

Verifying Agents in Rubric-Graded Environments

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Abstract

As AI agents take on increasingly open-ended and complex tasks, verifying their outputs has proven to be difficult. Rubric-graded agent environments—where a verifier judges multiple criteria against the deliverables and environment state changes produced by the agent—have emerged as a popular paradigm. We conduct the first systematic study of verifiers for rubric-graded agent environments. First, we create BankerVerifierBench (BVB), a meta-evaluation dataset of 3,204 human-judged rubric criteria across 21 investment-banking tasks. Next, we develop a methodology that derives from any rubric corpus the capabilities a verifier should possess, yielding a nine-capability taxonomy that we distill into three general design principles—reactive verification, environment alignment, and domain guidance—which we implement in Gandalf, an open-source verifier. Finally, we evaluate Gandalf against existing verifiers on BVB. We find that Gandalf outperforms all baselines on seven of nine capabilities and is Pareto optimal: its cheapest configuration (F1 0.633, \$42) exceeds the most expensive baseline (F1 0.538, \$414). Ablations show that environment alignment and domain guidance primarily reduce cost (up to 4× fewer tokens) rather than error, while architecture choice dominates model choice. Gandalf generalizes to an OpenClaw benchmark, a structurally different personal-productivity environment, achieving F1 score 0.951 and outperforming the next-best verifier by 7.5 F1 points.

Keywords

agentic verification, agents-as-a-judge, LLM-as-a-judge, rubric-based evaluation, agent benchmarks, verifiers

1 Introduction

Modern AI agents are systems that use large language models (LLMs) to interact with tools and environments in pursuit of a goal [10, 54, 73]. As these agents have grown increasingly capable and reliable, so too has the need to measure and optimize their

performance. Measurement and optimization go hand-in-hand: tool-use agents are evaluated within *environments*, and these same environments can be used for reinforcement learning (RL) to train improved models [38]. While some agentic benchmarks such as GDPval [46] are human-graded using pairwise preferences, enabling comparison between agents on leaderboards, the vast majority strive for automated pointwise grading, facilitating both benchmarking and reinforcement learning by using the grade as the reward signal.

Early efforts, encouraged by the success of reinforcement learning with verifiable rewards (RLVR) [13, 56], focused on *verifiable domains* where deterministic automated verification is possible. For example, SWE-bench [21] uses unit tests to verify software engineering, HotpotQA [71] uses exact-match scoring for multi-hop question-answering, and WebArena [80] uses programmatic checks for browser use. Such environments trade off verifiability against scope, open-endedness, and realism.

Recently, agent evaluation has expanded into *semi-verifiable domains* where judgment is required. Benchmarks such as BankerToolBench [25], APEX-Agents [61], CoreCraft [42], and ClawBench [77] use natural-language *rubrics*—fine-grained binary criteria that are objectively gradable—as a technique to define and capture correctness [12, 17, 62].

Verifying agent rollouts in such environments is a challenging task in its own right. Agents may produce multi-file deliverables (e.g., an Excel spreadsheet and a PowerPoint presentation) and invoke tools with side effects (e.g., sending an email). Verification requires checking diverse properties such as: whether an email was sent, whether an Excel model’s formulas propagate correctly across tabs, and whether a PowerPoint’s charts are internally consistent with the underlying data.

Verifiers for rubric-graded environments span a broad design space, ranging from using an LLM-as-a-judge on the trajectory [42] to making the verifier itself agentic: an *agent-as-a-judge* [75, 83]. Agentic judges themselves range from workflows (e.g., Archipelago [61])

to fully reactive agents [73] (e.g., ClawBench [77]). Despite growing interest from both research and industry, existing benchmarks treat the verifier as a subproblem—a means to grade rollouts or supply training rewards—rather than as an object of study. This gap, combined with the broad design space, motivates studying these verifiers in their own right.

To the best of our knowledge, we conduct the first systematic study of verifiers for agents in rubric-graded environments. To enable this, we produce a dataset of human annotations, analogous to prior work on meta-evaluation of LLM judging and rubric-based evaluation [43, 60]. The dataset consists of agent trajectories and final environment states (containing file deliverables), along with rubric criteria and human-produced judgments, across a number of tasks in the BankerToolBench (BTB) [25] agent environment. We call this verifier evaluation dataset BankerVerifierBench (BVB). We publicly release BVB, which consists of 3,204 judgment instances across 21 tasks, to facilitate future work on evaluating and improving verifiers for rubric-graded environments.

We develop a methodology to analyze rubrics and identify the raw *capabilities* a verifier needs to judge the criteria in a dataset. Applying this methodology to BVB, we identify nine capabilities that lead us to three general design principles for verifiers in rubric-graded environments. We implement these principles in *Gandalf*¹, a new open-source verifier for agent environments.

Our evaluation shows that *Gandalf* achieves state-of-the-art performance on BVB. We explain this performance through the lens of our design principles and capability taxonomy, finding that *Gandalf* achieves the best performance in seven of nine capabilities. Furthermore, *Gandalf* generalizes to new domains: we evaluate the verifier on an internal OpenClaw dataset and find that it achieves state-of-the-art performance on all six of six capabilities and remains Pareto optimal.

2 Background

In a *rubric-graded agent environment*, an agent receives a task and acts within a structured environment (e.g., a filesystem, a set of tools, and access to external data) to produce a deliverable, which may consist of one or more files together with changes to the environment. A verifier is then asked to assign a binary met/unmet judgment to each criterion in the task’s natural-language rubric. This contrasts with deterministically graded agent benchmarks, where criteria reduce to executable checks. Rubric-graded criteria are open-ended natural-language descriptions whose judgment often requires inspection of the deliverable, domain knowledge, and qualitative assessment. We adopt BankerToolBench (BTB) as the basis for our study and select three representative verifiers as objects of study.

BankerToolBench (BTB) environment. BTB [25] is a recently released benchmark of 100 end-to-end analytical workflows performed by junior investment bankers, including discounted cash-flow analyses, leveraged-buyout models, trading comparables, and merger models. Each task is long-horizon, taking a banker 5 hours on average. The agent receives a task description, a data room of pre-loaded files, and a fixed set of tools (a market-data platform, an

SEC EDGAR API, and a company-profile API, alongside a filesystem and pre-installed libraries such as `openpyxl` and `python-pptx`), and is expected to produce multi-file deliverables in standard office formats (`.xlsx`, `.pptx`, `.docx`, `.pdf`) accompanied by an expert-authored rubric of binary, weighted criteria. BTB rollouts are a demanding setting for verification: judging a single criterion may require joint reasoning across multiple heterogeneous artifacts.

Verifiers for rubric-graded environments. We study three open-source verifiers that engage with the deliverable to different degrees. *AutoRubric* [51] grades each criterion in an independent LLM call over the agent’s trajectory, with no access to the deliverable. *Archipelago* [61], released with APEX-Agents, captures a filesystem diff between initial and final environment states, extracts visual content via the Reducto document extraction service, and grades each criterion in an independent LLM call over the diff and extracted visuals without interacting with the deliverable directly. *Agent-as-a-Judge* [83] employs a workflow-based agent as the evaluator, planning and executing steps such as locating and reading files to reach a verdict.

3 BankerVerifierBench: Meta-evaluation for rubric-graded environments

We introduce BankerVerifierBench (BVB), the first meta-evaluation dataset for verifiers in rubric-graded agent environments. BVB extends prior meta-evaluation work for LLM judges [43, 60] and agent trajectories [37] to settings where criteria require inspecting multi-file binary deliverables and tool-mediated environment state rather than text alone. The dataset consists of 21 tasks drawn from the BTB task distribution, spanning the product groups and task types described in Section 2. Each task ships with an expert-authored rubric of binary criteria, weighted by importance and tagged with one of six categories; rubrics range from 47 to 286 criteria per task (median 160), totaling 3,204 criteria across the corpus. Each task is paired with one agent rollout, captured as the complete trajectory (messages, tool calls, tool responses) and the final environment state including all deliverable files in their native binary formats. Every criterion receives a binary verdict (met/unmet) from a domain expert as ground-truth: an initial 6 tasks (493 criteria) were graded by two reviewers independently with a senior reviewer issuing a master verdict (inter-annotator agreement 89.5%), and the remaining 15 tasks (2,711 criteria) were graded by a single reviewer plus senior master verdict; met-class prevalence on the full corpus is 78.7%.

4 Deriving requirements for verifiers from data

Tasks in rubric-graded agent environments come paired with a rubric of natural-language criteria. Rather than fixing a verifier architecture in advance and determining its capabilities, we start from the rubric and ask what capabilities does a verifier need to have. We describe a general methodology for deriving verifier requirements from any rubric corpus, then apply it to BVB. The methodology produces a taxonomy of verifier-side *capabilities*: each capability names a kind of check the verifier must perform to judge a criterion correctly. The taxonomy is verifier-side (labels describe what a verifier

¹<https://github.com/Handshake-AI-Research/gandalf-the-grader>

must check, not what the agent must produce) and architecture-agnostic (labels do not name a specific runtime, library, file format, or data source), so it applies across verifier types.

Methodology. Our pipeline takes a corpus of natural-language rubrics and produces a taxonomy of capabilities in three stages: free-text discovery, canonicalization, and closed-vocabulary tagging. All LLM calls use Gemini 3 Flash, and embeddings use Google’s text-embedding-005. The four prompts driving the pipeline are reproduced in Appendix A.

Stage 1: Free-text discovery. For each rubric criterion, an LLM receives the agent-facing task brief and the criterion text, and emits one to three short capability labels along with a one-sentence rationale per label. Three constraints are enforced programmatically: (i) the rationale must begin with “the verifier needs to ...” and quote a phrase from the criterion text, which enforces verifier-side framing; (ii) labels must not contain tokens naming a specific runtime, library, file format, or data source, which enforces architecture-agnosticism; and (iii) labels must follow a fixed lexical form.

Stage 2: Canonicalization. Each unique Stage 1 label is embedded and partitioned by agglomerative clustering into 80 fine-grained micro-clusters. An LLM names each micro-cluster and produces a definition, a diagnostic signal, a worked example, and a set of non-examples contrasting it with its nearest siblings. A final LLM call merges the 80 named micro-clusters into the canonical taxonomy under three hard constraints: between 8 and 10 canonical capabilities, no single capability covering more than 40% of corpus criteria, and every input micro-cluster mapped to exactly one canonical capability.

Stage 3: Closed-vocabulary tagging. Every criterion is re-tagged against the closed canonical taxonomy. An LLM receives the criterion, its task brief, and the full taxonomy (canonical names, definitions, diagnostic signals, non-examples), and emits one to three canonical capability tags per criterion ranked by confidence. For the analyses in Section 8.2, we use the highest-confidence tag per criterion to obtain a clean partition; the multi-tag distribution is consistent with the primary-tag results.

Application to BVB. Applying the methodology to the BVB rubric ($n = 3,204$ criteria) results in the nine capabilities listed in Table 1. The largest, *audit quantitative metric calculation*, accounts for 23.0% of rubric criteria; the smallest, *validate temporal and sequential integrity*, accounts for 3.3%.

In the BVB setting, these abstract capabilities take concrete form. *Audit quantitative metric calculation* ranges over EV/EBITDA multiples, transaction fees; *audit accounting logic and convention* covers sign rules and balance-sheet identities; *audit governance and strategic narrative* covers disclaimers, regulatory boilerplate, and acquisition-rationale claims. The same capability labels might carry to other domains although with different instantiations: for example, a clinical workflow would instantiate *audit accounting logic and convention* as dosage and contraindication checks against clinical guidelines; a productivity workflow would instantiate *audit governance and strategic narrative* as escalation policies and tone norms.

