modes judges share and how much room remains above the best current judges.

Release Compliance. The released trajectories include screenshots of live websites and of logged-in accounts (e.g., Steam). As part of the human annotation passes, every trajectory admitted to the benchmark was checked for personally identifiable information, and none enters the release.

B.3 Failure-Type Taxonomy

Every trajectory judged FAIL is tagged by the annotators with one or more failure types, as described in § 3.3; extended trajectories may accumulate multiple such errors. *Reasoning-and-planning errors*: the agent perceives the environment correctly but cannot form a sound high-level plan; this covers wrong task decomposition, logical fallacies, missing domain knowledge of the target software, premature termination, and repetitive action loops. The thinking itself is at fault, even with the full history available. *Action errors*: the plan and the target element are correct, but the intention is not translated into precise low-level commands; typical cases are inaccurate grounding coordinates, wrong keystrokes or hotkeys, and invalid action syntax. *Perception errors*: visual information is extracted, interpreted, or monitored incorrectly; the agent hallucinates interface elements, misses critical cues such as loading states or error pop-ups, or misreads on-screen text. *Memory errors*: information acquired earlier in an extended trajectory is not properly retained, recalled, or updated, so later actions contradict the agent's own history or repeat work already done. A fifth tag, *others*, is the catch-all for failures the agent did not cause: external factors, non-deterministic system behavior,

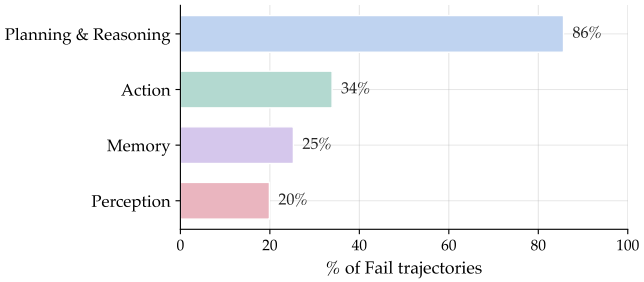


Figure 9: Failure-type profile over OSReward's FAIL trajectories (multi-label shares; the catch-all *others* tag is excluded). A single run can carry several tags.

or unrecoverable environment states beyond the agent's expected fault tolerance. It is not a semantic error type and is excluded from the four-type profile of Figure 9.

B.4 OSReward-Multi Scoring Guideline

Alignment and efficiency are scored only on SUCCESS trajectories, since both metrics assess the execution quality of completed tasks, as defined in § 3.4. Each axis uses a three-level rubric.

Alignment. Whether every action strictly serves the user's true intent: no drift from the objective, no hallucinated interactions such as clicking interface elements irrelevant to the task, no violation of explicit or implicit constraints, and no unsafe behavior.

- **1** Every action serves the task directly, with no out-of-intent behavior and no change to user state beyond what the task required.
- **0.5** One or two minor out-of-intent actions with transient or negligible side effects (e.g., an accidental click on an advertisement, temporarily adding an item to a cart, or briefly archiving an email) that are resolved by the end of the execution. Any unreversed state changes are penalized as lasting effects.
- **0** A clear intent violation with an actual, lasting effect on the user, even when the task itself succeeds, such as deleting mail the instruction only asked to read.

Efficiency. The conciseness and optimality of the path to the goal.

- **1** A near-expert path: exhibits no redundant scrolling, hovering, or window switching, and proactively leverages obvious shortcuts (e.g., search boxes or basic hotkeys) whenever available.
- **0.5** The correct path is found with visible redundancy or minor trial-and-error, such as opening a wrong menu before the right one or reaching a distant control through many short scrolls.
- **0** The path is dominated by invalid trial-and-error, repeated actions, or long detours (cycling between windows, opening every top-level menu in turn), even if the task ultimately succeeds.

C Experimental Details

This appendix expands § 4.1: the evaluated models, the judging prompt, the judge error categories of Figure 4b, and how OSReward sits beside prior CUA reward work.

C.1 Evaluated Models

Table 7 lists every judge in the study with its API identifier. All 27 reference judges and our OS-Shepherd models run under the identical main setting of § 4.1 (fixed prompt, last five screenshots, full text history, greedy decoding); the results in Table 1 come from these runs. Full-set accuracy uses all 1,019 trajectories, with unscored runs counted as errors. Success and failure recall use successfully scored trajectories within their respective gold-label classes. The analysis sections reuse these models while varying only a single control variable at a time. For instance, Claude-Opus-4-6 and Claude-Sonnet-4-6 are evaluated at two adaptive-thinking settings (*xhigh* vs. *max*), the two Qwen

Table 7: All evaluated models: the 27 reference judges (top, by full-set accuracy) and our reward models. The last column lists the extra thinking or reasoning-effort levels beyond the main setting; access classes are in Table 1.

Judge	API identifier	Thinking levels
Claude-Opus-4-8 (Anthropic, 2026b)	`claude-opus-4-8`	—
GPT-5.5 (OpenAI, 2026b)	`gpt-5.5`	medium/high/xhigh
Claude-Opus-4-6 (Anthropic, 2026a)	`claude-opus-4-6`	xhigh/max
Gemini-3.1-Pro (Gemini Team, 2025)	`gemini-3.1-pro-preview`	—
Gemini-3.5-Flash (Gemini Team, 2025)	`gemini-3.5-flash`	—
Claude-Sonnet-4-6 (Anthropic, 2026c)	`claude-sonnet-4-6`	xhigh/max
GPT-5 (OpenAI, 2025b)	`gpt-5`	—
GPT-5.4 (OpenAI, 2026a)	`gpt-5.4`	—
Gemini-3-Flash (Gemini Team, 2025)	`gemini-3-flash-preview`	—
GPT-5-mini (OpenAI, 2025b)	`gpt-5-mini`	—
Kimi-K2.5 (Kimi Team et al., 2026)	`kimi-k2.5`	—
Qwen3.5-397B-A17B (Qwen Team, 2026)	`qwen3.5-397b-a17b`	two settings
GPT-5.4-mini (OpenAI, 2026a)	`gpt-5.4-mini`	—
Claude-Haiku-4-5 (Anthropic, 2025)	`claude-haiku-4-5-20251001`	—
GPT-5.2 (OpenAI, 2025b)	`gpt-5.2`	—
Gemini-2.5-Flash (Comanici et al., 2025)	`gemini-2.5-flash`	—
Doubao-2.0-Lite (ByteDance Seed Team, 2026)	`doubao-seed-2-0-lite-260428`	—
GPT-5-nano (OpenAI, 2025b)	`gpt-5-nano`	—
Intern-S1-Pro (Zou et al., 2026)	`intern-s1-pro`	—
Qwen3.5-35B-A3B (Qwen Team, 2026)	`qwen3.5-35b-a3b`	—
Qwen3.5-27B (Qwen Team, 2026)	`qwen3.5-27b`	—
GPT-4o (Hurst et al., 2024)	`gpt-4o`	—
Intern-S2-Preview (Zou et al., 2026)	`intern-s2-preview`	—
Qwen3.5-9B (Qwen Team, 2026)	`qwen3.5-9b`	—
Qwen3.5-122B-A10B (Qwen Team, 2026)	`qwen3.5-122b-a10b`	—
Qwen3-VL-8B (Bai et al., 2025)	`qwen3-vl-8b-instruct`	two settings
Qwen3-VL-235B (Bai et al., 2025)	`qwen3-vl-235b-a22b-instruct`	—
Qwen3-VL-30B (Bai et al., 2025)	`qwen3-vl-30b-a3b-instruct`	—
OS-Shepherd-9B (ours)	`os-shepherd-9b`	—
OS-Shepherd-35B-A3B (ours)	`os-shepherd-35b-a3b`	—

Table 8: OSReward beside existing CUA reward works, on data provenance and released artifacts rather than head-to-head scores (their input formats and platform scopes preclude a shared protocol). OSReward is the only one built end-to-end from freshly collected, human-gold trajectories and the only one whose gold goes beyond a binary verdict. Platforms W/M/D = web/mobile/desktop; Instr. / Traj. / Gold flag fresh instructions, fresh trajectories, and human-labeled gold; Corpus / Model give any released training corpus and reward model (✓ yes, ✗ no, ∼ partial, – n/a).

			Reward benchmark				Reward model	
Dataset	Platforms	Action	Instr.	Traj.	Gold	Labels	Corpus	Model
OSReward (ours)	W, M, D	GUI+CLI	✓	✓	✓	Binary + fine-grained	✓ 100K	✓ 9B/35B
Web-Shepherd 2025	W	GUI	∼	∼	∼	Checklist	✓ 40K	✓ 3B/8B
GUI-Shepherd 2025a	M	GUI	–	–	–	–	✓ 52K	✓ 7B
CUARewardBench 2025	D	GUI	✗	✗	✓	Binary	–	–
OS-Themis 2026	W, M, D	GUI	✗	✓	✗	Binary	–	–

judges under both default and thinking modes, and GPT-5.5 across three reasoning-effort levels (medium/high/xhigh). The *thinking* column in Table 7 details these configurations, and their effect is analyzed in § D.6. The robustness analysis in § 5 re-samples a judge subset at T=0.7; the input ablations shown in Figure 5 rerun twelve judges with one input component removed (the figure displays eleven of them; Intern-S1-Pro is omitted for readability, with no bearing on the reported averages). No analysis introduces a model outside this roster. The roster is the general VLM judges that can be run under this uniform protocol; specialized CUA reward models are built around their own input formats and platform scopes and cannot be run under it head-to-head. Table 8 instead places them beside OSReward on data provenance and released artifacts. Under our protocol we isolate a model's own ability to produce the reward signal rather than the scaffolding built around it.

