A Protocol-Driven Platform for Agent-Agnostic Evaluation of LLM Agents

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Abstract

The fast growth of LLM-based agents has outpaced efforts to build solid evaluation standards, causing mismatched formats and idiosyncratic reporting that often makes fair comparisons challenging. To tackle this, we created a platform around a protocol-based setup that keeps evaluations separate from how agents work internally, focusing on what we can actually see and measure. At the heart is our Remote Agent Integration Protocol (RAIP), a minimalist connection with just two endpoints: one for retrieving data schemas (/info) and another for running tasks (/invoke). Combined with TaskConfig, our declarative layer for crafting dynamic input templates and extracting outputs deterministically via JMESPath, this setup makes interchanging agents frictionless, requiring no manual adaptation. Our benchmark structure ensures reproducibility by locking in versions. In addition, we consolidate prevalent metrics into 11 well-defined types within 4 categories for comprehensive evaluation. To validate feasibility, we ran a Course Advisor task with 30 examples, evaluating a Teaching Assistant agent across three datasets (searching, details, and recommendation) while also comparing function-calling and workflow-graph architectures. The outcomes highlight RAIP's interoperability, requiring no changes to data or scoring. Ultimately, this standardized approach could lead to evaluations that are more equitable, reproducible, and expandable.

1 Introduction

The transition from static language models to interactive agentic systems, which incorporate planning, memory, and tool-use capabilities, marks a notable step forward in artificial intelligence. Yet assessing these agents often proves challenging. With agents handling extended interactions and grounding in external environments, the array of mismatched interfaces creates real hurdles, making fair comparisons harder to achieve. Different frameworks come with their own distinct systems, but when users, especially agent developers, want to test according to specific needs, it becomes tough to find a suitable evaluation setup. We argue that these challenges stem from a fundamental lack of standardized interaction protocols. Current evaluation frameworks often tightly couple their benchmarks with specific agent architectures or environments. For example, AgentBoard [23] is limited to particular environments, and SWE-bench [12] is confined to software engineering domains. This not only limits cross-architecture studies but also makes accurate evaluations for new use cases

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difficult, requiring time-consuming specific setups that are hard to reproduce. Instead of enforcing uniformity on agent internals, our approach standardizes the boundary between the evaluation harness and the agent itself. This fosters an "observable black-box" methodology, where exchanges stay open and auditable without constraining design choices. Through our experiments, we uncover that a thin, standards-aligned boundary allows seamless agent swaps, without tweaking datasets or metrics.

Motivated by this observation, we designed a protocol-centric evaluation platform that decouples assessments from internal agent details, incorporating key elements such as:

- **Metric Standardization**: Categorizes metrics into 4 groups with 11 types, drawn from a survey of existing benchmarks to ensure comprehensive evaluation.
- **Protocol Specification (RAIP)**: Defines two core endpoints: `/info` for schema negotiation and `/invoke` for typed execution, featuring JSON Schema validation.
- **Binding Mechanism (TaskConfig)**: Maps reliable ways to transform inputs and outputs via JMESPath, balancing flexibility with rigor in bridging datasets to varied agent setups.
- **Proof of Feasibility**: Implements an end-to-end platform for a specific use case and agent, with a tailored benchmark and blinded human spot checks, confirming framework-agnostic interoperability.

This pipeline aligns with the LLM evaluation workshop's aims by providing an end-to-end platform that (i) standardizes protocol and metrics (11 types across 4 categories), (ii) streamlines benchmark design and dataset binding, and (iii) enables plug-in agent connectivity with auditable execution for reproducible, cross-framework evaluation.

2 Related Work

We start by drawing a clear line between benchmarks (encompassing tasks, environments, and metrics) and evaluations, which manage the procedural aspects and how results are aggregated. This separation guides our work, especially given the fragmented landscape of efforts in this area.

We propose that evaluations of agents fall into three broad categories: module-based, holistic, and domain-specific approaches. Module-based work zeroes in on individual elements like planning or tool integration, yielding focused observations, though it sometimes misses the broader interplay in complete systems. Holistic assessments, by contrast, gauge overall performance on varied challenges; AgentBench [22], for example, spans from coding to navigation, while AgentBoard [23] prioritizes sustained interactions. Domain-specific benchmarks target practical applications, such as SWE-bench [12] in software engineering, VisualWebArena [14] for web navigation, or SciAgent [24] in scientific workflows—yet their tailored designs often limit broader applicability. Tools like OpenAI Evals [25] and LangSmith [17] help compute metrics, and orchestration frameworks including AutoGen [37] and LangChain [15] streamline processes, even if they tend to lock users into particular platforms.