5 Design principles for verifiers

Reading the taxonomy as a specification surfaces three structural patterns in the capabilities: (i) the verification path varies across criteria, (ii) judging requires inspecting artifact-internal structure that text serialization erases, and (iii) judging requires domain knowledge not in the criterion text. Each pattern follows from the nature of natural-language rubrics over rich agent environments rather than from the financial-modeling setting of BVB. We address each with a design principle.

Principle 1 (P1): Reactive verification. We cannot predict the verification path from the criterion text alone: two criteria within a single capability can require different files to open, different tools to invoke, and different orders of operation, and the number of distinct paths grows with the rubric. The pattern is intrinsic to natural-language rubrics rather than a quirk of BVB: any domain that admits rubrics over open-ended deliverables will exhibit it. Our first principle is that the verifier should be a *reactive agent* [73] that, given a criterion, autonomously decides which artifacts to open, which tools to invoke, and in what order, terminating once it reaches a verdict. This shifts dispatch from architecture-time enumeration to inference-time reasoning by the underlying model. Every capability in the taxonomy exhibits this pattern.

Principle 2 (P2): Environment alignment. Several capabilities reduce to inspecting properties of the agent’s artifacts (formula structure, layout metadata, cross-file references) that do not survive flattening to text or rendering as images. The pattern generalizes beyond financial modeling: any environment with binary files, stateful tools, or structured data has analogous properties that serialization erases. Our second principle is that the verifier should run in the *same environment* as the rollout agent, with access to the same filesystem, libraries, and tools (including domain-specific Model Context Protocol (MCP) [18] tools). Beyond preserving signal, this makes the verifier domain-agnostic by construction: deploying it in a new RL environment requires only granting the same tool access as the rollout, with no domain-specific parsers or judge tooling. Six capabilities in the taxonomy exhibit this pattern.

Principle 3 (P3): Domain guidance. Several capabilities require knowledge that does not appear in the criterion text, such as accounting sign conventions or disclosure standards for an investment memo. Every domain has analogous conventions: medical workflows have clinical standards, legal workflows have citation rules, productivity workflows have communication norms. Our third principle is that the verifier should accept domain guidance at deployment time through a dedicated *guidance channel*, separate from the criterion text and from the architecture itself. Guidance enters as natural-language context independent of the verifier architecture. Two capabilities in the taxonomy exhibit this pattern.

6 Gandalf: a verifier for rubric-graded environments

We implement the design principles of Section 5 in *Gandalf*, a portable Python application. Gandalf instantiates P1 by building on the OpenHands SDK [67], an open-source agent harness. To satisfy P2, Gandalf is designed to be run directly inside the same

Table 1: The nine capabilities induced from the BVB corpus. The right-hand column reports each capability’s share of the 3,204 corpus criteria as a primary tag (top-ranked in Stage 3).

Capability	Description	%
Audit quantitative metric calculation	Recompute a derived figure from its inputs and compare against the deliverable.	23.0
Verify literal data point accuracy	Confirm a constant in the deliverable matches a constant in the brief or source data.	15.5
Reconcile cross-component data linkage	Trace a value across two locations in the deliverable (across sheets, tabs, or files).	14.9
Verify structural component inventory	Confirm the deliverable contains the prescribed sections, files, and columns.	12.1
Inspect visual presentation and style	Evaluate fonts, colors, alignment, layout, and branding against the specification.	11.6
Audit accounting logic and convention	Check signs, identities, and component completeness against domain conventions.	7.6
Validate document labeling and metadata	Confirm textual labels (tab names, axis titles, headers) match the specification verbatim.	6.5
Audit governance and strategic narrative	Confirm required disclosures are present and qualitative claims cohere with the analysis.	5.4
Validate temporal and sequential integrity	Verify chronological alignment, period sequencing, and stage-boundary integrity.	3.3

environment as the rollout agent, including connecting to the same MCP tools. Gandalf supports P3 through a configuration system that includes accepting natural-language judge guidance; while guidance is domain-specific (e.g., sign conventions for financial models), the mechanism is domain-agnostic.

Going beyond the design principles, Gandalf’s configuration system supports specifying the LLM to be used by the verifier agent, allowing a benchmark designer to trade off between accuracy and cost. As a performance optimization, Gandalf supports batching criteria to judge multiple criteria together at once. Rubrics in BTB average around 150 criteria per task, which would be prohibitively expensive to verify in separate reactive agent sessions that would have overlap (e.g., re-opening the same files). Batching amortizes this cost.

7 Evaluation

We evaluate Gandalf along with three baselines described in Section 2: Archipelago (serialize-then-grade), Agent-as-a-Judge (workflow-based file inspection), and AutoRubric (text-only trajectory grading). The evaluation answers three questions: (1) how do verifiers compare on accuracy and cost (Section 7.1); (2) what is the impact of Gandalf’s design principles (Section 7.2); and (3) how sensitive is Gandalf to configuration choices like batch size and model family (Section 7.3)?

We report F1 score as our primary measure of verifier performance, treating a criterion judged as unmet as the positive class. This choice reflects the label imbalance in the corpus: the majority of criterion–rollout pairs are satisfied, so F1 on the minority (unmet) class is more discriminating than raw accuracy. Unless otherwise noted, Gandalf runs at batch size $b=16$ with Gemini 3 Flash, with guidance and environment-aligned MCP tools enabled; we

justify this operating point in Section 7.3. We report cost in terms of evaluating over the entire dataset.

7.1 Gandalf wins on accuracy and cost

Figure 1 plots cost against F1 for all four verifiers across two model families: Gemini and GPT. The headline finding is that *verifier architecture matters more than model choice*: Gandalf with any backing model outperforms every other verifier with any backing model. In the GPT family, the cheapest Gandalf configuration (GPT-5.4-Nano, \$42) achieves F1 0.633, exceeding the most expensive Archipelago configuration (GPT-5.4, \$414, F1 0.538) by 9.5 points at one-tenth the cost.

Within each verifier, scaling to a larger model yields diminishing returns. For Gandalf, F1 ranges from 0.633 (GPT-5.4-Nano) to 0.664 (Gemini 3 Pro), a span of 3.1 points across a 7× cost increase. Archipelago shows a wider spread (0.473–0.604), suggesting that weaker architectures benefit more from stronger models, but even Archipelago’s best configuration (Gemini 3 Pro, \$422) falls short of Gandalf’s cheapest. Agent-as-a-Judge (AAAJ) and AutoRubric cluster below F1 0.47 regardless of model, with one exception: AutoRubric with GPT-5.4 reaches 0.472, where the stronger model partially compensates for the lack of artifact access through better trajectory reasoning.

7.2 Design principles trade error for cost

In Table 2, we isolate the contribution of P2 (environment alignment) and P3 (judge guidance) by toggling each in turn, fixing the base model to Gemini 3 Flash. The ablations measure the cost of substituting for P2 and P3 within a P1-equipped verifier rather than the principle’s full impact. Because Gandalf is reactive (P1), the agent loop can partially compensate for missing tools or missing

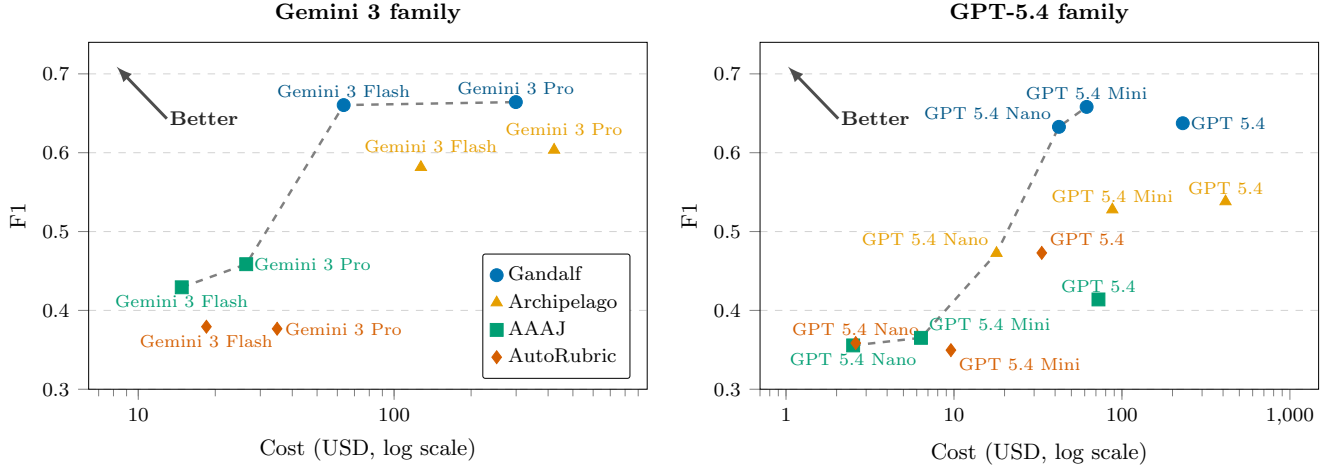


Figure 1: Cost vs. F1 across verifiers on BVB, split by model family. Left: Gemini 3 (Flash, Pro). Right: GPT (Nano, Mini, 5.4). Gandalf ($b=16$) dominates across both families. Costs computed from public API pricing: Gemini 3 Flash \$0.50/\$3.00, Gemini 3 Pro \$2.00/\$12.00, GPT-5.4-Nano \$0.20/\$1.25, GPT-5.4-Mini \$0.75/\$4.50, GPT-5.4 \$2.50/\$15.00 per 1M input/output tokens.

Table 2: Gandalf ablations on BVB. The default configuration (★) uses Gemini 3 Flash with batch size $b=16$, guidance, and MCP tools.

Design principles			Batch size			Model		
Config	F1	Cost	Config	F1	Cost	Config	F1	Cost
★ Guidance + MCP	.660	\$64	$b=64$	.635	\$32	Gemini 3 Pro	.664	\$299
No guidance, MCP	.649	\$73	$b=32$	.644	\$40	★ Gemini 3 Flash	.660	\$64
No guidance, no MCP	.661	\$102	★ $b=16$	.660	\$64	GPT-5.4	.637	\$230
			$b=8$	.667	\$100	GPT-5.4-Mini	.658	\$62
			$b=4$	.673	\$159	GPT-5.4-Nano	.633	\$42

guidance through additional inference-time exploration: aggregate F1 stays high, and the principle’s contribution surfaces in cost. The principle’s full impact, which non-P1 architectures cannot substitute around, manifests in the cross-verifier comparison (Section 7.1) and the capability-level breakdown (Section 8.2).

P2: Environment alignment. The cleanest isolation of P2 would hold guidance fixed and remove MCP. In our setup this run is uninformative: the guidance we authored for BVB references MCP-exposed capabilities, so without MCP it points at tools the verifier cannot reach. We therefore read P2’s contribution from the joint ablation. Removing both guidance and MCP (*No Guidance + No MCP*) leaves F1 unchanged (0.661 vs 0.660) but raises cost by 60% (\$64 to \$102), as the verifier compensates by writing ad-hoc Python scripts to parse binary files and issuing tool calls to extract information that a single MCP call would have returned in a more structured manner. Within a P1-equipped verifier, environment alignment is a cost optimization: the agent loop is expressive enough to work around missing tools, but doing so is substantially more expensive.

P3: Judge guidance. Removing judge guidance (the natural-language domain conventions injected into the verifier’s prompt, e.g., sign rules in financial modeling, disclosure standards for investment memos) hurts on both axes: F1 drops from 0.660 to 0.649 (1.1 points) and cost rises from \$64 to \$73 (14%). Without guidance, the verifier takes more exploratory tool calls to infer conventions that guidance would have stated directly, and the additional exploration only partially recovers the lost accuracy. Within a P1-equipped verifier, guidance is a strict improvement on both axes: it encodes domain knowledge that the verifier would otherwise rediscover through trial and error at higher cost.