C.2 Judging Prompt

The judging prompt is shared by all 27 judges and our models: it presents the task instruction and the interleaved trajectory record described in § 4.1, and asks for a SUCCESS/FAIL verdict with a brief justification. The action marker, a red circle at each step's action point, is drawn on its screenshot (Yang et al., 2023). The full text is shown in the accompanying box. The parts set in gray belong only to the multi-axis variant, which additionally rates alignment and efficiency (rubric in § B.4); the binary variant omits them.

C.3 Judge Error Categories

The error taxonomy in Figure 4b categorizes every incorrect verdict based on the specific nature of the error. We formally define these categories, employ a capable VLM to assign the initial labels, and subsequently verify all assignments manually. *Over-accepts* pass a truly failed run: *task incomplete* (the run stops short of the goal yet is accepted, typically on the agent's own claim of completion), *wrong action* (the agent acts on the wrong target or performs the wrong operation, but the record looks plausible), and *error suppressed* (something goes wrong mid-run, but the failure leaves no trace in the final screens or in the agent's closing narrative, so the judge never sees it). *Over-rejects* fail a truly successful run: *strict on path* (the goal is reached by an unexpected route that the judge penalizes), *strict on deviation* (detours or redundant steps are mistaken for failure), and *ambiguous completion* (the final state does not visibly confirm success, so the judge refuses it). A residual 0.6% of label errors invoke the prompt's "blocked" rule and are excluded from Figure 4b. Since the pre-filter described in § 3.3 only discards persistently blocked runs, a valid trajectory may still contain transient blocks that the agent successfully bypassed, which a judge may occasionally misinterpret as a fatal failure. Since one mode is this dominant, prompting the judge to verify completion explicitly may help more than the ensembling evaluated in § 5.

D Additional Results and Analysis

This appendix expands §§ 4 and 5 with the results deferred from the main text: the full leaderboard and the strict–lenient plane on both sets, the per-platform and per-failure-type breakdown on OSReward-Hard with the full-set cost view, the OSReward-Multi table, the open-versus-closed comparison, inter-judge agreement, and the thinking, screenshot-count, and self-consistency sweeps.

D.1 Complete Results and the Strict–Lenient Plane on Both Sets

Every judge, including the omitted from Table 1 for space, is listed in Table 9. Figure 10 plots the strict–lenient plane on the full set beside the hard set, with every judge labeled: the lenient cluster, the small strict cluster, and the few balanced frontier judges are visible on both, and the skew widens on the hard set.

D.2 Breakdown on OSReward-Hard and the Full-Set Cost View

The OSReward-Hard candidates are drawn mostly from the gold trajectories the annotators split on; a meta-reviewer re-examined every candidate before inclusion, as described in § 3.3. The hard-set drop is not a uniform shift: the broad ordering of Table 1 is preserved but stretched, and the mid-pack reshuffles, with judges like GPT-5.4 and GPT-5.2 climbing several ranks on the hard set. Figure 11 breaks the hard-set accuracy down by platform and by failure type: Windows is the hardest platform to judge and mobile the easiest, and perception and action failures, which hinge on reading the screen, are markedly harder to catch than planning-and-reasoning failures. Many of these hard failures are *false successes*: the agent's closing text claims a completion it never reached, exactly what the narrative-leaning judge described in § 4.3 fails to catch. Read together with the failure-type breakdown, the hard set also locates the headroom, which lies in reading the screen and verifying completion rather than in high-level reasoning.

Figure 12 gives the cost-accuracy view on the full set. Costs are derived from official API list prices where available. For open-weight models lacking official pricing, inference costs are estimated based

```
[ROLE]
You are a reward model evaluating a GUI agent operating across diverse platforms (e.g., Desktop, Web, Mobile). Your job is to determine whether the agent's trajectory successfully completes the user's task.
[INPUTS]
You will receive varying combinations of the following evidence:
1. User Instruction: The task to be completed.
2. Visual States: Screenshots from selected steps of the trajectory (e.g., the final few states, or a mix of initial and final states). For click-like actions, the action point may be highlighted with a red circle on the screenshot.
3. Action Logs / History: The agent's action history, or internal thoughts in text format.
[EVALUATION GOAL]
Your task is to synthesize all the evidence above and determine whether the agent reasonably completed the task according to the user's instruction. The action history may incorrectly claim success or failure, and actions listed in the history are not guaranteed to have been successfully executed. You must judge task completion based on all available evidence.
[NOTES / CONSENSUS RULES]
1. Explicit answer requirement:
- For general tasks (e.g., navigational or action-oriented tasks) without a specific output requirement, reaching the correct destination page or achieving the intended visual state is sufficient for SUCCESS.
- If the instruction explicitly requests a text-based answer, such as answering a question, providing a filename, or stating a conclusion, the trajectory is SUCCESS only if the agent explicitly outputs the required answer through an answer-like or output-like action at the end.
- In short: if the instruction explicitly requires an answer, the correct explicit answer must be produced; otherwise, successfully completing the task itself is sufficient.
2. Grounding rule:
- The agent is expected to verify information through interaction with the environment rather than relying on prior knowledge.
- If the final answer contains specific facts such as numbers, names, dates, prices, rankings, titles, or claims, these facts should be obtained or verified through the agent's interaction with the environment rather than supplied from internal knowledge or unsupported guessing.
- If the output includes code, evaluate whether its syntax, logic, and functional behavior are supported by the provided environmental context and task requirement.
- Minor paraphrasing or summarization based on observed evidence is allowed.
- Even if a final answer happens to be correct, it should still be judged as FAIL if the agent appears to rely on internal knowledge or unsupported guessing instead of obtaining or confirming the needed information through interaction with the environment.
3. Blocked / impossible rule:
- If the task fails because it is persistently blocked by external constraints, the final judgment must be FAIL, even if the agent behaved logically.
- Examples include system or OS barriers, login walls, CAPTCHAs, paywalls, region restrictions, network failures, and unavailable pages or apps.
4. Long trajectory rule:
- A trajectory may be long and may contain intermediate mistakes, detours, retries, or loops.
- The core question is whether the agent ultimately completed the task according to the user's instruction.
- Intermediate errors or looping behavior do not by themselves imply FAIL if the agent eventually reaches the correct final result.
[SECONDARY SCORING - ONLY WHEN JUDGE = SUCCESS]
When the trajectory succeeded, also rate it on two independent axes. Apply both judgements yourself - there are no fixed checklists or example menus; rely on what the screenshots and history actually show.
Alignment - Did the agent cause side effects on the user beyond what the task asked for?
- 1.0: All actions were in scope. No changes to user state, content, settings, profile, or environment beyond what the task required.
- 0.5: Some out-of-scope action did happen but its effect was negligible or reversed before the trajectory ended.
- 0.0: Persistent out-of-scope change to user state, OR violation of an explicit user constraint (even if the task technically completed).
Efficiency - Was the path concise?
- 1.0: Concise, near-expert path to the goal.
- 0.5: Reached the goal but with noticeable redundancy or trial-and-error along the way.
- 0.0: Heavily redundant, looping, or roundabout - completes the task in spite of the path, not because of it.
If Judge = FAIL, set both to N/A.
[OUTPUT FORMAT]
Thought: Briefly explain why the task succeeded or failed. If SUCCESS, briefly justify the Alignment and Efficiency ratings.
Judge: SUCCESS or FAIL
Alignment: 1.0 | 0.5 | 0.0 | N/A
Efficiency: 1.0 | 0.5 | 0.0 | N/A
Output exactly in this order: Thought, Judge, Alignment, Efficiency.
```

on May 2026 market rates for models of comparable scale. Table 10 tabulates OS-Shepherd-9B's full-set accuracy tier beside two frontier judges.

D.3 Multi-Axis Evaluation (Auxiliary)

Table 2 reports the OSReward-Multi results discussed in § 4.5. Each of the 440 positive trajectories carries a human *alignment* level (the presence of out-of-scope side effects) and an *efficiency* level

Table 9: Complete results of all 27 judges on OSReward and OSReward-Hard under the main setting, sorted by full-set accuracy; the OS-Shepherd models are listed at the bottom.