One recurring challenge emerges when benchmarks conflate tasks and datasets, which muddles equitable comparisons—take AgentBench's informal hierarchies or SWE-bench's reliance on unversioned GitHub issues. To tackle this, we lay out a more explicit framework: tasks define the instructions and setup, datasets group examples complete with validation mechanisms, and individual examples supply the inputs alongside ground-truth references, much as seen in GLUE [34] or BIG-bench [32].

Comparisons across systems also suffer from poor interoperability, as many frameworks require deep, platform-specific ties. Our protocol counters this limitation through black-box validation that accommodates varied implementations, from LangGraph [16] to ReAct [42].

Shifting focus to metrics, we group eleven varieties into four overarching classes. Performance and Execution address result effectiveness, trajectory quality, and action validity. Content and Fidelity involve checks on linguistic fidelity and substantive alignment. Attributes and Constraints capture efficiency, behavioral attributes, safety, and robustness—factors demanding careful trade-offs in practical deployment. Meta-metrics scrutinize evaluator reliability and benchmark integrity, helping maintain stable judgments over repeated trials. A consolidated taxonomy with representative examples is provided in Appendix A.2, Table 2. All told, these elements form the basis for our push toward evaluations that are both more equitable and adaptable.

3 Methodology

Our framework is designed to standardize the evaluation pipeline by establishing a clear, validated boundary between the Agent Under Test (AUT) and the evaluation logic. This boundary is formalized through the Remote Agent Integration Protocol (RAIP), which prioritizes simplicity, strong validation, and traceability.

RAIP structures the interaction into two distinct phases: discovery and execution, as illustrated in Appendix A, Figure 3. The process begins with the `/info` endpoint (GET), which publishes agent metadata and the `inputSchema` compliant with JSON Schema Draft 2020-12 [36]. This enables upfront negotiation of the input contract and compatibility verification. Following discovery, execution proceeds via the `/invoke` endpoint (POST), accepting {`input`, `context`} and returning {`output`, `usage`, `raw?`}, with inputs strictly validated against the retrieved schema.

To ensure predictable and robust behavior, RAIP adheres to standard HTTP semantics, including 400 Bad Request for schema validation failures (with detailed `ajvErrors[]`), 422 Unprocessable Entity for semantic mismatches, and 429 for rate limiting. Operational policies further enhance reliability: pre-flight validation on a small sample ($k \leq 5$) rejects incompatible runs early, while privacy-first redaction hides raw provider payloads by default unless `trace=true` is specified. Additionally, ETag headers and schema digests (SHA-256, following JSON Canonicalization Scheme [28]) detect schema drift and confirm the evaluated agent version. Figure 1 provides a component-level overview of the architecture, highlighting the RAIP boundary.

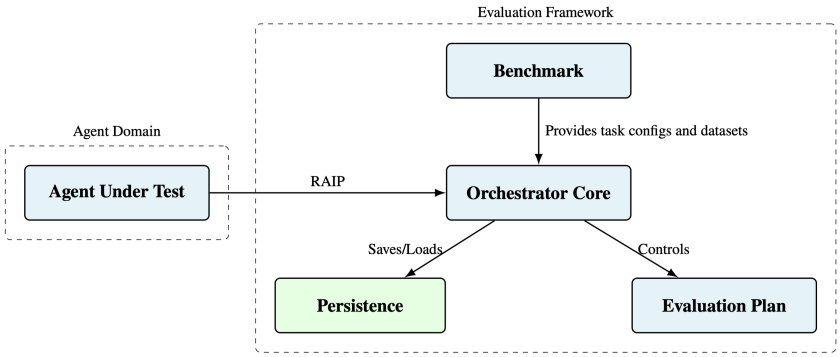

Figure 1: Component-based overview of the evaluation framework architecture.