7.3 Gandalf is robust within its design space

Batch size. We vary batch size, the number of criteria graded by one agent trajectory. F1 rises monotonically as batch size shrinks, from 0.635 at $b=64$ to 0.673 at $b=4$, with cost rising from \$32 to \$159 across the same range. The curve flattens below $b=16$: dropping from $b=16$ to $b=4$ buys 1.3 F1 points at 2.5× the cost. At $b=32$ and below, each session is small enough for the verifier to attend to every criterion individually while amortizing file-reading and tool

calls across the batch; below this point, additional sessions largely duplicate the same inspection work without extracting new signal. We fix $b=16$ for all cross-verifier comparisons as a deliberate cost-accuracy tradeoff.

Model choice. Table 2 also reports Gandalf at $b=16$ across five models spanning two providers. Gemini 3 Pro achieves the highest F1 (0.664), followed closely by Gemini 3 Flash (0.660) and GPT-5.4-Mini (0.658). The full spread from the weakest model (GPT-5.4-Nano, 0.633) to the strongest is 3.1 F1 points, a modest range given the diversity of model scale and cost. The ranking does not simply follow model size: GPT-5.4 (0.637) underperforms GPT-5.4-Mini (0.658), suggesting that factors beyond raw capability such as instruction-following fidelity or tool-use calibration mediate verifier performance. The 3.1-point spread across model choices and the plateau in batch size are both smaller than the gap between Gandalf and any other verifier on the cost-F1 frontier (Section 7.1): configuration choices move Gandalf along its frontier, but they do not move it off.

8 Discussion

We now step back and ask two questions about the evaluation results: (1) does Gandalf generalize beyond BVB (Section 8.1); and (2) why do different verifiers perform differently (Section 8.2)?

8.1 Gandalf generalizes beyond BVB

To investigate whether Gandalf generalizes, we collected another internal dataset analogous to BVB in a new domain: we additionally evaluate on an OpenClaw (OPC) benchmark of persona-driven personal-productivity workflows: managing schedules, coordinating with contacts, planning lifestyle tasks. OpenClaw differs from BVB in domain (consumer), tool surface (messaging clients, calendar and booking services, a weather API), and evidence type (many OpenClaw tools are stateful, so verification depends on determining if the environment has changed such as whether a message was sent or an event created). This dataset consists of 396 criteria judgments across 24 tasks.

Figure 2 plots F1 against cost across all four verifiers on the OpenClaw dataset. Gandalf achieves F1 of 0.951, leading the next-best verifier (Archipelago with Gemini 3 Flash, 0.876) by 7.5 points, and is again Pareto optimal: the cheaper verifiers (Archipelago, AutoRubric) sacrifice 7–10 F1 points. The results replicate the BVB finding that *verifier architecture dominates model choice*: Gandalf with Gemini 3 Flash outperforms every other verifier regardless of backing model. The non-agentic verifiers cluster in a narrow band (0.849–0.876), suggesting that once serialization captures most of the evidence, a stronger model or richer serialization yields diminishing returns.

8.2 Verifiers’ errors are explained by gaps in capabilities

Table 3 breaks down errors by capability taxonomy generated in Section 4. Each baseline fails specifically on capabilities where its missing principles would have helped, while Gandalf wins everywhere except two narrow exceptions we return to at the end of this

section. The table includes RewardKit (RK), a concurrent agentic verifier covered in Section 8.3 below.

AutoRubric. AutoRubric is a non-agentic verifier: it grades each criterion in an isolated LLM call over the agent’s trajectory, with no artifact access and no domain guidance. It satisfies none of the three principles. Errors are high and undifferentiated across capabilities: 32.8–61.5% on BVB, where most evidence lives in the deliverable, and 9.4–31.8% on OPC, where trajectories at least carry tool-call content.

AAAj. AAAj inspects files through its own toolset rather than the rollout’s environment, with no domain guidance. It is a workflow-based (rather than reactive) agent, lacking all of P1–P3. Errors concentrate on the inspection-bound capabilities P2 covers: on BVB, *verify literal data point accuracy* (38.2%), *audit quantitative metric calculation* (35.1%), and *reconcile cross-component data linkage* (31.4%) are its three worst rows; on OPC, *reconcile cross-component data linkage* reaches 40.0%. The single BVB row AAAj wins, *audit governance and strategic narrative*, is the only one where neither structural inspection nor cross-component tracing applies and the criteria reduce to judging textual content. On OPC the same capability flips: Gandalf wins (error rate 6.1% vs AAAj’s 43.9% error rate), because OPC’s instances require tool-state inspection (e.g., whether a message was sent) rather than text judgment, moving the bottleneck back into P2’s territory.

Archipelago. Archipelago is workflow-based and grades each criterion from a serialized snapshot of the deliverable, giving it a partial form of P2; it has neither P1 nor P3. Table 4 reports its per-capability FP and FN rates on BVB (FP denotes over-rejection of a met criterion; FN denotes an unmet criterion passing). Errors split bimodally along P2’s fault line: on the four capabilities that require native artifact inspection, FN exceeds FP by 4.4–5.6% in absolute terms (e.g., *inspect visual presentation and style*: FP 10.5%, FN 16.1%) because deficient outputs pass when serialization erases the disqualifying signal. On the other five capabilities, FP exceeds FN by up to 6.5% (e.g., *validate temporal and sequential integrity*: FP 12.1%, FN 5.6%): the LLM judge over-rejects on inferences from rendered evidence. The pattern reproduces and sharpens on OPC: the Gandalf–Archipelago gap on *reconcile cross-component data linkage* widens from 6.9% on BVB to 35.0% on OPC.

Where the framework does not predict. Gandalf’s only losses are two BVB rows where the gap is narrow (1–2%) and the bottleneck is the LLM applying conventions or judging coherence over text both verifiers can see: *audit accounting logic and convention* (Archipelago by 2.1%) and *audit governance and strategic narrative* (AAAj by 1.1%). The principles pay off where artifact-grounded inspection is the bottleneck, not where the bottleneck is reasoning over rendered text. The OPC result on *audit governance and strategic narrative* reinforces the point in the other direction: when its criteria require tool-state inspection, P2 reasserts itself and Gandalf wins by 37.8%.

8.3 Comparison with RewardKit

RewardKit [15] is the verification component of Harbor, developed concurrently with Gandalf. Like Gandalf, RewardKit employs an agentic verifier that can interact with the agent’s output artifacts,

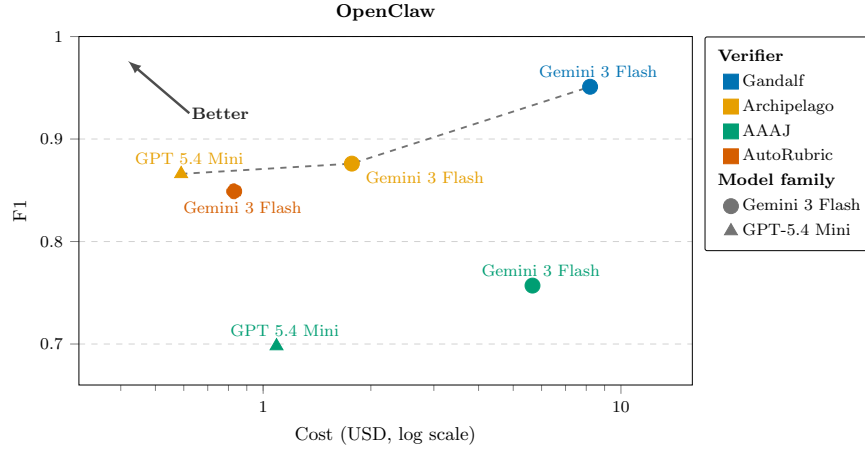


Figure 2: Cost vs. F1 across verifiers on OpenClaw (24 episodes), with Gemini 3 Flash (circles) and GPT-5.4 Mini (triangles) model families. Gandalf with Gemini 3 Flash sits at the Pareto frontier (F1 0.951, \$8.20).

Table 3: Per-capability error rates (%) for all five verifiers — Gandalf (Gan), Archipelago (Arc), Agent-as-a-Judge (AAAJ), AutoRubric (Aut), and RewardKit (RK) — on BVB and OpenClaw. Bold: best verifier on each row within each corpus (ties bolded). Cells marked — denote capabilities not present in the OPC corpus. RewardKit on BVB is on its $n=2,634$ subset (see Section 8.3).

Capability	n	BVB						OPC				
		Gan.	Arc.	AAAJ	Aut.	RK		Gan.	Arc.	AAAJ	Aut.	RK
Audit quantitative metric calculation	736	12.0	15.6	35.1	61.5	17.0	—	—	—	—	—	—
Verify literal data point accuracy	497	12.3	15.3	38.2	59.2	12.8	200	4.5	10.0	25.5	21.5	13.5
Reconcile cross-component data linkage	478	13.4	20.3	31.4	57.1	16.5	20	0.0	35.0	40.0	20.0	35.0
Verify structural component inventory	388	10.8	12.6	25.5	52.1	9.6	53	1.9	13.2	18.9	9.4	15.1
Inspect visual presentation and style	373	17.2	26.5	34.9	51.5	18.3	—	—	—	—	—	—
Audit accounting logic and convention	244	16.0	13.9	30.3	60.2	16.8	—	—	—	—	—	—
Validate document labeling and metadata	207	13.5	15.0	30.0	41.5	9.7	41	7.3	24.4	31.7	12.2	17.1
Audit governance and strategic narrative	174	19.5	21.8	18.4	32.8	19.2	66	6.1	25.8	43.9	31.8	16.7
Validate temporal and sequential integrity	107	15.9	17.8	20.6	45.8	18.7	12	8.3	25.0	16.7	16.7	16.7
Aggregate	3,204	13.6	17.4	31.7	54.7	15.2	396	4.5	16.2	28.5	20.2	15.7

making it the most architecturally similar baseline in our study. For each criterion, RewardKit spawns an isolated Claude Code session pointed at the agent’s output workspace; the judge can explore the filesystem, write scripts, and run shell commands to reach a verdict. Criteria are configured via TOML files and fall into two classes: programmatic (Python functions that inspect files or run shell commands) and judge-based (LLM or agent evaluation). We evaluate RewardKit in its agent-judge mode, both with and

without access to environment-aligned MCP tools (+MCP); the latter toggle is the closest analogue to Gandalf’s P2 within RewardKit’s architecture. The key architectural difference is in *how* the verifier accesses the environment: RewardKit operates through a general-purpose code CLI (the judge writes and executes ad-hoc scripts to inspect deliverables), whereas Gandalf runs inside the rollout agent’s own environment with access to the same domain-specific

Table 4: Archipelago FP and FN rates (%) per capability on BVB, sorted by FN–FP gap. Capabilities that require native artifact inspection are FN-dominant; those that reduce to judgment over rendered evidence are FP-leaning.

Capability	<i>n</i>	FP rate	FN rate	FN–FP
<i>Native inspection required (FN-dominant)</i>				
Inspect visual presentation and style	373	10.5	16.1	+5.6
Validate document labeling and metadata	207	4.8	10.1	+5.3
Reconcile cross-component data linkage	478	7.5	12.8	+5.2
Verify structural component inventory	388	4.1	8.5	+4.4
<i>Judgment on rendered content (FP-leaning)</i>				
Audit accounting logic and convention	244	7.4	6.6	−0.8
Verify literal data point accuracy	497	8.2	7.0	−1.2
Audit governance and strategic narrative	174	12.1	9.8	−2.3
Audit quantitative metric calculation	736	10.6	5.0	−5.6
Validate temporal and sequential integrity	107	12.1	5.6	−6.5

Table 5: Comparison of RewardKit and Gandalf on BankerVerifierBench. Gandalf achieves the highest F1 while being the cheapest verifier, owing to Gemini 3 Flash’s lower per-token rates. Token counts are summed across prompt and response; costs are computed at public API list prices (Gemini 3 Flash: \$0.50/\$3.00 per MTok in/out; Claude Sonnet 4.6: \$3.00/\$15.00 per MTok in/out).