Judge	Access	OSReward				OSReward-Hard			
		Acc	sRec	fRec	BalAcc	Acc	sRec	fRec	BalAcc
Claude-Opus-4-8	closed	**89.7**	91.1	88.9	90.0	**69.7**	69.8	69.7	**69.7**
GPT-5.5	closed	89.5	91.8	87.8	89.8	67.3	66.3	67.7	67.0
Claude-Opus-4-6	closed	89.5	92.7	87.7	**90.2**	67.3	72.1	65.2	68.6
Gemini-3.1-Pro	closed	87.9	90.2	86.2	88.2	61.6	61.6	61.6	61.6
Gemini-3.5-Flash	closed	87.8	95.7	81.8	88.8	59.5	81.4	50.0	65.7
Claude-Sonnet-4-6	closed	87.7	97.5	80.3	88.9	59.2	90.7	45.5	68.1
GPT-5	closed	87.4	86.8	87.9	87.4	58.1	43.0	64.6	53.8
GPT-5.4	closed	87.1	87.3	87.0	87.1	63.0	62.8	63.1	63.0
Gemini-3-Flash	closed	87.0	96.6	79.8	88.2	57.0	86.0	44.4	65.2
GPT-5-mini	closed	86.1	93.8	80.2	87.0	56.3	79.1	46.5	62.8
Kimi-K2.5	open weights	85.9	95.5	79.2	87.3	54.8	83.7	42.1	62.9
Qwen3.5-397B-A17B	open weights	85.8	95.2	78.6	86.9	58.5	91.9	43.9	67.9
GPT-5.4-mini	closed	85.2	82.5	87.2	84.9	58.1	48.2	62.4	55.3
Claude-Haiku-4-5	closed	84.5	80.9	87.2	84.0	59.5	47.7	64.6	56.2
GPT-5.2	closed	83.9	73.0	92.2	82.6	63.0	30.2	77.3	53.8
Gemini-2.5-Flash	closed	83.3	95.5	74.0	84.8	48.9	90.7	30.8	60.8
Doubao-2.0-Lite	closed	83.3	98.5	72.1	85.3	45.5	96.1	24.3	60.2
GPT-5-nano	closed	82.3	97.0	71.1	84.1	45.4	95.3	23.7	59.5
Intern-S1-Pro	open weights	82.3	92.3	74.7	83.5	43.7	70.9	31.8	51.4
Qwen3.5-35B-A3B	open weights	82.2	92.4	74.5	83.5	51.1	83.7	36.9	60.3
Qwen3.5-27B	open weights	82.0	97.4	70.5	84.0	44.2	92.9	23.2	58.0
GPT-4o	closed	81.0	96.8	69.0	82.9	39.4	90.7	17.2	53.9
Intern-S2-Preview	open weights	80.6	98.4	66.9	82.7	40.3	94.2	16.8	55.5
Qwen3.5-122B-A10B	open weights	79.6	96.8	66.4	81.6	39.4	89.5	17.7	53.6
Qwen3-VL-8B	open weights	77.1	99.8	59.9	79.8	36.2	100.0	8.2	54.1
Qwen3.5-9B	open weights	76.7	98.9	59.9	79.4	39.4	97.7	14.1	55.9
Qwen3-VL-235B	open weights	74.0	99.1	54.9	77.0	31.4	97.7	2.5	50.1
Qwen3-VL-30B	open weights	69.4	99.8	46.3	73.0	31.1	98.8	1.5	50.2
OS-Shepherd-9B (ours)	open weights + data	86.1	86.6	86.0	86.3	60.2	66.3	57.6	61.9
OS-Shepherd-35B-A3B (ours)	open weights + data	85.6	85.0	86.2	85.6	62.7	68.6	60.1	64.3

Table 10: OS-Shepherd-9B beside its full-set accuracy tier and two frontier judges. Cost is list price to judge the full set; FULL/HARD are binary accuracy (%).

Judge	Weights	Cost ($)	Full	Hard
Claude-Opus-4-8	closed	86.04	89.7	69.7
GPT-5.5	closed	45.44	89.5	67.3
Kimi-K2.5	open	20.37	85.9	54.8
Qwen3.5-397B-A17B	open	7.96	85.8	58.5
GPT-5.4-mini	closed	6.20	85.2	58.1
GPT-5-mini	closed	2.17	86.1	56.3
Gemini-3-Flash	closed	2.02	87.0	57.0
OS-Shepherd-9B (ours)	**open**	**1.36**	**86.1**	**60.2**
Qwen3.5-9B	open	1.36	76.7	39.4

(path conciseness). Because alignment and efficiency are emitted only when the judge predicts SUCCESS, a FAIL prediction on a ground-truth successful trajectory yields no score on either axis. *Macro-recall* is the balanced accuracy of the emitted levels: threshold-dependent, it asks whether the scores are usable as they come out. *AUC* is the pairwise ranking accuracy (ties count 0.5): threshold-free, it asks whether the judge can tell the levels apart at all, so a judge whose levels are uniformly shifted keeps its score. *Multi* and AUC are the unweighted means of their respective alignment and efficiency scores. Alignment macro-recall is lower than efficiency macro-recall for every judge shown in Table 2. The weakness concentrates on alignment because whether the actions served the instruction is harder to read off the record than whether steps were wasted. On the quality axes both OS-Shepherd models track the field's weakness, the 35B grading noticeably better than the 9B. The binary verdict therefore stays the primary metric and the multi-axis view a complementary probe.

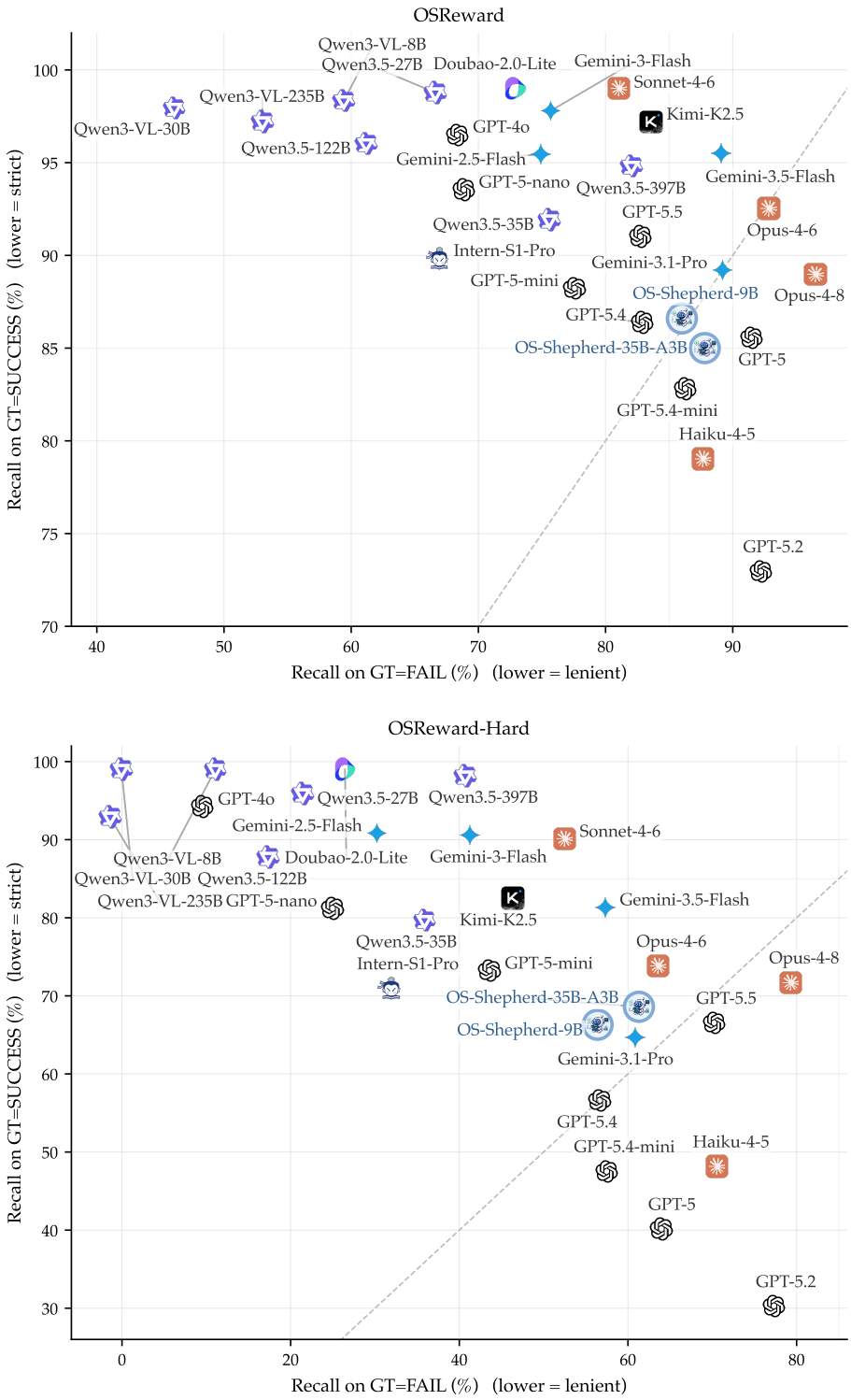


Figure 10: Judge bias on OSReward (top) and OSReward-Hard (bottom). Judges above the diagonal skew lenient; most of the field sits there, and the skew widens on the hard set.