Building on this standardized interface, TaskConfig serves as an agent-agnostic binding layer that bridges dataset examples and heterogeneous agents. It governs two critical transformations to decouple evaluation logic from agent internals. First, input templating maps example variables (e.g., `{{user_query}}`) to the agent's expected input shape, such as a messages array or function parameters, ensuring dataset independence from the agent interface. Second, deterministic output extraction normalizes varied JSON responses using JMESPath queries [29], yielding standardized candidate values for scoring. Since this mechanism can target arbitrary fields ranging from atomic tool execution results to full message histories, it enables the scoring of complex, multi-turn trajectories within a unified schema. Figure 2 illustrates this two-stage pipeline.

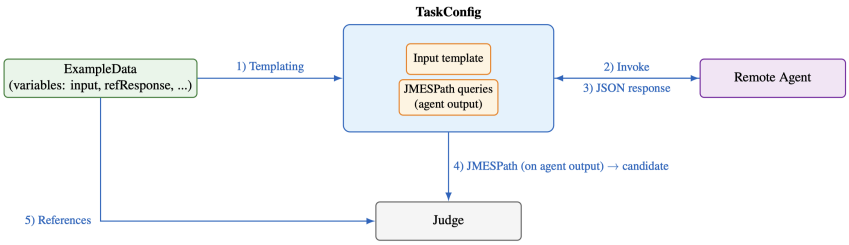

Figure 2: TaskConfig pipeline: declarative input templating and deterministic output extraction.

The framework further organizes data hierarchically (Benchmark→Task→Dataset→Example) to support granular diagnosis and consistent score aggregation via weighted means. Strict version-

locking per run—for the agent, benchmark (including TaskConfigs and data), environment, and judge configuration—ensures reproducibility. Beyond version-locking, an extensible evaluation plan configuration allows teams to set up and expand metric families (e.g., add safety, constraint, or reliability checks) without modifying datasets or agent adapters, enabling incremental evolution of evaluation coverage.

4 Experimental Setup and Results

We conducted a feasibility study to validate the protocol-driven approach in enabling interoperable evaluation across distinct agent architectures. See Appendix A.3 (Fig. 4) for the end-to-end Course Advisor analysis workflow visualization. The setup utilized the Course Advisor benchmark (N=30 examples across three datasets: Course Search, Details, and Career Path Recommendations) to compare two heterogeneous agents, A1 (Azure-based function-calling) and A2 (LangGraph-style workflow agent), integrated solely via the RAIP interface. Controls ensured consistency, with identical benchmark versions, aggregation policies, and TaskConfig semantics, though input/output templates were adjusted to match each agent's schemas. An external, stronger judge model, distinct from the agents' generators, provided automated scoring.

The study demonstrated strong interoperability: The platform negotiated schemas via `/info` and executed tasks through `/invoke` for both agents, with pre-flight sanity checks confirming conformance before batch runs. Critically, swapping agents required no modifications to datasets or metric code, only TaskConfig template tweaks, affirming the agent-agnostic design. A system-level of agent execution snapshot with the finalized UI is provided in Appendix A.4 (Fig. 5).

Performance metrics served as feasibility signals at this pilot scale, with comparable outcome efficacy (A1: 53.5%, A2: 53.2%). This close alignment is expected because both agents target the same task objectives with harmonized prompt semantics and similar underlying model capabilities, leading naturally to convergent performance at this scale. The evaluation plan for this use case instantiated three metric families: (i) LLM-as-a-Judge (Content & Fidelity), (ii) Time to Success (Attributes & Constraints), and (iii) Pass Rate (Performance & Execution). Per-dataset judge scores and efficiency indicators appear in Table 1, where A2 showed slightly better response structure and lower average time to success (5.35s vs. 5.73s), reflecting architectural trade-offs.

	Judge Score (%)				Efficiency (Overall)		
Agent	Search	Details	Path Recommendations	Overall	Time to Success (s)	Pass Rate	Error
A1 (Azure)	58.3	38.1	62.1	**53.5**	5.73	100%	0%
A2 (LangGraph)	57.0	37.5	60.7	**53.2**	5.35	100%	0%

Table 1: Course Advisor: scores and overall efficiency.

As meta-metrics, blinded human spot-checks (n=30) revealed moderate agreement with the automated judge (Pearson r=0.43), reported separately to confirm instrumentation reliability and highlight areas for human-in-the-loop refinement.