Verifier	Model	F1	Tokens (M)	Cost (\$)
RewardKit	Claude Sonnet 4.6	0.879	52.6	162.67
RewardKit +MCP	Claude Sonnet 4.6	0.905	51.7	160.76
Gandalf	Gemini 3 Flash	0.951	70.0	35.76

tools (e.g., MCP servers) the agent used during task execution. Table 5 summarizes the headline result.

Gandalf’s higher token count reflects the cost of environment-aligned verification: inspecting artifacts through native tools and tracing values across files takes more agentic steps than writing ad-hoc scripts in a code CLI. Despite consuming roughly 35% more tokens, Gandalf is approximately 4.5× cheaper than RewardKit because it runs on Gemini 3 Flash rather than Claude Sonnet 4.6. The combination of a 7.2-point F1 advantage over the best RewardKit variant and a substantially lower cost makes Gandalf the stronger choice for RL reward signals, where verifier accuracy impacts training quality [48].

Capability-level breakdown. RewardKit is evaluated on a subset ($n=2,634$ of 3,204): a fraction of grading runs failed to complete because the criterion list became too large for the verifier to handle. Gandalf handles such cases by batching; RewardKit has no batching functionality. On its subset, RewardKit’s aggregate error is 15.2% on BVB (Table 3), between Gandalf and Archipelago. Per-capability, RewardKit matches or beats Gandalf on three capabilities reducible to direct filesystem inspection (*verify structural component inventory* 9.6% vs. 10.8%, *validate document labeling and metadata* 9.7% vs. 13.5%, *verify literal data point accuracy* 12.8% vs. 12.3%), and

trails Gandalf on the remaining six by up to 3.6% on *audit quantitative metric calculation* and 3.1% on *reconcile cross-component data linkage*. The pattern is consistent with RewardKit’s design: a general-purpose code CLI suffices when the verifier needs to read a value out of a file, but underperforms when verification requires resolving references through the rollout agent’s own tool surface. RewardKit’s polarity is also distinct: with an FN/FP ratio of 0.29, it is the only verifier in our study biased toward over-rejection rather than toward letting deficient outputs pass.

9 Related work

Agent environments. Agent benchmarks frequently rely on deterministic checks against final state, expected tool calls, or unit tests [4, 21, 28, 30, 31, 35, 40, 44, 45, 49, 65, 72]. In pursuit of greater scope and realism, recent benchmarks in semi-verifiable domains have embraced rubric-based grading. Such benchmarks include BankerToolBench [25], APEX-Agents [61], CoreCraft [42], GTA-2 [64], ClawBench [77], Claw-Eval [74], and AgencyBench [29]. Across both lines, these works treat the verifier as a means to an end, not the object of study.

Rubrics. Rubrics are a popular approach to defining correctness in semi-verifiable domains [32, 57]. Rubrics may be authored by domain experts [1, 2, 58] or generated synthetically [5, 34, 50, 63]. RubricBench [76] evaluates rubric generators themselves against human preferences. A line of work investigates rubrics in the context of training [12, 62]; some of this work investigates training with synthetic rubrics [17, 20, 52, 55]. Rubric-ARM [69] jointly optimizes a rubric generator and a judge, optimizing judgment accuracy for matching human preference ranking. Unlike these works, we take rubrics as a given and study the verifiers that consume them.

Verifier designs. Verifiers, both inside and outside the context of environments, cover a broad design space [11, 27, 75]. A line of work optimizes LLM-as-a-judge for evaluating text through prompting or training [22, 23, 36, 82], and a related line decomposes evaluation into per-criterion judgments via rubrics [16, 26, 51, 53, 79]. Benchmarks commonly apply such techniques for outcome grading

in agent environments by evaluating a serialized trajectory or serialized output files [42, 74]. In contrast, some environments propose workflow-based agents as verifiers [9, 14, 47, 59, 61, 81, 83], while others propose reactive agents [3, 6–8, 33, 39, 66, 68]. Despite the broad design space, no principled account describes which design choices matter for which verification capabilities.

Meta-evaluation of verifiers. Motivated by the importance of verifiers in benchmarks, meta-evaluation benchmarks evaluate verifiers themselves, covering LLM-as-a-judge for preference rankings [24, 41, 60, 78] and LLM-as-a-judge for rubric grading [43]. Verifiers can be domain-specific, motivating domain-specific benchmarks such as AgentRewardBench [37] for web agents and meta-evaluations such as TinyV [70] and Huang et al. [19] for mathematics. BVB is the first meta-evaluation dataset that covers rubric-graded agent environments, where rubric criteria cover deliverable files and side-effecting tool calls.

10 Conclusion

Our results motivate the adoption of guidable environment-aligned reactive agents as the Pareto-optimal design for verifying agents in rubric-graded domains. We hope that the public release of BVB will help facilitate continued research on building verifiers for agents, and that the open-source release of Gandalf will unlock more realistic benchmarks for agents.

Limitations. The BVB dataset contains a single rollout per task; we did not evaluate the sensitivity of verifiers to the rollout distribution. Our study measures verifier F1 score against human labels; we did not evaluate whether verifier accuracy advantage translates to better-trained agents through RL. Our study is limited to BVB and our internal OpenClaw dataset; we expect Gandalf will generalize to domains beyond these two and hope to see this validated by future benchmarks.

References

- [1] Afra Feyza Akyurek, Advait Gosai, Chen Bo Calvin Zhang, Vipul Gupta, Jaehwan Jeong, Anisha Gunjal, Tahseen Rabbani, Maria Mazzone, David Randolph, Mohammad Mahmoudi Meymand, Gurshaan Chattha, Paula Rodriguez, Diego Mares, Pavit Singh, Michael Liu, Subodh Chawla, Pete Cline, Lucy Ogaz, Ernesto Hernandez, Zihao Wang, Pavi Bhattar, Marcos Ayestaran, Bing Liu, and Yunzhong He. 2025. PRBench: Large-Scale Expert Rubrics for Evaluating High-Stakes Professional Reasoning. arXiv:2511.11562 [cs.CL]. <https://arxiv.org/abs/2511.11562>
- [2] Rahul K. Arora, Jason Wei, Rebecca Soskin Hicks, Preston Bowman, Joaquin Quiñero Candela, Foivos Tsimpouras, Michael Sharman, Meghan Shah, Andrea Vallone, Alex Beutel, Johannes Heidecke, and Karan Singhal. 2025. Health-Bench: Evaluating Large Language Models Towards Improved Human Health. arXiv:2505.08775 [cs.CL]. <https://arxiv.org/abs/2505.08775>
- [3] Elad Ben Avraham, Changhao Li, Ron Dorfman, Roy Ganz, Oren Nuriel, Amir Dudai, Aviad Aberdam, Noah Flynn, Elman Mansimov, Adi Kalyanpur, and Ron Litman. 2026. DREAM: Deep Research Evaluation with Agentic Metrics. arXiv:2602.18940 [cs.AI]. <https://arxiv.org/abs/2602.18940>
- [4] Zehui Chen, Weihua Du, Wenwei Zhang, Kuikun Liu, Jiangning Liu, Miao Zheng, Jingming Zhuo, Songyang Zhang, Dahua Lin, Kai Chen, and Feng Zhao. 2024. T-Eval: Evaluating the Tool Utilization Capability of Large Language Models Step by Step. In *Proceedings of the 62nd Meeting of the Association for Computational Linguistics (ACL)*. Bangkok, Thailand, 9510–9529.
- [5] Jonathan Cook, Tim Rocktäschel, Jakob Foerster, Dennis Aumiller, and Alex Wang. 2024. TtCKing All the Boxes: Generated Checklists Improve LLM Evaluation and Generation. arXiv:2410.03608 [cs.AI]. <https://arxiv.org/abs/2410.03608>
- [6] Chaouqun Cui, Jing Huang, Shijing Wang, Liming Zheng, Qingchao Kong, and Zhixiong Zeng. 2026. Agentic Reward Modeling: Verifying GUI Agent via Online Proactive Interaction. arXiv:2602.00575 [cs.RO]. <https://arxiv.org/abs/2602.00575>
- [7] Gaole Dai, Shiqi Jiang, Ting Cao, Yuqing Yang, Yuanchun Li, Rui Tan, Mo Li, and Lili Qiu. 2026. ProRe: A Proactive Reward System for GUI Agents via Reasoner-Actor Collaboration. In *Proceedings of the 14th International Conference on Learning Representations (ICLR)*. Rio de Janeiro, Brazil.
- [8] Shengyuan Ding, Xinyu Fang, Ziyu Liu, Yuhang Zang, Yuhang Cao, Xiangyu Zhao, Haodong Duan, Xiaoyi Dong, Jianze Liang, Bin Wang, Conghui He, Dahua Lin, and Jiaqi Wang. 2026. ARM-Thinker: Reinforcing Multimodal Generative Reward Models with Agentic Tool Use and Visual Reasoning. In *Proceedings of the 2026 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. Denver, CO.
- [9] Arduin Findeis, Floris Weers, Guoli Yin, Ke Ye, Ruoming Pang, and Tom Gunter. 2025. Can External Validation Tools Improve Annotation Quality for LLM-as-a-Judge?. In *Proceedings of the 63rd Meeting of the Association for Computational Linguistics (ACL)*. Vienna, Austria, 15997–16020.
- [10] Luyu Gao, Aman Madaan, Shuyan Zhou, Uri Alon, Pengfei Liu, Yiming Yang, Jamie Callan, and Graham Neubig. 2023. PAL: Program-aided Language Models. In *Proceedings of the 40th International Conference on Machine Learning (ICML)*. Honolulu, HI, 10764–10799.
- [11] Xinyan Guan, Yanjiang Liu, Xinyu Lu, Boxi Cao, Ben He, Xianpei Han, Le Sun, Jie Lou, Bowen Yu, Yaojie Lu, and Hongyu Lin. 2024. Search, Verify and Feedback: Towards Next Generation Post-training Paradigm of Foundation Models via Verifier Engineering. arXiv:2411.11504 [cs.AI]. <https://arxiv.org/abs/2411.11504>
- [12] Anisha Gunjal, Anthony Wang, Elaine Lau, Vaskar Nath, Yunzhong He, Bing Liu, and Sean Hendryx. 2026. Rubrics as Rewards: Reinforcement Learning Beyond Verifiable Domains. In *Proceedings of the 14th International Conference on Learning Representations (ICLR)*. Rio de Janeiro, Brazil.
- [13] Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Peiyi Wang, Qihao Zhu, Runxin Xu, Ruoyu Zhang, Shiroon Ma, Xiao Bi, Xiaokang Zhang, Xingkai Yu, Yu Wu, Z. F. Wu, Zhibin Gou, Zhihong Shao, Zhuoshu Li, Ziyi Gao, Aixin Liu, Bing Xue, Bingxuan Wang, Bochao Wu, Bei Feng, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chong Ruan, Damai Dai, Deli Chen, Dongjie Ji, Erhang Li, Fangyun Lin, Fucong Dai, Fuli Luo, Guangbo Hao, Guanting Chen, Guowei Li, H. Zhang, Hanwei Xu, Honghui Ding, Huazuo Gao, Hui Qu, Hui Li, Jianzhong Guo, Jia Shi Li, Jingchang Chen, Jingyang Yuan, Jinhao Tu, Junjie Qiu, Junlong Li, J. L. Cai, Jiaqi Ni, Jian Liang, Jin Chen, Kai Dong, Kai Hu, Kaichao You, Kaige Gao, Kang Guan, Kexin Huang, Kuai Yu, Lean Wang, Lecong Zhang, Liang Zhao, Litong Wang, Liyue Zhang, Lei Xu, Leyi Xia, Mingchuan Zhang, Minghua Zhang, Minghui Tang, Mingxu Zhou, Meng Li, Miaojun Wang, Mingming Li, Ning Tian, Panpan Huang, Peng Zhang, Qiancheng Wang, Qinyu Chen, Qishi Du, Ruiqi Ge, Ruisong Zhang, Ruizhe Pan, Runji Wang, R. J. Chen, R. L. Jin, Ruyi Chen, Shanghao Lu, Shangyan Zhou, Shanhua Chen, Shengfeng Ye, Shiyu Wang, Shuiping Yu, Shunfeng Zhou, Shutong Pan, S. S. Li, Shuang Zhou, Shaoqing Wu, Tao Yun, Tian Pei, Tianyu Sun, T. Wang, Wangding Zeng, Wen Liu, Wenfeng Liang, Wenjun Gao, Wenqin Yu, Wentao Zhang, W. L. Xiao, Wei An, Xiaodong Liu, Xiaohan Wang, Xiaokang Chen, Xiaotao Nie, Xin Cheng, Xin Liu, Xin Xie, Xingchao Liu, Xinyu Yang, Xinyuan Li, Xuecheng Su, Xuheng Lin, X. Q. Li, Xiangyue Jin, Xiaojin Shen, Xiaosha Chen, Xiaowen Sun, Xiaoxiang Wang, Xinnan Song, Xinyi Zhou, Xianzu Wang, Xinxia Shan, Y. K. Li, Y. Q. Wang, Y. X. Wei, Yang Zhang, Yanhong Xu, Yao Li, Yao Zhao, Yaofeng Sun, Yaohui Wang, Yi Yu, Yichao Zhang, Yifan Shi, Yiliang Xiong, Ying He, Yishi Piao, Yisong Wang, Yixuan Tan, Yiyang Ma, Yiyuan Liu, Yongqiang Guo, Yuan Ou, Yudian Wang, Yue Gong, Yuheng Zou, Yujia He, Yunfan Xiong, Yuxiang Luo, Yuxiang You, Yuxuan Liu, Yuyang Zhou, Y. X. Zhu, Yanping Huang, Yaohui Li, Yi Zheng, Yuchen Zhu, Yunxian Ma, Ying Tang, Yukun Zha, Yuting Yan, Z. Z. Ren, Zehui Ren, Zhangli Sha, Zhe Fu, Zhexun Xu, Zhenda Xie, Zhengyan Zhang, Zhewen Hao, Zhicheng Ma, Zhigang Yan, Zhiyu Wu, Zihui Gu, Zijia Zhu, Zijun Liu, Zilin Li, Ziwei Xie, Ziyang Song, Zizheng Pan, Zhen Huang, Zhipeng Xu, Zhongyu Zhang, and Zhen Zhang. 2025. DeepSeek-R1 incentivizes reasoning in LLMs through reinforcement learning. *Nature* 645, 8081 (Sept. 2025), 633–638.
- [14] Jiuzhou Han, Wray Buntine, and Ehsan Shareghi. 2025. VerifiAgent: a Unified Verification Agent in Language Model Reasoning. In *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Suzhou, China, 16410–16431.
- [15] Harbor Framework Team. 2026. Harbor: A framework for evaluating and optimizing agents and models in container environments. <https://github.com/harbor-framework/harbor>
- [16] Helia Hashemi, Jason Eisner, Corby Rosset, Benjamin Van Durme, and Chris Kedzie. 2024. LLM-Rubric: A Multidimensional, Calibrated Approach to Automated Evaluation of Natural Language Texts. In *Proceedings of the 62nd Meeting of the Association for Computational Linguistics (ACL)*. Bangkok, Thailand, 13806–13834.
- [17] Yun He, Wenzhe Li, Hejia Zhang, Songlin Li, Karishma Mandyam, Sopan Khosla, Yuanhao Xiong, Nanshu Wang, Xiaoliang Peng, Beibin Li, Shengjie Bi, Shishir G. Patil, Qi Qi, Shengyu Feng, Julian Katz-Samuels, Richard Yuanzhe Pang, Sujun Gongugondla, Hunter Lang, Yue Yu, Yundi Qian, Maryam Fazel-Zarandi, Licheng Yu, Amine Benhaloum, Hany Awadalla, and Manaa Faruqi. 2025. AdvancedIF: Rubric-Based Benchmarking and Reinforcement Learning for Advancing LLM Instruction Following. arXiv:2511.10507 [cs.CL]. <https://arxiv.org/abs/2511.10507>
- [18] Xinyi Hou, Yanjie Zhao, Shenao Wang, and Haoyu Wang. 2025. Model Context Protocol (MCP): Landscape, Security Threats, and Future Research Directions.