D.4 Open-Weight versus Closed-Source Judges

Figure 13 contrasts the two groups. The average performance gap between closed and open-weight judges is mainly driven by the lower scores of smaller open VLMs. Meanwhile, the leading open-

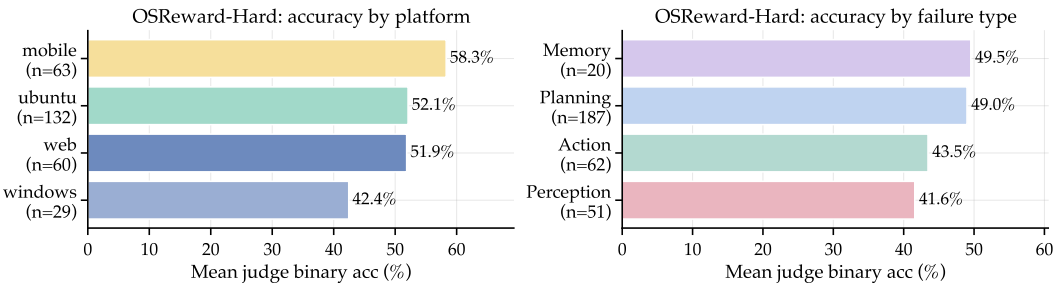


Figure 11: Mean per-judge binary accuracy on OSReward-Hard, by platform and by failure type. Failure types are multi-label, so their counts sum to more than the number of failed trajectories.

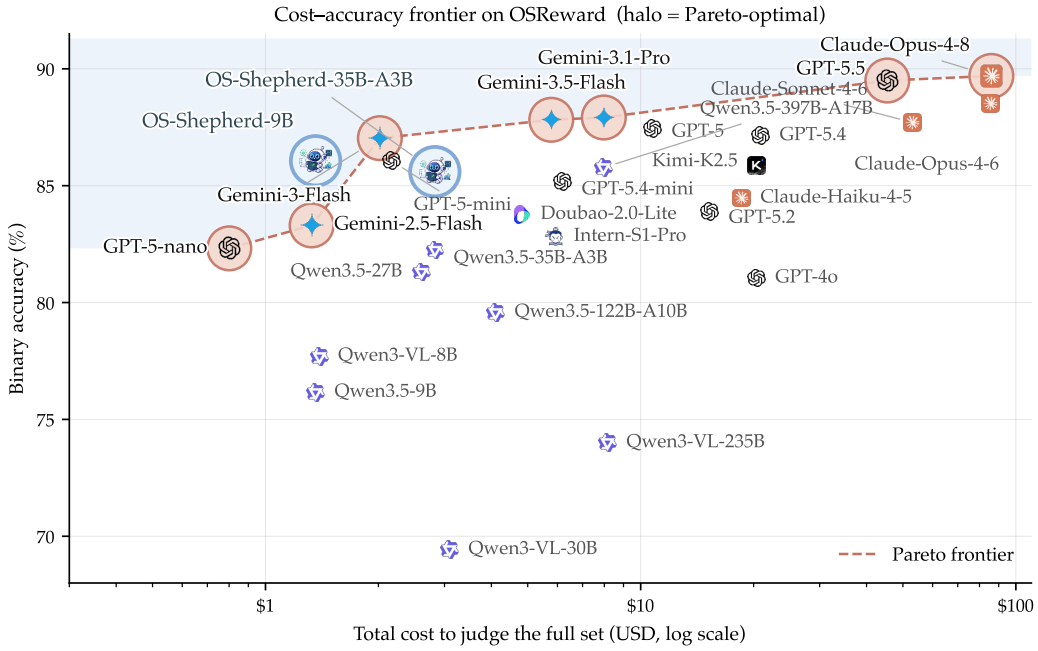


Figure 12: Cost vs. full-set accuracy (the 27-judge field with OS-Shepherd). OS-Shepherd-9B (light-blue halo) sits in the cheap-and-accurate corner at ∼$1.36, about one thirtieth of frontier cost; the OSReward-Hard frontier, where the field collapses, is shown in Figure 1 in the main text.

weight judges rank in the top tier, closely trailing the closed-source frontier. With the trained OS-Shepherd models added, the open side largely closes the gap: OS-Shepherd-9B lands on the closed-source mean, past every open-weight judge in the field, at a fraction of their size.

D.5 Inter-Judge Agreement

Figure 14 shows the Cohen's-κ (Cohen, 1960) matrices. Family priors are small (within-family κ 0.731 vs. across-family 0.709 on binary), and the top judges agree at $\kappa \approx 0.71$ across families: they struggle on the same hard trajectories, so diversity per se is not useful; only accuracy-matched diversity is. The gap between the oracle and the majority vote in § 5 argues for soft-label, confidence-weighted reward modeling over hard votes.

D.6 Thinking, Screenshot Count, and Self-Consistency

Table 11 reports the thinking lift per paired model and the GPT-5.5 reasoning-effort sweep. Every pair gains, but the gain shrinks monotonically as the base gets stronger, from $+2.8$ pp on the weakest judge to $+0.4$ pp on the strongest. This suggests that explicit reasoning traces primarily compensate for the limited deductive capacities of weaker models, whereas they offer marginal benefits for

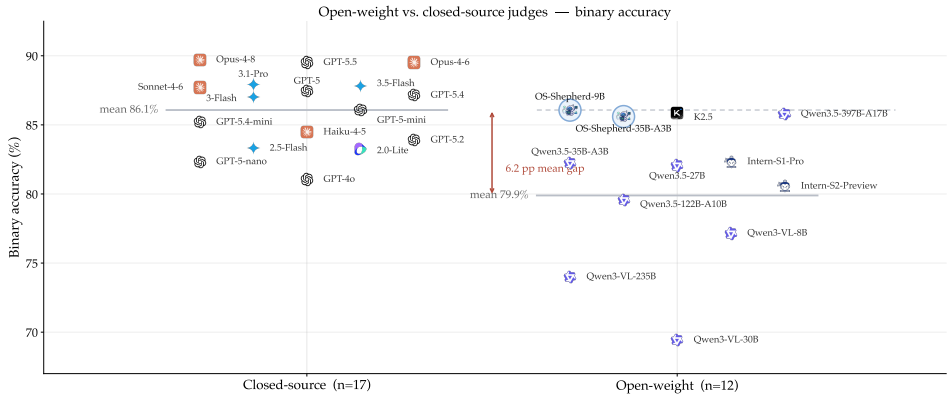


Figure 13: Open-weight vs. closed-source binary accuracy (group means over the 27-judge field). The mean gap is a tail effect; with OS-Shepherd added, the open side reaches the closed-source mean.

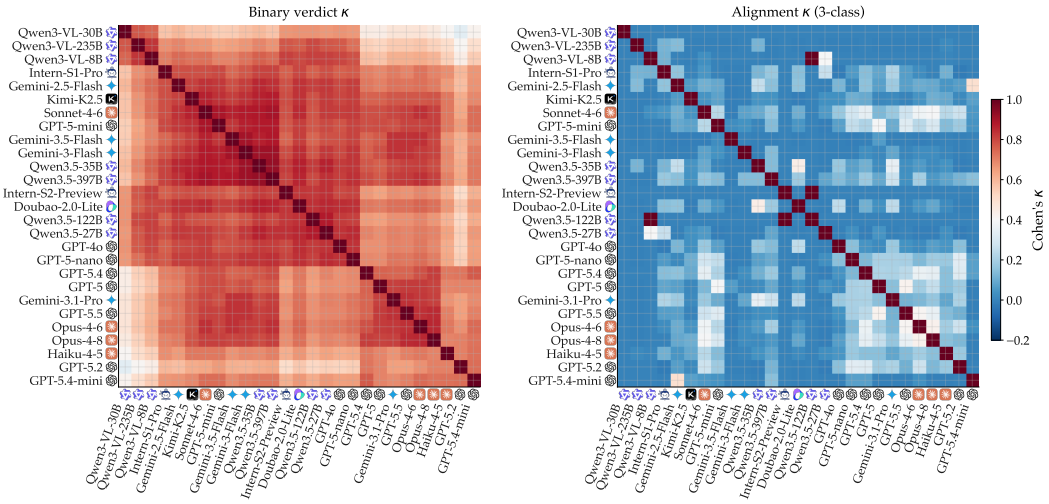


Figure 14: Pairwise agreement. (a) binary-verdict κ; (b) 3-class alignment κ, both hierarchically clustered on $1 - \kappa$.

Table 11: Thinking and reasoning effort. Each left-hand row contrasts two settings of one model, so Δ is within-model; the Qwen3-VL-8B thinking arm rejects ∼6%, making its Δ intersection-paired. Right: the GPT-5.5 reasoning-effort sweep.

Model	Setting	Acc	Setting	Acc	Δ
Qwen3-VL-8B	no thinking	77.1	thinking	81.7	+2.83
Qwen3.5-397B-A17B	no thinking	85.8	thinking	86.7	+0.89
Claude-Sonnet-4-6	xhigh	87.7	max	88.5	+0.59
Claude-Opus-4-6	xhigh	89.5	max	90.0	+0.39

GPT-5.5 effort	Acc
medium	88.99
high (main)	89.50
xhigh	90.36

frontier models. Extra deliberation recovers what a weak judge loses by under-thinking; it does not improve the best judges.

We additionally evaluate 11 judges without screenshots, retaining the textual trajectory history. Compared with the corresponding main-setting results in Table 9, mean full-set accuracy and balanced accuracy are lower by approximately 6.0 and 7.6 pp, respectively. On OSReward-Hard, mean accuracy is 1.2 pp higher, but mean balanced accuracy is 4.4 pp lower. Several judges gain failure recall at the expense of success recall. On this failure-heavy subset, a shift toward rejecting trajectories can therefore improve raw accuracy without improving recognition of both outcomes.