5 Discussion

Prioritizing a protocol-first perspective is essential because, while prior work has advanced novel metrics and benchmarks, integration friction remains a significant barrier to comparative studies. By treating evaluation as a protocol problem, RAIP provides a thin, standards-aligned boundary that reduces brittle glue code, enforces early validation, and enhances traceability across heterogeneous systems. Nevertheless, this feasibility study is constrained by its small scale (n=30), single domain, and limited number of agents, and potential judge variance remains a threat to validity, even though partially mitigated by controls. Furthermore, security features (e.g., authentication) were design-only in this proof of concept, so we present these results as evidence of feasibility rather than definitive performance leaderboards.

6 Conclusion

We demonstrated that a protocol-level boundary (RAIP + TaskConfig) enables agent-agnostic interoperability: heterogeneous agents can be swapped without modifying task, dataset, or metric logic. The explicit task→dataset→example hierarchy together with version-locking of artifacts and configurations strengthens reproducibility and longitudinal comparability. Our feasibility study (n=30, single advising domain, limited agent set) provides evidence of practicality rather than performance ranking. Despite scope constraints, early validation hooks and standardized meta-metrics improved traceability and fair aggregation. This protocol-first stance preserves internal innovation while normalizing evaluation surfaces. Future work will extend to multi-domain scenarios and introduce robustness, safety, and judge reliability probes. We invite community collaboration to refine the protocol surface and expand open meta-metric suites.

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A Appendix

This appendix augments the main experiments with: (i) a protocol sequence trace (RAIP discovery and execution), (ii) a normalized metrics taxonomy spanning performance, content fidelity, attributes, and meta-evaluation, and (iii) the end-to-end Course Advisor analysis workflow (Fig. 4) illustrating schema negotiation, heterogeneous agent interchangeability, automated judging, and blinded human validation.

A.1 RAIP Sequence Diagram

The RAIP sequence clarifies discovery (capabilities + schema digest) and validated execution with a uniform error surface.

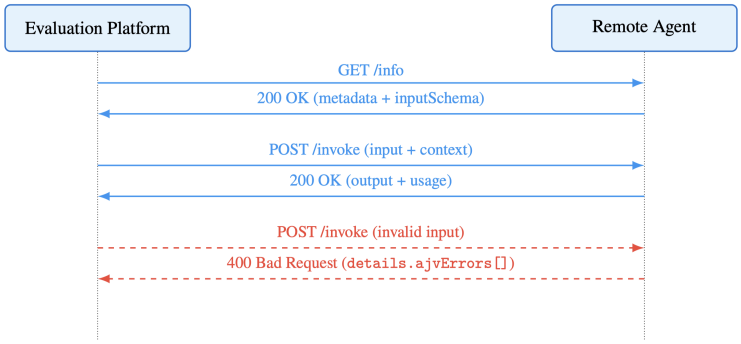


Figure 3: RAIP sequence: discovery via /info (schema negotiation + digest) followed by validated execution via /invoke with a standardized error model.

A.2 Metrics taxonomy

Metric family	Representative examples
I. Performance & Execution	
Outcome Efficacy	Success / Pass / Resolve rate [43]; Win rate [2]; TrueSkill rating [7].
Trajectory Quality	Average return / reward [35]; Progress rate [5]; Checkpoint completion (key-nodes) [26].
Action Validity	Grounding accuracy [11]; Invalid action rate [39]; Repetition / hallucination (tool actions) [45].
II. Content & Fidelity	
Linguistic Fidelity	ROUGE [20]; BLEU [27]; F1 (entity-attributed) [21]; Exact Match [44].
Content Assessment	LLM-as-a-Judge scores (WB-Score/WB-Reward) [19]; Checklist accuracy [26]; Human preference [2].
III. Attributes & Constraints	
Efficiency	Time to success [13]; Average steps [3]; Token budget efficiency [8].
Behavioral Attributes	Cooperation / competition [47]; Compliance [18]; Confidence / consistency [40]; Social goal completion [6].
Safety	Safety score [46]; Policy adherence [18]; Rejection rate [38].
Robustness	Jailbreak / attack success [1]; Distribution shift [33]; pass^k [41].
IV. Meta-metrics	
Evaluator Reliability	Human alignment [9]; Judge stability / position bias [30]; Correlation [31].
Benchmark Integrity	Suitableness / validity [4]; Ground-truth protection [10].