- arXiv:2503.23278 [cs.CR]. <https://arxiv.org/abs/2503.23278>
- [19] Yuzhen Huang, Weihao Zeng, Xingshan Zeng, Qi Zhu, and Junxian He. 2025. From Accuracy to Robustness: A Study of Rule- and Model-based Verifiers in Mathematical Reasoning. arXiv:2505.22203v2 [cs.LG]. <https://arxiv.org/abs/2505.22203v2>
 - [20] Zenan Huang, Yihong Zhuang, Guoshan Lu, Zeyu Qin, Haokai Xu, Tianyu Zhao, Ru Peng, Jiaqi Hu, Zhanming Shen, Xiaomeng Hu, Xijun Gu, Peiyi Tu, Jiaxin Liu, Wenyu Chen, Yuzhuo Fu, Zhiting Fan, Yanmei Gu, Yuanyuan Wang, Zhengkai Yang, Jianguo Li, and Junbo Zhao. 2025. Reinforcement Learning with Rubric Anchors. arXiv:2508.12790 [cs.AI]. <https://arxiv.org/abs/2508.12790>
 - [21] Carlos E. Jimenez, John Yang, Alexander Wettig, Shunyu Yao, Kexin Pei, Ofir Press, and Karthik Narasimhan. 2024. SWE-bench: Can Language Models Resolve Real-World GitHub Issues?. In *Proceedings of the 12th International Conference on Learning Representations (ICLR)*. Vienna, Austria.
 - [22] Seungone Kim, Jamin Shin, Yejin Cho, Joel Jang, Shayne Longpre, Hwaran Lee, Sangdo Yoon, Seungjin Shin, Sungdong Kim, James Thorne, and Minjoon Seo. 2024. Prometheus: Inducing Fine-grained Evaluation Capability in Language Models. In *Proceedings of the 12th International Conference on Learning Representations (ICLR)*. Vienna, Austria.
 - [23] Seungone Kim, Juyoung Suk, Shayne Longpre, Bill Yuchen Lin, Jamin Shin, Sean Welleck, Graham Neubig, Moontae Lee, Kyungjae Lee, and Minjoon Seo. 2024. Prometheus 2: An Open Source Language Model Specialized in Evaluating Other Language Models. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Miami, FL, 4334–4353.
 - [24] Nathan Lambert, Valentina Pyatkin, Jacob Morrison, LJ Miranda, Bill Yuchen Lin, Khyathi Chandu, Nouha Dziri, Sachin Kumar, Tom Zick, Yejin Choi, Noah A. Smith, and Hannaneh Hajishirzi. 2025. RewardBench: Evaluating Reward Models for Language Modeling. In *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics (NAACL)*. Albuquerque, NM, 1755–1797.
 - [25] Elaine Lau, Markus Dücker, Ronak Chaudhary, Hui Wen Goh, Rosemary Wei, Vaibhav Kumar, Saed Qunbar, Guram Gogia, Yi Liu, Scott Mills, Nasim Boraz-janizadeh, Ulyana Tkachenko, Samuel Eshun Danquah, Collin Schweiker, Vijay Karumathil, Asrith Devalaraju, Varsha Sandadi, Haemi Nam, Punit Arani, Ray Epps, Abdullah Arif, Sahil Bhaiwala, Curtis Northcutt, Skyler Wang, Anish Athalye, Jonas Mueller, and Francisco Guzmán. 2026. BankerToolBench: Evaluating AI Agents in End-to-End Investment Banking Workflows. arXiv:2604.11304 [cs.AI]. <https://arxiv.org/abs/2604.11304>
 - [26] Yuyang Lee, Joonghoon Kim, Jaehye Kim, Hyowon Cho, Jaewook Kang, Pilsung Kang, and Najeon Kim. 2025. CheckEval: A reliable LLM-as-a-Judge framework for evaluating text generation using checklists. In *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Suzhou, China, 15771–15798.
 - [27] Dawei Li, Bohan Jiang, Liangjie Huang, Alimohammad Beigi, Chengshuai Zhao, Zhen Tan, Amrita Bhattacharjee, Yuxuan Jiang, Canyu Chen, Tianhao Wu, Kai Shu, Lu Cheng, and Huan Liu. 2025. From Generation to Judgment: Opportunities and Challenges of LLM-as-a-judge. In *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Suzhou, China, 2757–2791.
 - [28] Junlong Li, Wenshuo Zhao, Jian Zhao, Weihao Zeng, Haoze Wu, Xiaochen Wang, Rui Ge, Yuxuan Cao, Yuzhen Huang, Wei Liu, Junteng Liu, Zhaochen Su, Yiyang Guo, Fan Zhou, Lueyang Zhang, Juan Michelini, Xingyao Wang, Xiang Yue, Shuyan Zhou, Graham Neubig, and Junxian He. 2026. The Tool Decathlon: Benchmarking Language Agents for Diverse, Realistic, and Long-Horizon Task Execution. In *Proceedings of the 14th International Conference on Learning Representations (ICLR)*. Rio de Janeiro, Brazil.
 - [29] Keyu Li, Junhao Shi, Yang Xiao, Mohan Jiang, Jie Sun, Yunze Wu, Dayuan Fu, Shijie Xia, Xiaojie Cai, Tianze Xu, Weiye Si, Wenjie Li, Dequan Wang, and Pengfei Liu. 2026. AgencyBench: Benchmarking the Frontiers of Autonomous Agents in 1M-Token Real-World Contexts. arXiv:2601.11044 [cs.AI]. <https://arxiv.org/abs/2601.11044>
 - [30] Minghao Li, Yingxiu Zhao, Bowen Yu, Feifan Song, Hangyu Li, Haiyang Yu, Zhoujun Li, Fei Huang, and Yongbin Li. 2023. API-Bank: A Comprehensive Benchmark for Tool-Augmented LLMs. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Singapore, 3102–3116.
 - [31] Xiangyi Li, Kyoung Whan Choe, Yimin Liu, Xiaokun Chen, Chujun Tao, Bingran You, Wenbo Chen, Zonglin Di, Jiankai Sun, Shenghan Zheng, Jiajun Bao, Yuanli Wang, Weixiang Yan, Yiyuan Li, and Han chung Lee. 2026. ClawsBench: Evaluating Capability and Safety of LLM Productivity Agents in Simulated Workspaces. arXiv:2604.05172 [cs.AI]. <https://arxiv.org/abs/2604.05172>
 - [32] Bill Yuchen Lin, Yuntian Deng, Khyathi Chandu, Faeze Brahman, Abhilasha Ravichander, Valentina Pyatkin, Nouha Dziri, Ronan Le Bras, and Yejin Choi. 2025. WildBench: Benchmarking LLMs with Challenging Tasks from Real Users in the Wild. In *Proceedings of the 13th International Conference on Learning Representations (ICLR)*. Singapore.
 - [33] Lanbo Lin, Jiayao Liu, Tianyuan Yang, Li Cai, Yuanwu Xu, Lei Wei, Sicong Xie, and Guannan Zhang. 2026. JADE: Expert-Grounded Dynamic Evaluation for Open-Ended Professional Tasks. arXiv:2602.06486 [cs.AI]. <https://arxiv.org/abs/2602.06486>
 - [34] Tianci Liu, Ran Xu, Tony Yu, Ilgee Hong, Carl Yang, Tuo Zhao, and Haoyu Wang. 2025. OpenRubrics: Towards Scalable Synthetic Rubric Generation for Reward Modeling and LLM Alignment. arXiv:2510.07743 [cs.CL]. <https://arxiv.org/abs/2510.07743>
 - [35] Xiao Liu, Hao Yu, Hanchen Zhang, Yifan Xu, Xuanyu Lei, Hanyu Lai, Yu Gu, Hangliang Ding, Kaiwen Men, Kejuan Yang, Shudan Zhang, Xiang Deng, Aohan Zeng, Zhengxiao Du, Chenhui Zhang, Sheng Shen, Tianjun Zhang, Yu Su, Huan Sun, Minlie Huang, Yuxiao Dong, and Jie Tang. 2024. AgentBench: Evaluating LLMs as Agents. In *Proceedings of the 12th International Conference on Learning Representations (ICLR)*. Vienna, Austria.
 - [36] Yang Liu, Dan Iter, Yichong Xu, Shuohang Wang, Ruochen Xu, and Chenguang Zhu. 2023. G-Eval: NLG Evaluation using GPT-4 with Better Human Alignment. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Singapore, 2511–2522.
 - [37] Xing Han Lü, Amirhossein Kazemnejad, Nicholas Meade, Arkil Patel, Dongchan Shin, Alejandra Zambrano, Karolina Stańczak, Peter Shaw, Christopher J. Pal, and Siva Reddy. 2025. AgentRewardBench: Evaluating Automatic Evaluations of Web Agent Trajectories. In *Proceedings of the 2nd Conference on Language Modeling (COLM)*. Montreal, Canada.
 - [38] Xufang Luo, Yuge Zhang, Zhiyuan He, Zilong Wang, Siyun Zhao, Dongsheng Li, Luna K. Qiu, and Yuqing Yang. 2025. Agent Lightning: Train ANY AI Agents with Reinforcement Learning. arXiv:2508.03680 [cs.AI]. <https://arxiv.org/abs/2508.03680>
 - [39] Zeyao Ma, Jing Zhang, Xiaokang Zhang, Jiaxi Yang, Zongmeng Zhang, Jiajun Zhang, Yuheng Jing, Lei Zhang, Hao Zheng, Wenting Zhao, Junyang Lin, and Binyuan Hui. 2026. Scaling Agentic Verifier for Competitive Coding. arXiv:2602.04254 [cs.CL]. <https://arxiv.org/abs/2602.04254>
 - [40] Shiva Krishna Reddy Malay, Shrawan Nayak, Jishnu Sethumadhavan Nair, Sagar Dadasam, Aman Tiwari, Sathwik Tejaswi Madhusudhan, Sridhar Krishna Nemala, Srinivas Sunkara, and Sai Rajeswar. 2026. EnterpriseOps-Gym: Environments and Evaluations for Stateful Agentic Planning and Tool Use in Enterprise Settings. arXiv:2603.13594 [cs.AI]. <https://arxiv.org/abs/2603.13594>
 - [41] Saumya Malik, Valentina Pyatkin, Sander Land, Jacob Morrison, Noah A. Smith, Hannaneh Hajishirzi, and Nathan Lambert. 2026. RewardBench 2: Advancing Reward Model Evaluation. In *Proceedings of the 14th International Conference on Learning Representations (ICLR)*. Rio de Janeiro, Brazil.
 - [42] Sushant Mehta, Logan Ritchie, Suhaas Garre, Ian Niebres, Nick Heiner, and Edwin Chen. 2026. EnterpriseBench Corecraft: Training Generalizable Agents on High-Fidelity RL Environments. arXiv:2602.16179 [cs.AI]. <https://arxiv.org/abs/2602.16179>
 - [43] Tianjun Pan, Xuan Lin, Wenyan Yang, Qianyu He, Shisong Chen, Licai Qi, Wanqing Xu, Hongwei Feng, Bo Xu, and Yanghua Xiao. 2026. RubricEval: A Rubric-Level Meta-Evaluation Benchmark for LLM Judges in Instruction Following. arXiv:2603.25133 [cs.AI]. <https://arxiv.org/abs/2603.25133>
 - [44] Shishir G. Patil, Huanzhi Mao, Fanjia Yan, Charlie Cheng-Jie Ji, Vishnu Suresh, Ion Stoica, and Joseph E. Gonzalez. 2025. The Berkeley Function Calling Leaderboard (BFCL): From Tool Use to Agentic Evaluation of Large Language Models. In *Proceedings of the 42nd International Conference on Machine Learning (ICML)*. Vancouver, Canada, 48371–48392.
 - [45] Shishir G. Patil, Tianjun Zhang, Xin Wang, and Joseph E. Gonzalez. 2024. Gorilla: Large Language Model Connected with Massive APIs. In *Proceedings of the 38th Conference on Neural Information Processing Systems (NeurIPS)*. Vancouver, Canada, 126544–126565.
 - [46] Tejal Patwardhan, Rachel Dias, Elizabeth Proehl, Grace Kim, Michele Wang, Olivia Watkins, Simón Posada Fishman, Marwan Aljubei, Phoebe Thacker, Laurence Fauconnet, Natalie S. Kim, Patrick Chao, Samuel Miserendino, Gildas Chabot, David Li, Michael Sharman, Alexandra Barr, Amelia Glaese, and Jerry Tworek. 2026. GDPval: Evaluating AI Model Performance on Real-World Economically Valuable Tasks. In *Proceedings of the 14th International Conference on Learning Representations (ICLR)*. Rio de Janeiro, Brazil.
 - [47] Hao Peng, Yunjia Qi, Xiaozhi Wang, Zijun Yao, Bin Xu, Lei Hou, and Juanzi Li. 2025. Agentic Reward Modeling: Integrating Human Preferences with Verifiable Correctness Signals for Reliable Reward Systems. In *Proceedings of the 63rd Meeting of the Association for Computational Linguistics (ACL)*. Vienna, Austria, 15934–15949.
 - [48] Andreas Plesner, Francisco Guzmán, and Anish Athalye. 2026. An Imperfect Verifier is Good Enough: Learning with Noisy Rewards. arXiv:2604.07666 [cs.LG]. <https://arxiv.org/abs/2604.07666>
 - [49] Yujia Qin, Shihao Liang, Yining Ye, Kunlun Zhu, Lan Yan, Yaxi Lu, Yankai Lin, Xin Cong, Xiangru Tang, Bill Qian, Sihan Zhao, Lauren Hong, Runchu Tian, Ruobing Xie, Jie Zhou, Mark Gerstein, Dahai Li, Zhiyuan Liu, and Maosong Sun. 2024. ToolLLM: Facilitating Large Language Models to Master 16000+ Real-world APIs. In *Proceedings of the 12th International Conference on Learning Representations (ICLR)*. Vienna, Austria.
 - [50] Mohit Raghavendra, Anisha Gunjal, Bing Liu, and Yunzhong He. 2026. Agentic Rubrics as Contextual Verifiers for SWE Agents. arXiv:2601.04171 [cs.LG]. <https://arxiv.org/abs/2601.04171>