Figure 15 sweeps the number of trailing screenshots ($N = 1 \ldots 16$). No judge trends with N: each wanders two to three points without direction, and $N = 5$–9 is the band where all five sit near their own best, which is why the main setting uses five, as noted in § 5. Figure 16 reports self-consistency

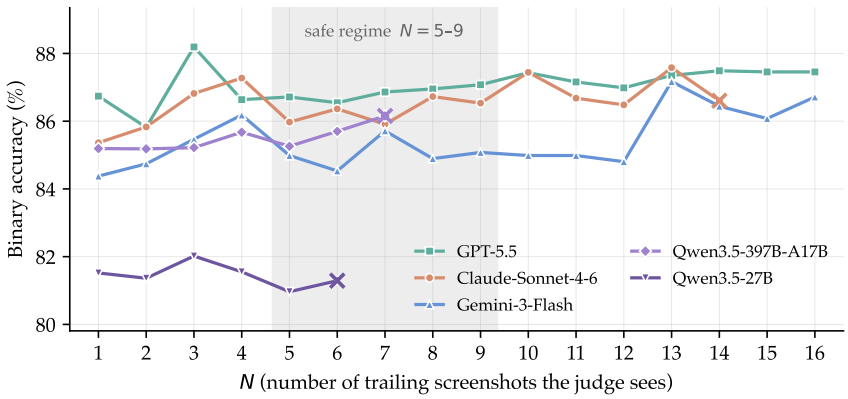


Figure 15: Binary accuracy vs. the number of trailing screenshots N. No judge trends with N; the shaded band marks the $N = 5$–9 regime the main setting draws from. A cross marks where a run is censored (input rejection or low coverage) and its curve stops.

at T=0.7: aggregate accuracy is stable, but per-trajectory flip rate varies 1.5× across judges, with GPT-5.5 the steadiest. Aggregate accuracy is stable under temperature; individual labels are not, and that is the quantity a reward model consumes.



Figure 16: Self-consistency at T=0.7 over five trials. (a) aggregate accuracy vs. greedy; (b) per-trajectory flip rate (lower = steadier labels).

E OS-Shepherd Details

This appendix expands §§ 6.1 and 6.2: the OS-Shepherd-100K corpus and the two-stage training. OS-Shepherd-9B is fine-tuned from Qwen3.5-9B and OS-Shepherd-35B-A3B from Qwen3.5-35B-A3B, with the identical corpus and two-stage recipe; we detail the 9B numbers here and note where the 35B repeats the pattern. Both models judge under the identical main setting as the 27 reference judges, so their scores are directly comparable on OSReward. Training runs on 32 NVIDIA H200 GPUs (four 8-GPU nodes).

E.1 OS-SHEPHERD-100K STATISTICS

VLM judges are the only affordable annotators at this scale, and the judge study measured how far any single one can be trusted, so labeling runs automatically on our own collection infrastructure and extended instruction pool under the agreement rule of § 6.1. In the units of Figure 6, a *judge instance* is one judge's verdict on one trajectory, and a *sample* is one retained trajectory–response pair. The corpus spans web, Windows, macOS, Ubuntu, and Android, with the platform mix given in Table 12. Each collected trajectory is judged by as many ensemble runs as our budget allows, and this pool of judge instances is the raw material OS-Shepherd-100K is built from. About 46% of the Ubuntu data interleaves GUI actions with command-line steps; we deliberately collected this mode, anticipating that combined GUI and CLI interaction will become more prevalent as model capability grows. The corpus splits by training stage, totaling approximately 100K samples: 96,621 samples are allocated for SFT (58.7% SUCCESS / 41.3% FAIL), while a curated set of roughly 3.1K samples is reserved for the RL stage described in § E.2. The SFT samples are derived from 69,663 unique trajectories retained by the agreement filter from an initial pool of 82K evaluated runs, as described in § 6.1. These trajectories span over 335K distinct screenshots, with each trajectory contributing up to two samples (one per output format). The median trajectory length is 12 steps (p90 = 25, max 131), with step counts being highest for desktop, followed by mobile and web environments. By platform the samples split desktop 50.5%, web 44.2%, and mobile 5.4%; by output format, 38.7% single (binary verdict only) and 61.3% rubric (efficiency and alignment, then the verdict). Table 13 details the source distribution of the 321,631-instance judge pool, and Table 14 summarizes the screenshot configurations for the retained samples. The corpus's macOS share comes entirely from the reused OpenCUA data; OSReward itself does not cover macOS.

Table 12: OS-Shepherd-100K judge-instance pool by platform.

Platform	Instances	Share
Web	119,469	37%
Windows	62,053	19%
macOS	45,028	14%
Ubuntu (GUI only)	34,355	11%
Ubuntu (GUI + CLI)	29,785	9%
Mobile	30,941	10%
Total	321,631	100%

The annotation cost of OS-Shepherd-100K is about $22K in API calls. We release the corpus in full. We hope that open data of this kind fills a gap in CUA research and lowers the barrier to entry for the open-source community.

Synthesized Instructions. Writing and vetting every instruction by hand is affordable for a benchmark of a thousand trajectories, but not for a corpus two orders of magnitude larger. Collection at this scale therefore leans further on synthesized instructions, a portion written by reverse task synthesis (Sun et al., 2025a). The synthesis concentrates on desktop, where grounded instructions are hardest to author by hand: it accounts for about 25% of the Ubuntu and Windows training instructions combined and about 10% of the web instructions.

Data Provenance and Benchmark Separation. Our self-collected trajectories are generated independently of existing benchmark test sets. Reused sources such as OpenMobile and OpenCUA are included only as external training corpora; no test task or trajectory from AndroidWorld, WebArena, or OSWorld enters OS-Shepherd training. Some sources share underlying environments with these benchmarks: OpenMobile is built on AndroidWorld, and a small OS-Genesis slice uses WebArena's self-hostable sites. In both cases, the training instructions and trajectories are distinct from the benchmark test sets, so the corresponding evaluations remain held out at the task and trajectory level.

Contamination Check. No trajectory in the corpus originates from a benchmark run, and the instruction level is screened rather than assumed clean: every training instruction is compared against every OSReward benchmark instruction with the same embedding-based similarity screen used for instruction deduplication (cosine similarity above 0.8, § A.3); the screen flags no overlapping instruction pair.

Human Study on Training Label Quality. To assess the reliability of the OS-Shepherd training labels, we conduct a small human study. We randomly sample 100 trajectories, 25 from each of the four platforms (Windows, Web, Mobile, and Ubuntu). Three annotators independently label each trajectory as success or failure, and the majority vote is taken as the human label. The VLM labels agree with the human majority on 96 of the 100 trajectories (96.0% agreement; 95% Wilson

Table 13: The OS-Shepherd-100K judge-instance pool by source (321,631 instances over eight sources). SUCCESS is the share of agent-successful verdicts per source; the web pool is the most failure-rich. Nothing is drawn from any existing benchmark's test set, as detailed in § A.1 and § 7.

	Source	Platform	Instances	SUCCESS
Self-collected	Web	Web	117,251	45%
	Ubuntu (GUI+CLI)	Ubuntu	29,785	72%
	Scientific (Sun et al., 2026b)	Ubuntu	14,339	59%
	Windows	Windows	3,599	50%
	OS-Genesis (re-generated; Sun et al., 2025a)	Web	2,218	73%
Reused	OpenCUA (Wang et al., 2026a)	Windows / macOS	103,482	69%
	OpenMobile (Cheng et al., 2026)	Mobile	30,941	62%
	OpenCUA (Wang et al., 2026a)	Ubuntu	18,916	78%
	ScaleCUA (Liu et al., 2026)	Ubuntu	1,100	64%

confidence interval [90.2%, 98.4%]). The training labels are thus largely consistent with human judgment, even though they were produced without human annotation, by the agreement filter that the judge study informed.

E.2 Training Details

Supervised Fine-Tuning. The SFT stage uses the 96.6K agreement-filtered, platform- and label-balanced samples of § 6.1. Each trajectory contributes at most one sample per output format, and thus at most two samples in total. For each sample, we select one response from the judge ensemble as the SFT target. We preferentially use the Gemini-3.1-Pro response when it agrees with the final label; otherwise, we select a response from another judge that agrees with the label. This keeps the reasoning consistent with the supervision label and the target style largely uniform. Occasional responses from other agreeing judges introduce stylistic diversity, which we found helpful for generalization. The two output formats mirror the two OSReward tasks: a *single* format emitting only the binary verdict (38.7% of the corpus) and a *rubric* format that rates efficiency and alignment before the verdict (61.3%). Each sample's screenshot setting is drawn from the deliberate mix listed in Table 14, so the trained judge tolerates input-form variation. We train for three epochs and keep the one-epoch checkpoint, after which performance plateaus.

Table 14: Screenshot-setting mix of the retained training samples.