- //arxiv.org/abs/2601.04171
- [51] Delip Rao and Chris Callison-Burch. 2026. Autorubric: Unifying Rubric-based LLM Evaluation. arXiv:2603.00077 [cs.CL]. <https://arxiv.org/abs/2603.00077>
 - [52] MohammadHossein Rezaei, Robert Vacareanu, Zihao Wang, Clinton Wang, Bing Liu, Yunzhong He, and Afra Feyza Akyurek. 2025. Online Rubrics Elicitation from Pairwise Comparisons. arXiv:2510.07284 [cs.CL]. <https://arxiv.org/abs/2510.07284>
 - [53] Jon Saad-Falcon, Rajan Vivek, William Berrios, Nandita Shankar Naik, Matija Franklin, Bertie Vidgen, Amanpreet Singh, Douwe Kiela, and Shikib Mehri. 2025. LMUnit: Fine-grained Evaluation with Natural Language Unit Tests. In *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Suzhou, China, 3303–3324.
 - [54] Timo Schick, Jane Dwivedi-Yu, Roberto Dessi, Roberta Raileanu, Maria Lomeli, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. 2023. Toolformer: Language Models Can Teach Themselves to Use Tools. In *Proceedings of the 37th Conference on Neural Information Processing Systems (NeurIPS)*. New Orleans, LA, 68539–68551.
 - [55] Rulin Shao, Akari Asai, Shannon Zejiang Shen, Hamish Ivison, Varsha Kishore, Jingming Zhuo, Xinran Zhao, Molly Park, Samuel G. Finlayson, David Sontag, Tyler Murray, Sewon Min, Pradeep Dasigi, Luca Soldaini, Faeze Brahman, Wen tau Yih, Tongshuang Wu, Luke Zettlemoyer, Yoon Kim, Hannaneh Hajishirzi, and Pang Wei Koh. 2025. DR Tulu: Reinforcement Learning with Evolving Rubrics for Deep Research. arXiv:2511.19399 [cs.CL]. <https://arxiv.org/abs/2511.19399>
 - [56] Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, Y. K. Li, Y. Wu, and Daya Guo. 2024. DeepSeek-Math: Pushing the Limits of Mathematical Reasoning in Open Language Models. arXiv:2402.03300 [cs.CL]. <https://arxiv.org/abs/2402.03300>
 - [57] Ved Sirdeshmukh, Kaustubh Deshpande, Johannes Mols, Lifeng Jin, Ed-Yetemai Cardona, Dean Lee, Jeremy Kriz, Willow Primack, Summer Yue, and Chen Xing. 2025. MultiChallenge: A Realistic Multi-Turn Conversation Evaluation Benchmark Challenging to Frontier LLMs. In *Proceedings of the 63rd Meeting of the Association for Computational Linguistics (ACL)*. Vienna, Austria, 18632–18702.
 - [58] Giulio Starace, Oliver Jaffe, Dane Sherburn, James Aung, Jun Shern Chan, Leon Maksin, Rachel Dias, Evan Mays, Benjamin Kinsella, Wyatt Thompson, Johannes Heidecke, Amelia Glaese, and Tejal Patwardhan. 2025. PaperBench: Evaluating AI’s Ability to Replicate AI Research. In *Proceedings of the 42nd International Conference on Machine Learning (ICML)*. Vancouver, Canada, 56843–56873.
 - [59] Rui Sun, Zuo Bai, Wentao Zhang, Yuxiang Zhang, Li Zhao, Shan Sun, and Zhengwen Qiu. 2025. FinResearchBench: A Logic Tree based Agent-as-a-Judge Evaluation Framework for Financial Research Agents. In *Proceedings of the 6th ACM International Conference on AI in Finance (ICAIF)*. Singapore, 656–664.
 - [60] Sijun Tan, Siyuan Zhuang, Kyle Montgomery, William Y. Tang, Alejandro Cuadron, Chenguang Wang, Raluca Ada Popa, and Ion Stoica. 2025. JudgeBench: A Benchmark for Evaluating LLM-based Judges. In *Proceedings of the 13th International Conference on Learning Representations (ICLR)*. Singapore.
 - [61] Bertie Vidgen, Austin Mann, Abby Fennelly, John Wright Stanly, Lucas Rothman, Marco Burstein, Julien Benckek, David Ostrofsky, Anirudh Ravichandran, Debnil Sur, Neel Venugopal, Alannah Hsia, Isaac Robinson, Calix Huang, Olivia Varones, Daniyal Khan, Michael Haines, Austin Bridges, Jesse Boyle, Koby Twist, Zach Richards, Chirag Mahapatra, Brendan Foody, and Osvald Nitski. 2026. APEX-Agents. arXiv:2601.14242 [cs.CL]. <https://arxiv.org/abs/2601.14242>
 - [62] Vijay Viswanathan, Yanchao Sun, Shuang Ma, Xiang Kong, Meng Cao, Graham Neubig, and Tongshuang Wu. 2025. Checklists Are Better Than Reward Models For Aligning Language Models. In *Proceedings of the 39th Conference on Neural Information Processing Systems (NeurIPS)*. Mexico City, Mexico, 114728–114754.
 - [63] Manyá Wadhwa, Zayne Sprague, Chaitanya Malaviya, Philippe Laban, Junyi Jessy Li, and Greg Durrett. 2025. EvalAgent: Discovering Implicit Evaluation Criteria from the Web. In *Proceedings of the 2nd Conference on Language Modeling (COLM)*. Montreal, Canada.
 - [64] Jize Wang, Xuanxuan Liu, Yining Li, Songyang Zhang, Yijun Wang, Zifei Shan, Xinyi Le, Cailian Chen, Xinpeng Guan, and Dacheng Tao. 2026. GTA-2: Benchmarking General Tool Agents from Atomic Tool-Use to Open-Ended Workflows. arXiv:2604.15715 [cs.CL]. <https://arxiv.org/abs/2604.15715>
 - [65] Jize Wang, Zerun Ma, Yining Li, Songyang Zhang, Cailian Chen, Kai Chen, and Xinyi Le. 2024. GTA: A Benchmark for General Tool Agents. In *Proceedings of the 38th Conference on Neural Information Processing Systems (NeurIPS)*. Vancouver, Canada, 75749–75790.
 - [66] Xinchun Wang, Ruida Hu, Pengfei Gao, Chao Peng, and Cuiyun Gao. 2025. An Agent-based Evaluation Framework for Complex Code Generation. In *Proceedings of the 40th IEEE/ACM International Conference on Automated Software Engineering (ASE)*. Seoul, South Korea, 2427–2439.
 - [67] Xingyao Wang, Boxuan Li, Yufan Song, Frank F. Xu, Xiangru Tang, Mingchen Zhuge, Jiayi Pan, Yueqi Song, Bowen Li, Jaskirat Singh, Hoang H. Tran, Fuqiang Li, Ren Ma, Mingzhang Zheng, Bill Qian, Yanjun Shao, Niklas Muennighoff, Yizhe Zhang, Binyuan Hui, Junyang Lin, Robert Brennan, Hao Peng, Heng Ji, and Graham Neubig. 2025. OpenHands: An Open Platform for AI Software Developers as Generalist Agents. In *Proceedings of the 13th International Conference on Learning Representations (ICLR)*. Singapore.
 - [68] Ran Xu, Jingjing Chen, Jiayu Ye, Yu Wu, Jun Yan, Carl Yang, and Hongkun Yu. 2026. Incentivizing Agentic Reasoning in LLM Judges via Tool-Integrated Reinforcement Learning. In *Proceedings of the 14th International Conference on Learning Representations (ICLR)*. Rio de Janeiro, Brazil.
 - [69] Ran Xu, Tianci Liu, Zihan Dong, Tony Yu, Ilgee Hong, Carl Yang, Linjun Zhang, Tao Zhao, and Haoyu Wang. 2026. Alternating Reinforcement Learning for Rubric-Based Reward Modeling in Non-Verifiable LLM Post-Training. arXiv:2602.01511 [cs.CL]. <https://arxiv.org/abs/2602.01511>
 - [70] Zhangchen Xu, Yuetai Li, Fengqing Jiang, Bhaskar Ramasubramanian, Luyao Niu, Bill Yuchen Lin, and Radha Poovendran. 2025. TinyV: Reducing False Negatives in Verification Improves RL for LLM Reasoning. arXiv:2505.14625 [cs.LG]. <https://arxiv.org/abs/2505.14625>
 - [71] Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W. Cohen, Ruslan Salakhutdinov, and Christopher D. Manning. 2018. HotpotQA: A Dataset for Diverse, Explainable Multi-hop Question Answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Brussels, Belgium, 2369–2380.
 - [72] Shunyu Yao, Noah Shinn, Pedram Razavi, and Karthik Narasimhan. 2025. τ -bench: A Benchmark for Tool-Agent-User Interaction in Real-World Domains. In *Proceedings of the 13th International Conference on Learning Representations (ICLR)*. Singapore.
 - [73] Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. 2023. ReAct: Synergizing Reasoning and Acting in Language Models. In *Proceedings of the 11th International Conference on Learning Representations (ICLR)*. Kigali, Rwanda.
 - [74] Bowen Ye, Rang Li, Qibin Yang, Yuanxin Lin, Linli Yao, Hanglong Lv, Zhihui Xie, Chenxin An, Lei Li, Lingpeng Kong, Qi Liu, Zhifang Sui, and Tong Yang. 2026. Claw-Eval: Toward Trustworthy Evaluation of Autonomous Agents. arXiv:2604.06132 [cs.AI]. <https://arxiv.org/abs/2604.06132>
 - [75] Runyang Yu, Hongru Cai, Caiqi Zhang, Qiancheng Xu, Meng Liu, Tiezheng Yu, Yongqi Li, and Wenjie Li. 2026. A Survey on Agent-as-a-Judge. arXiv:2601.05111 [cs.CL]. <https://arxiv.org/abs/2601.05111>
 - [76] Qiyuan Zhang, Junyi Zhou, Yufei Wang, Fuyuan Lyu, Yidong Ming, Can Xu, Qingfeng Sun, Kai Zheng, Peng Kang, Xue Liu, and Chen Ma. 2026. RubricBench: Aligning Model-Generated Rubrics with Human Standards. arXiv:2603.01562 [cs.AI]. <https://arxiv.org/abs/2603.01562>
 - [77] Yuxuan Zhang, Yubo Wang, Yipeng Zhu, Penghui Du, Junwen Miao, Xuan Lu, Wendong Xu, Yunzhuo Hao, Songcheng Cai, Xiaochen Wang, Huaisong Zhang, Xian Wu, Yi Lu, Minyi Lei, Kai Zou, Huifeng Yin, Ping Nie, Liang Chen, Dongfu Jiang, Wenhui Chen, and Kelsey R. Allen. 2026. ClawBench: Can AI Agents Complete Everyday Online Tasks? arXiv:2604.08523 [cs.CL]. <https://arxiv.org/abs/2604.08523>
 - [78] Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. 2023. Judging LLM-as-a-Judge with MT-Bench and Chatbot Arena. In *Proceedings of the 37th Conference on Neural Information Processing Systems (NeurIPS)*. New Orleans, LA, 46595–46623.
 - [79] Karen Zhou and Chenhao Tan. 2026. AutoChecklist: Composable Pipelines for Checklist Generation and Scoring with LLM-as-a-Judge. arXiv:2603.07019 [cs.CL]. <https://arxiv.org/abs/2603.07019>
 - [80] Shuyan Zhou, Frank F. Xu, Hao Zhu, Xuhui Zhou, Robert Lo, Abishek Sridhar, Xianyi Cheng, Tianyue Ou, Yonatan Bisk, Daniel Fried, Uri Alon, and Graham Neubig. 2024. WebArena: A Realistic Web Environment for Building Autonomous Agents. In *Proceedings of the 12th International Conference on Learning Representations (ICLR)*. Vienna, Austria.
 - [81] Fengbin Zhu, Xiang Yao Ng, Ziyang Liu, Chang Liu, Xianwei Zeng, Chao Wang, Tianhui Tan, Xuan Yao, Pengyang Shao, Min Xu, Zixuan Wang, Jing Wang, Xin Lin, Junfeng Li, Jingxian Zhu, Yang Zhang, Wenjie Wang, Fuli Feng, Richang Hong, Huanbo Luan, Ke-Wei Huang, and Tat-Seng Chua. 2025. FinDeepResearch: Evaluating Deep Research Agents in Rigorous Financial Analysis. arXiv:2510.13936 [cs.CL]. <https://arxiv.org/abs/2510.13936>
 - [82] Lianghui Zhu, Xinggang Wang, and Xinlong Wang. 2025. JudgeLM: Fine-tuned Large Language Models are Scalable Judges. In *Proceedings of the 13th International Conference on Learning Representations (ICLR)*. Singapore.
 - [83] Mingchen Zhuge, Changsheng Zhao, Dylan Ashley, Wenyi Wang, Dmitrii Khizbullin, Yunyang Xiong, Zechun Liu, Ernie Chang, Raghuraman Krishnamoorthi, Yuandong Tian, Yangyang Shi, Vikas Chandra, and Jürgen Schmidhuber. 2025. Agent-as-a-Judge: Evaluate Agents with Agents. In *Proceedings of the 42nd International Conference on Machine Learning (ICML)*. Vancouver, Canada, 80569–80611.

Appendix

A Taxonomy construction prompts

We provide the four prompts used by the three-stage taxonomy-construction pipeline (Section 4). All LLM calls use Gemini 3 Flash and embeddings use Google’s text-embedding-005. Variables in `{{ ... }}` are populated at runtime with task and criterion data.

Stage 1 prompt: capability discovery. Run once per criterion to emit free-text capability labels and a verifier-side rationale.

You are a methodologist designing a capability taxonomy for evaluating agentic/LLM-as-Judge verifiers (NOT for evaluating the agent). For each rubric criterion below, name 1-3 short skills the VERIFIER must possess to grade that criterion correctly, regardless of how the verifier is implemented (tool-using judge, code-execution judge, multi-agent judge, single-prompt judge, etc.).

Verifier-side framing (read carefully)

A "capability" here is a property of the VERIFIER, not of the agent.

- Right framing: "the verifier needs to <verb a verifier does> <noun describing what it inspects in the deliverable or task spec>". Example verbs: inspect, locate, recompute, cross-check, recognize, decompose, trace, measure, compare, audit, parse, interpret, classify.
- Wrong framing (DO NOT produce): naming what the agent has to do to satisfy the criterion. Example forbidden agent-construction head-verbs: build, construct, produce, create, design, develop, write, draft, generate, populate, deliver, prepare, assemble, compile, render.
(Note: words like `document`, `layout`, `output`, `format`, `present` are FINE when used as nouns or adjectives, e.g. `document\_title\_content\_verification\_capability` or `present\_value\_audit\_capability`.)
- Wrong framing (DO NOT produce): naming a specific tool, file format, or runtime. Forbidden tokens anywhere in the capability name: excel, xlsx, pptx, pdf, openpyxl, pandas, python, jinja, json, csv, mcp, sec, edgar, sql, api.
- The verifier is judge-architecture-agnostic. The capability MUST be expressible for a verifier that:
 - (a) reads the deliverable file and computes things itself,
 - (b) reads the agent's generation script as proxy,
 - (c) calls a remote tool to fetch source-of-truth data,
 - (d) reasons over a rendered preview without executing code.
 If your capability only makes sense for one of these, restate it more abstractly.

Output format (HARD constraints)

Each capability name MUST satisfy ALL of:

- 4 to 8 words inclusive.
- lower_snake_case (only [a-z_]; no digits, no hyphens, no spaces).
- ENDS WITH `\_capability` (counts as one of the 4-8 words).
- Reads as "<verb-or-adjective>_<thing-the-verifier-inspects>_capability".
- Distinct from sibling capabilities WITHIN this same rubric category.
If two criteria in the same category map to the same capability, only emit it once per criterion, but make sure the contrasting one (if any) is genuinely different, not a paraphrase.