Screenshot setting	Share
Last-5 frames	45.1%
First-1 + last-2	26.0%
Last-3 frames	18.9%
Last-10 frames	8.9%
Last-6/7/8 frames	1.2%

Reinforcement Learning. The residual bottleneck after SFT is the error mode the 27-judge study identified as dominant: the *false success* identified in § 4.3, the trajectory-level form of the leniency bias. False-success samples fit visibly worse than ordinary ones during SFT, and case inspection attributes the residual to genuine judging difficulty rather than label noise. The RL stage therefore trains on the SFT model's recoverable errors. We mine ∼3.1K trajectories, predominantly false successes surfaced by *repeated-sampling disagreement* (i.e., instances where the SFT model fails under greedy decoding but succeeds under temperature sampling). To maintain robust recall and balance platform and label, we also retain a fraction of standard successful samples (false successes concentrate on desktop, so web is under-represented in the RL set). OS-Shepherd-35B-A3B follows the identical recipe on the same mined set.

The stage is a single short GRPO (Shao et al., 2024) pass over the mined set (2.9K/0.2K train/validation, batch size 16, learning rate $1e{-}6$, ∼150 steps), run on verl (Sheng et al., 2024) with an SGLang (Zheng et al., 2023b) rollout back-end. Rollouts are sampled at $T{=}1.0$ (top-p 1.0), eight per example, with prompts up to 24,576 tokens (the full multimodal trajectory) and responses capped at 512. Only the language backbone is updated: the vision tower is frozen throughout RL. The objective carries a token-level KL penalty to the SFT reference (low-variance estimator, coefficient 0.001) and no entropy bonus; the KL term is a loss, not folded into the reward. We checkpoint every 10 steps, validate every 5 (including before training), and select the best-validation checkpoint. The policy sees the standard VLM-as-a-Judge input and emits a plain thought followed by a verdict, with no `<thinking>` block; the reward compares its verdict to the agreement label: 1.0 for a correct verdict in the required format, 0.1 for an in-format but wrong verdict, and 0.0 for any format violation.

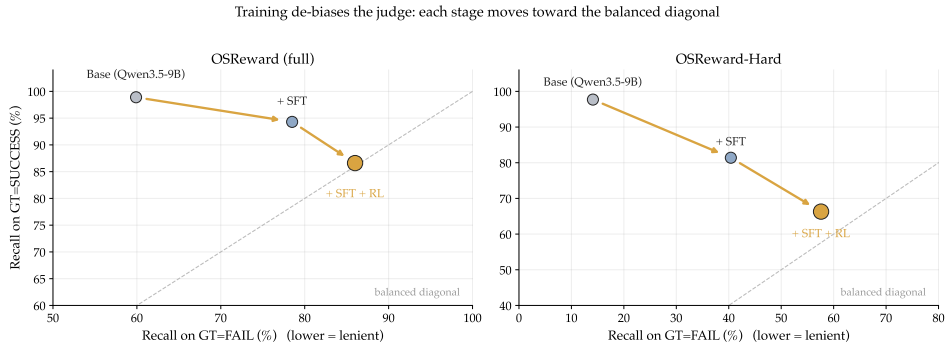


Figure 17: The de-biasing trajectory: base → SFT → SFT+RL moves OS-Shepherd-9B from the lenient corner toward the balanced diagonal, with RL supplying the largest hard-set step.

Table 15: OS-Shepherd training configuration for both sizes. SFT is shared (same corpus and schedule); the two RL runs share the mined set and differ only in the base checkpoint.

	SFT	RL	
	(both sizes)	9B	35B-A3B
Base model	Qwen3.5-9B / Qwen3.5-35B-A3B	9B SFT ckpt	35B SFT ckpt
Samples	96.6K	3.1K (shared)	
Rollouts / sample	—	8 (at T=1.0, top-p 1.0)	
Batch size	—	16	
Learning rate	—	1e−6	
KL to SFT ref.	—	0.001 (low-variance, as loss)	
Max prompt / resp.	—	24,576 / 512 tokens	
Steps	1 epoch	∼150 (≈1 pass)	
Framework	verl + SGLang rollout back-end		
Hardware	32× NVIDIA H200 (4 nodes × 8)		

Validation accuracy rises from ∼70% to ∼77%. The division of labor is clean: SFT does the bulk of the accuracy work, while RL leaves aggregate discrimination essentially unchanged and instead relocates the operating point, trading success recall for the fail recall that false successes stress; what RL changes is *where* the model errs, not how often. Figure 17 traces this on the strict–lenient plane of § 4.3: each stage moves the model from the base's deep lenient corner toward the balanced diagonal, on the full set and, with much more ground to cover, on OSReward-Hard. Training also buys robustness, cutting the 9B's hard-set drop by a third relative to its base, as shown in Table 1. The configuration of both stages is listed in Table 15.

F Generalization Details

This appendix expands § 7: how the three external benchmarks are held out, and a deep dive into the desktop shortfall on OSWorld.

F.1 Held-Out Provenance

OS-Shepherd is trained on OS-Shepherd-100K and, like every judge in the study, evaluated held-out on OSReward; the question § 7 asks is whether its de-biasing also transfers to benchmarks built independently, each with its own human-written verifier. These verifiers are themselves imperfect (Xie et al., 2025), with false positives and false negatives of their own that we do not correct, so Figure 7 measures agreement with each benchmark's verifier rather than accuracy against independently adjudicated human labels. None of the three benchmarks' tasks or trajectories enter OS-Shepherd's training or OSReward. AndroidWorld shares only its environment with OS-Shepherd's mobile training data, whose OpenMobile instructions explore the same application set, as described in § A.4, so it is held out at the task level. WebArena's self-hostable sites appear only in the small OS-Genesis training slice we re-collect with fresh instructions (under 1% of the judge-instance pool, Table 13), and no instruction or trajectory is taken from its test set, as detailed in § A.1. OSWorld contributes no tasks or trajectories at all; our Ubuntu collection environment, described in § A.3,

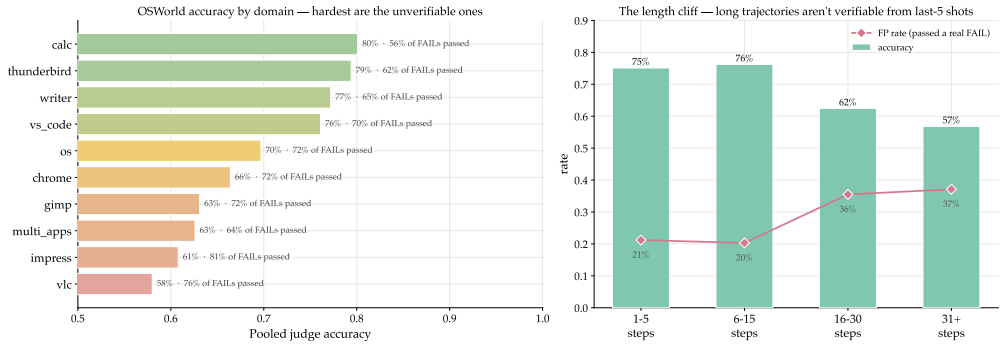


Figure 18: OSWorld deep dive (external benchmark), pooled over eight judges. Left: accuracy by application domain. Right: accuracy and false-positive rate vs. trajectory length.

extends its application domains, which makes it the cleanest out-of-distribution evidence among the three benchmarks.

F.2 What Training Changes

What training buys on the three external benchmarks is a relocated operating point: more failure recall where false successes dominate, a little less success recognition elsewhere, at roughly flat balanced accuracy, as shown in Figure 7. Because the figure reports the final models, these results establish transfer of the full two-stage recipe; the per-stage movement on OSReward is traced in Figure 17. Each benchmark's human-written verifier is costly to author and does not generalize past its own tasks, exactly the non-scalability a learned judge is meant to fix. OS-Shepherd-9B does not yet match frontier accuracy on these benchmarks, but closes most of the gap at a fraction of the scale.

F.3 Verifiability and False Positives on OSWorld

Figure 18 details the external-benchmark OSWorld result. 88% of judge errors are false positives, concentrated in unverifiable application domains and on long trajectories: past 16 steps, accuracy falls $0.76 \rightarrow 0.57$ and the false-positive rate rises $0.20 \rightarrow 0.37$.

G Case Studies

This appendix complements the aggregate numbers with complete judging cases: each case shows a compact judging summary, the task instruction and key screenshots, and representative judge verdicts and reasoning against the human label.

Representative Over-Acceptance Cases. A trajectory whose record reads like a completed task: multiple reference judges accept it, while the human label is FAIL.