Good examples (illustrative archetypes -- DO NOT just copy them; produce labels that fit the actual criterion):

```
- `numeric_value_recomputation_capability`
- `formula_dependency_tracing_capability`
- `cross_section_consistency_checking_capability`
- `external_source_factual_lookup_capability`
- `unit_and_scale_normalization_capability`
- `qualitative_intent_interpretation_capability`
- `multi_period_completeness_auditing_capability`
- `visual_layout_inspection_capability`
```

Bad examples (rejected by post-validation; do NOT produce these):

```
- `excel_workbook_check_capability` -> contains forbidden token `excel`.
- `build_dcf_model_capability` -> agent-side head-verb `build`.
- `formula_audit` -> missing `_capability` suffix.
- `verifier_reads_the_workbook_thoroughly_to_validate_capability` -> >8 words.
- `recompute_capability` -> <4 words; not specific.
- `accuracy_capability` -> generic virtue, not a verifier skill.
```

Each criterion's rationale (also required)

For each criterion, include a `rationale` string of 1-2 sentences, explaining why the verifier needs the capabilities you listed. The rationale MUST:

- Start literally with "the verifier needs to".
- Mention something concrete from the criterion text (a quoted phrase, a number, a section name) so we can audit grounding.
- NOT mention the agent's process or how the agent should accomplish anything.

Task context (read-only)

```
Task ID: {{ task_id }}
Cohort: {{ cohort }}
Rubric category: {{ rubric_category }}
```

Task brief (instructions the agent received)

This is provided ONLY so you can understand WHAT deliverable the verifier will inspect. The capability you name is about INSPECTING the deliverable, not about the agent's process to produce it.

```
<task_brief>
{{ task_brief }}
</task_brief>
```

Criteria to annotate ({{ n }} criterion(a) in this batch)

```
{% for c in criteria %}
### Criterion {{ loop.index0 }}
- **Text**: {{ c.criterion }}
- **Category**: {{ c.category }}
- **Direction (FYI only, do not let this bias you)**: {{ c.direction }}
```

```
{% endfor %}
```

Output

Return a JSON array, one element per criterion, in the SAME order as above.

```
[
  {
    "criterion_idx": 0,
    "capabilities": ["<lower_snake_case_capability_1>", "<...>"],
    "rationale": "the verifier needs to ..."
  }
]
```

Constraints again, summarised:

- 1-3 capabilities per criterion (never 0, never >3).
- Each capability: 4-8 words, lower_snake_case, MUST end with `\_capability`.
- No agent-side head-verbs (build/produce/create/design/develop/...).
- No tool/format tokens (excel/xlsx/python/openpyxl/pandas/json/csv/sec/edgar/api/sql).
- Rationale starts with "the verifier needs to " and quotes from the criterion.
- Output ONLY the JSON array. No preamble, no commentary, no markdown fence.

Stage 2 prompt (a): per-cluster canonicalization. Run once per micro-cluster to assign a canonical name, definition, diagnostic signal, example, and contrastive non-examples.

You are a methodologist consolidating short, machine-tractable verifier-capability labels for an agentic/LLM-as-Judge evaluation taxonomy.

What is a "capability"?

A capability is a property of the VERIFIER (the LLM-as-Judge/Agent-as-a-Judge/Any-other-judge), not of the agent. It names a verification skill the verifier needs in order to grade a rubric criterion correctly, regardless of whether the verifier uses tools, executes code, or just reasons over a rendered preview. Capability labels MUST NOT mention specific tools, file formats, or runtimes.

Input

Below is a single CLUSTER of {{ n_members }} member-labels emitted by a Phase 1 free-text discovery pass. They have been grouped by a deterministic embedding + clustering step. Most members are paraphrases of the same underlying verifier skill; some members may be drift.

Cluster id: `{{ cluster\_id }}`

Member-label frequency in the corpus (ranked):

```
{% for m in member_labels %}- `{{ m.label }}` (frequency: {{ m.freq }})
{% endfor %}
```

A few representative example criteria from this cluster (verbatim from the rubric):

```
{% for ex in example_criteria %}- *(task: {{ ex.task_id }}, category:
{{ ex.category }})* {{ ex.criterion }}
{% endfor %}
```

Task

Pick ONE canonical name for this cluster, plus a short description, a diagnostic signal, an example pattern, and 1-3 contrastive non-examples ("if it's about X, prefer the ``<sibling>`` capability instead").

Naming constraints (HARD)

The canonical ``name`` MUST satisfy ALL of:

- 4 to 8 underscore-separated words (counting ``_capability`` as one word).
 - lower_snake_case, only [a-z_].
 - Ends with ``_capability``.
 - Reads as "`<verb-or-adjective>_<thing-the-verifier-inspects>_capability`".
 - No agent-side construction verbs (build/construct/produce/create/design/develop/write/draft/generate/populate/deliver/prepare/assemble/compile/output/render).
 - No tool/format tokens (excel/xlsx/pptx/pdf/openpyxl/pandas/python/jinja/json/csv/mcp/sec/edgar/sql/api).
 - Distinct enough from common siblings
- (cross-section consistency, external lookup, completeness/scope, semantic intent, unit normalization, structural-grading) that it could not be paraphrased into one of them.

Output

Return a single JSON object (NOT an array):

```
{
  "name": "<lower_snake_case_capability>",
  "description": "<1-2 sentences: what observable verification skill this is>",
  "diagnostic_signal": "<1 sentence: what is visible in the trace if the verifier exercised this capability vs. failed to>",
  "example_pattern": "<1-2 sentences: a concrete narrative of the verifier exercising this skill on a deliverable>",
  "non_examples": [
    "if the criterion is about <adjacent skill X>, prefer the `<sibling_capability>` label.",
    "...
  ]
}
```

No preamble, no commentary, no markdown fence -- only the JSON object.

Stage 2 prompt (b): final merge. Run once over all canonicalized clusters to produce the final taxonomy of 8–10 capabilities under the size and coverage constraints.

You are finalising a small, distinct verifier-capability taxonomy that will help characterize what a verifier running in a Reinforcement Learning environment needs to do. You are given a slate of `{{ n_in }}` candidate capabilities already produced by a clustering step, and you must merge near-duplicates and produce a final list of `{{ min_caps }}`–`{{ max_caps }}` canonical capabilities.

Background

A capability is a property of the VERIFIER, not of the agent. Each canonical capability must be expressible for verifiers of any architecture (tool-using, code-executing, or pure-reasoning).

Capability names MUST NOT mention specific tools, file formats, or runtimes.

Candidate slate

Each candidate has its current name, description, and the share of corpus criteria (out of `{{ n_total }}`) where it was the dominant tag at the cluster level.

```
{% for c in candidates %}- name: `{{ c.name }}`
  share: {{ c.share }}% (n_criteria_dominated: {{ c.n }})
  description: {{ c.description }}
  diagnostic_signal: {{ c.diagnostic_signal }}
{% endfor %}
```

Merge rules (HARD)

1. **Final count.** Output between `{{ min_caps }}` and `{{ max_caps }}` canonical capabilities (inclusive).
2. **No giant bucket.** No single canonical capability may dominate more than `{{ max_share_pct }}`% of the corpus. If a candidate currently exceeds this share, propose a SPLIT: emit two or more sub-capabilities whose union covers the same members but each respects the cap.
3. **No singletons.** No canonical capability may dominate fewer than 2% of the corpus. Merge such candidates into the nearest semantic neighbor.
4. **Pairwise distinctness.** For every pair of canonical capabilities (A, B) that could plausibly be confused, A's ``non_examples`` or B's ``non_examples`` MUST mention the other and explain the boundary.
5. **Coverage.** Every input candidate must map to exactly one canonical capability via the ``member_input_names`` field below. No silent drops.

Naming constraints (HARD)

Same as in the upstream prompt:

- 4 to 8 underscore-separated words (counting ``_capability`` as one word).
- lower_snake_case, only [a-z_].
- Ends with ``_capability``.
- Reads as "`<verb-or-adjective>_<thing-the-verifier-inspects>_capability`".
- No agent-side head-verbs (build/produce/create/design/develop/write/draft/generate/populate/deliver/prepare/assemble/compile/output/render).
- No tool/format tokens (excel/xlsx/pptx/pdf/openpyxl/pandas/python/jinja/json/csv/mcp/sec/edgar/sql/api).

Output

Return a JSON array:

```
[
  {
    "name": "<lower_snake_case_capability>",
    "description": "<1-2 sentences>",
    "diagnostic_signal": "<1 sentence>",
    "example_pattern": "<1-2 sentence narrative>",
    "non_examples": ["if <pattern>, prefer `<sibling_capability>`",
```



```

    "..."],
    "member_input_names": ["<candidate name 1>", "<candidate name 2>",
    "..."]
  }
]

```

No preamble, no commentary, no markdown fence -- only the JSON array.

Stage 3 prompt: closed-vocabulary tagging. Run once per criterion to assign one to three taxonomy capabilities, ranked by confidence.

You are a methodologist tagging rubric criteria with the verifier capabilities required to grade them. The taxonomy below is fixed. Pick 1-3 capabilities per criterion from the closed vocabulary -- do NOT invent new names.

Verifier-side framing (read carefully)

A "capability" is a property of the VERIFIER, not of the agent. It names a verification skill the verifier must possess to grade the criterion correctly, regardless of the verifier's internal architecture (tool-using, code-executing, single-prompt, multi-agent, etc.).

This is judge-architecture-agnostic on purpose: the same tag applies whether the verifier reads the deliverable file directly, parses the agent's generation script, calls a remote tool, or reasons over a rendered preview.

Capability taxonomy (closed vocabulary -- pick from these only)

```

{% for cap in capabilities %}
### `{{ cap.name }}`
- **Description**: {{ cap.description }}
- **Diagnostic signal**: {{ cap.diagnostic_signal }}
- **Example pattern**: {{ cap.example_pattern }}
{% if cap.non_examples %}- **Boundaries**:
{% for ne in cap.non_examples %}    - {{ ne }}
{% endfor %}{% endif %}
{% endfor %}

```

Task context

```

Task ID: {{ task_id }}
Cohort: {{ cohort }}
Rubric category: {{ rubric_category }}

```

Task brief (instructions the agent received)

This is provided ONLY so you can understand what deliverable the verifier will inspect. The capability you assign is about INSPECTING the deliverable, not about how the agent might produce it.

```

<task_brief>
{{ task_brief }}
</task_brief>

```

Criteria to tag ({{ n }} criteria in this batch)

```

{% for c in criteria %}

```

```

### Criterion {{ loop.index0 }}
- **Text**: {{ c.criterion }}
- **Category**: {{ c.category }}

{% endfor %}

# Tagging rules

1. Each criterion MUST be assigned 1-3 capability names, in
   MOST-RELEVANT-FIRST order.
2. Capability names MUST exactly match a `name` from the taxonomy above
   (case-sensitive, including the `_capability` suffix). No paraphrasing.
3. Tag based on what the criterion REQUIRES the verifier to do, not on
   whether any specific verifier implementation actually does it.
4. Reserve very-broad / structural-grading capabilities for criteria
   where the grading process itself is the focus (e.g. a self-consistency
   check), not as a default top-up tag.

# Output

Return a JSON array, one element per criterion, in the SAME order as
above. Each element MUST set `criterion_idx` to the criterion's index
above.

[
  {
    "criterion_idx": 0,
    "capabilities": ["<capability_name_1>", "<capability_name_2>",
    "..."]
  }
]

Output ONLY the JSON array. No preamble, no commentary, no markdown
fence.

```