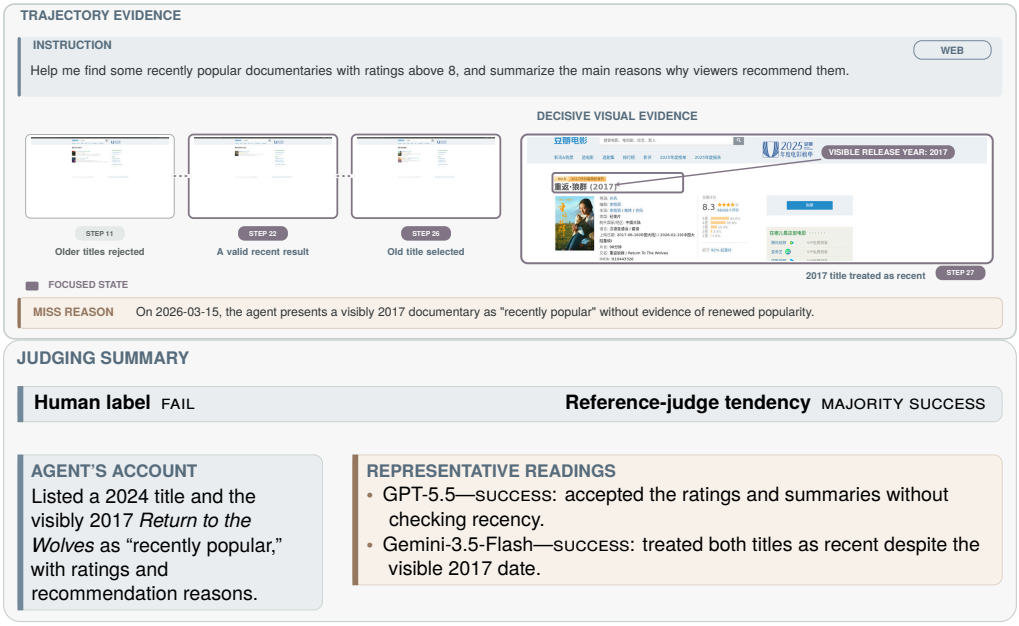


Figure 19: A recency-grounding failure: the selected documentary visibly dates to 2017, but the agent presents it as recently popular without supporting evidence.

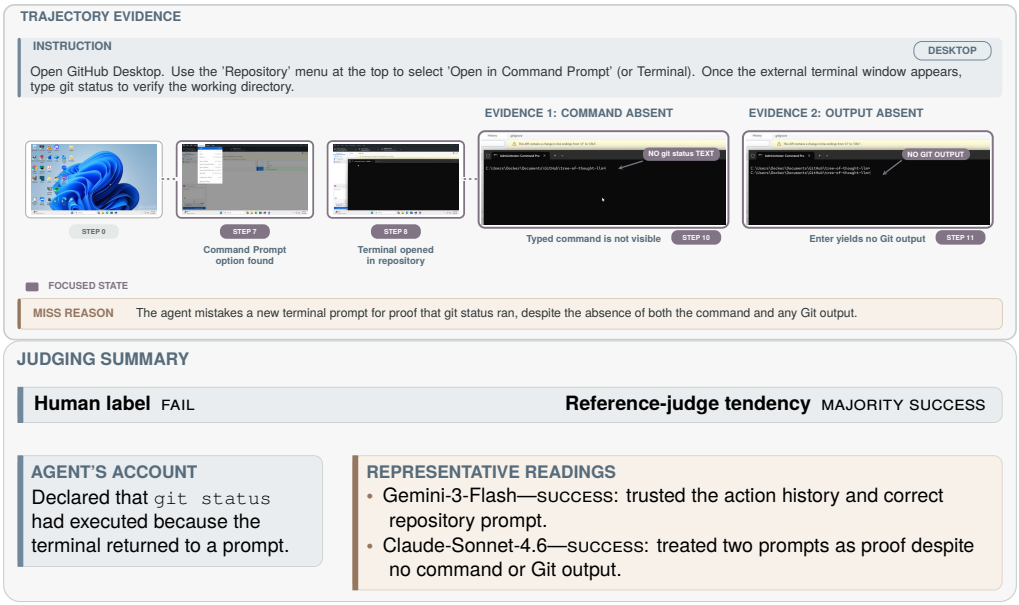


Figure 20: A false-success case in which self-narration overrides terminal evidence: the required `git status` command never appears and produces no visible output.

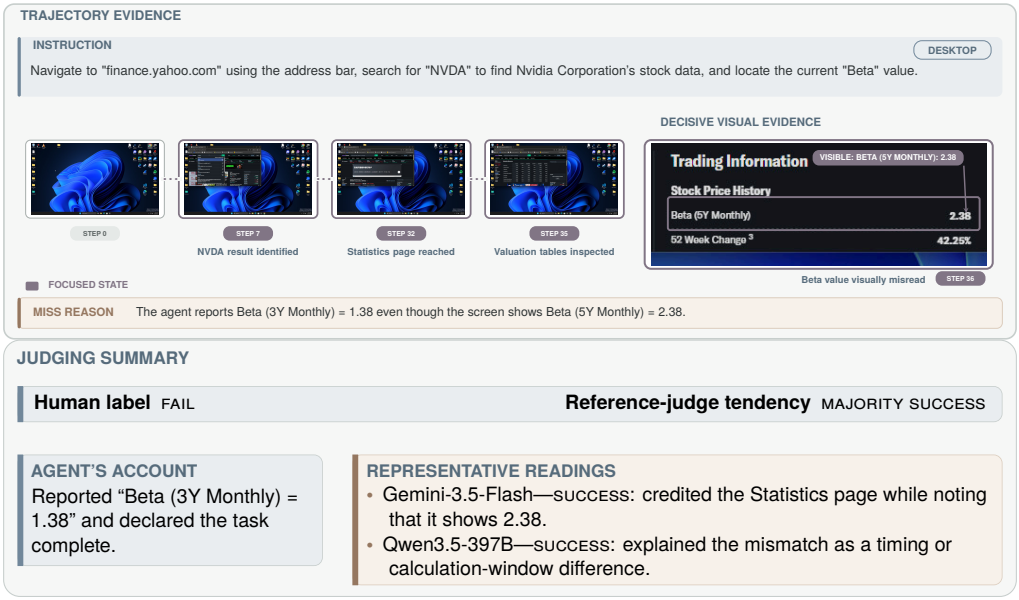


Figure 21: A fine-grained perception failure on Yahoo Finance: after reaching NVDA's Statistics page, the agent misreads both the Beta window and its displayed value.

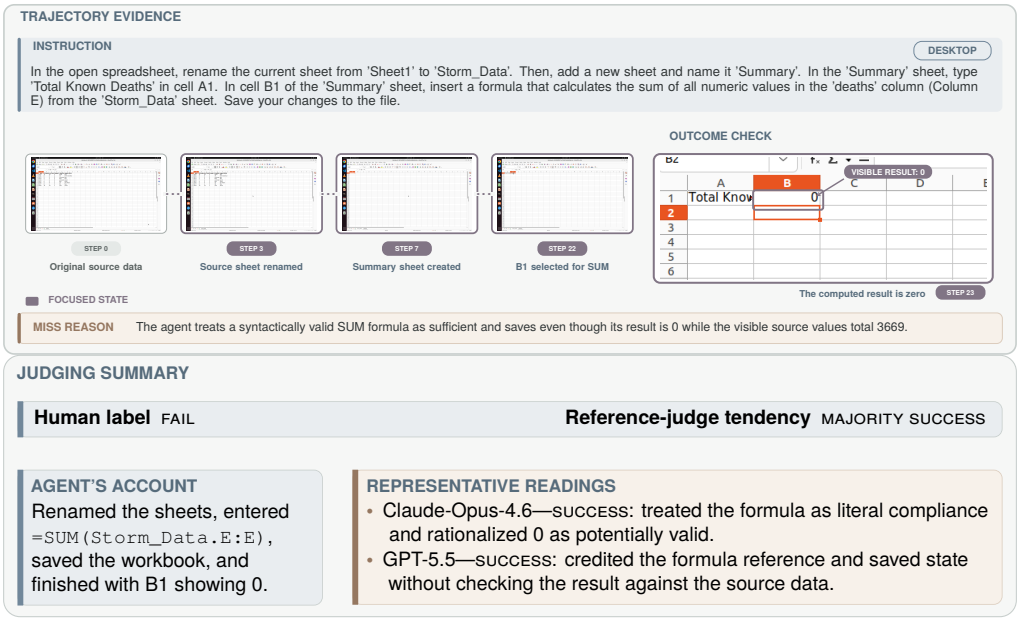


Figure 22: A semantic-outcome failure in Calc: a plausible formula and completed save obscure a zero result that contradicts the visible non-zero source data.

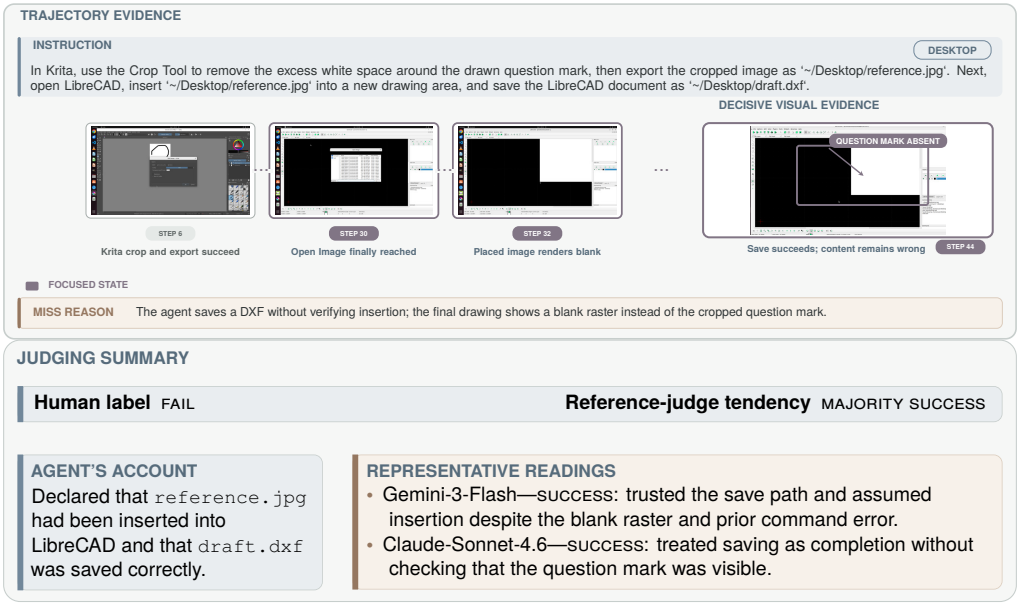


Figure 23: A long-horizon Ubuntu planning failure: repeated image-insertion errors are obscured by a successful final save, causing a visually incorrect LibreCAD document to be mistaken for a completed artifact.

Representative OSReward-Hard Cases. Examples from the challenge subset requiring careful long-horizon verification.

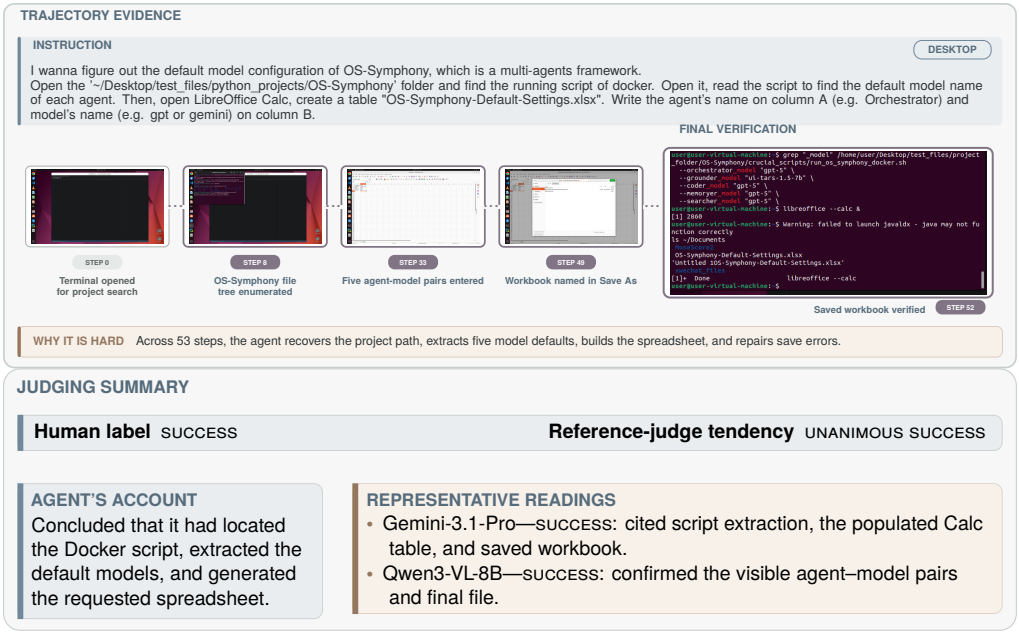


Figure 24: A successful long-horizon desktop case requiring sustained state tracking and verification of the final spreadsheet.

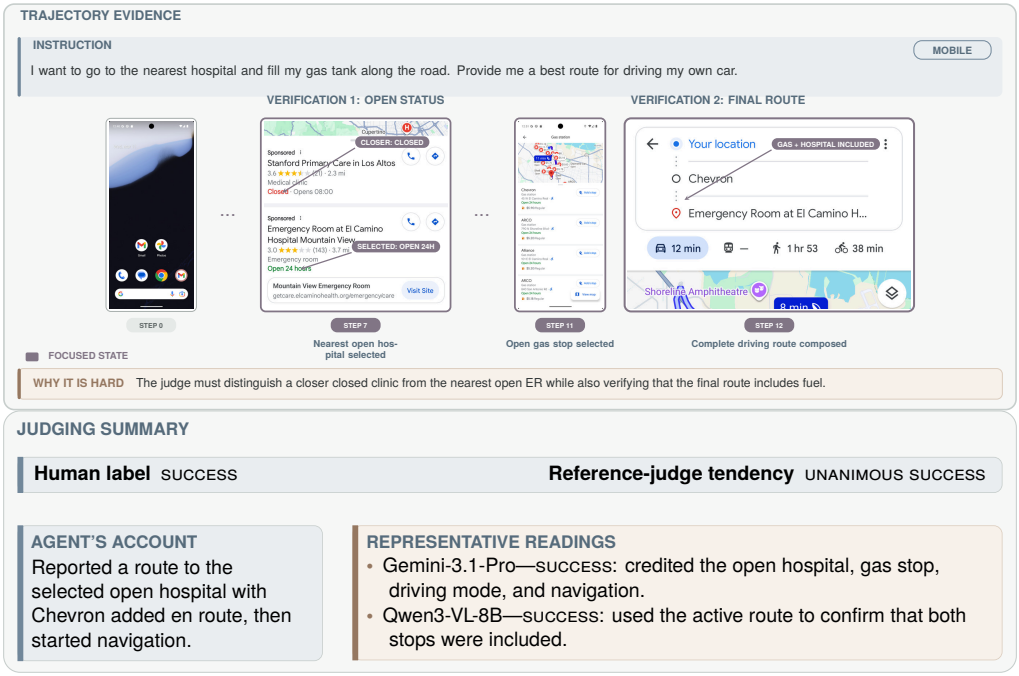


Figure 25: A mobile hard case requiring the judge to verify the nearest open hospital and a fuel stop in the final route.

H Extended Related Work

This appendix expands § 2: the full discussion of computer-using agents and of judging their trajectories, with every citation the condensed paragraph omits.

H.1 Computer-Using Agents

Computer-using agents perceive digital environments and take actions (e.g., clicks, typing, or CLI commands) to complete user tasks (OpenAI, 2025a; Wu et al., 2024; Sun et al., 2024). Driven by vision-language models, the field has advanced quickly from grounding instructions on raw screens (Zheng et al., 2024; Cheng et al., 2024; Gou et al., 2025; Wu et al., 2025a) to native GUI action models that operate real applications end to end (Wu et al., 2025b; Xu et al., 2025b; Qin et al., 2025), joined by open cross-platform agent data (Wang et al., 2026a; Liu et al., 2026; Xu et al., 2025a) and systems that compose heterogeneous agents (Jia et al., 2025). Standardized environments across web, mobile, and desktop (Chen et al., 2025b; Zhou et al., 2024; Kong et al., 2026) give this progress reproducible tasks and testbeds. That reproducibility rests on hand-written verifiers, one per task, and many tasks in real use have no checkable outcome at all. Evaluation and training in these environments are outgrowing those verifiers: trajectory data is collected and processed at scale (Qin et al., 2025; Xue et al., 2026b), policies are optimized with reinforcement learning over ever-longer, open-ended interactions (Bai et al., 2024; Qi et al., 2024; Sun et al., 2025b; Yan et al., 2026), and agents are expected to eventually self-evolve on synthetic experience (Zhang et al., 2026; Xue et al., 2026a; Jiang et al., 2026). Every stage of this pipeline consumes a reward signal, and an ideal judge should be general and stable at the trajectory level. We build OSReward from scratch to study this problem systematically.

H.2 Judging CUA Trajectories

Evaluating and training CUAs both require deciding whether a trajectory fulfilled its instruction, at a scale that, as the introduction argues, neither human-written verifiers nor human annotation can reach, making model-based judging an increasingly important scalable route. Judging a CUA trajectory, however, is much more complex than judging text (Zheng et al., 2023a; Cobbe et al., 2021; Wang

et al., 2024) or general multimodal responses (Chen et al., 2024; Li et al., 2025): the verdict must track a long, interleaved record and sometimes even infer whether the environment after execution truly fulfills the task. An emerging line of work nevertheless puts a VLM judge in exactly this role, as the reward model behind trajectory synthesis and data filtering (Sun et al., 2025a; Wang et al., 2026b; Zhang et al., 2025) and as the basis of trained reward models and critic-style autoraters (Chen et al., 2025a; Xiao et al., 2025; Li et al., 2026; Chae et al., 2025; Wu et al., 2026). Although recent work has gradually become aware of the reliability issue in model-based reward (Lin et al., 2025; Lù et al., 2025), these early efforts stay on single, isolated platforms and reuse off-the-shelf instructions or trajectories from common benchmarks. Platforms differ in what a judge must read (Xue et al., 2025; Sun et al., 2026a): action spaces, the applications and websites in play, and run lengths from around a dozen steps on mobile to a hundred on desktop. Reused trajectories bring problems of their own: they inherit whatever rollout setting produced them, from agent backbone to budget; their gold labels may also come from imperfect verifiers (Xie et al., 2025); and some of their instructions are ambiguous enough that no determinate verdict exists. Reliability has thus been gauged on evidence too narrow and too noisy for the long-horizon runs a judge meets in practice, while the judges fit for real use stay too expensive at scale. In this work, we take on both gaps: OSReward is, to our knowledge, the first to measure VLM-judge reliability across platforms on fresh, human-gold trajectories, and OS-Shepherd turns what it reveals into an open, low-cost reward model, and both are placed beside prior CUA reward work in Table 8.