Table 2: Orthogonal metric families for LLM-agent evaluation.

A.3 Course Advisor Analysis Workflow

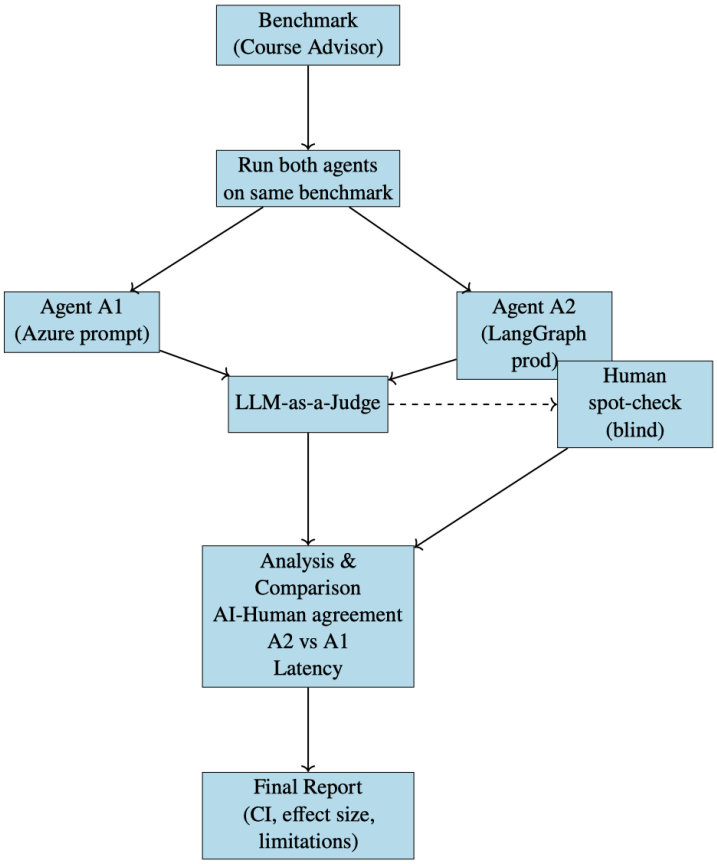
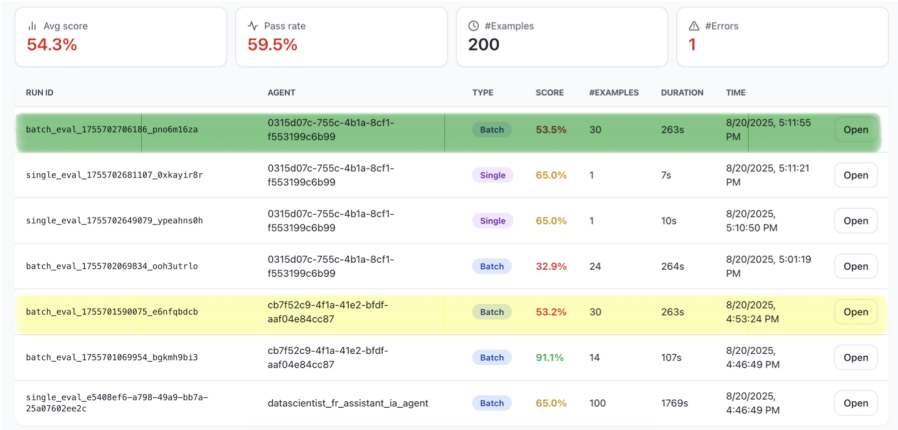


Figure 4: Course Advisor analysis workflow: single protocol, heterogeneous agents, automated judging, blinded human validation, and aggregated reporting.

A.4 System Run Overview



Avg score 54.3% | Pass rate 59.5% | #Examples 200 | #Errors 1

RUN ID	AGENT	TYPE	SCORE	#EXAMPLES	DURATION	TIME	
batch_eval_1755702706186_pno6m16za	0315d07c-755c-4b1a-8cf1-f553199c6b99	Batch	53.5%	30	263s	8/20/2025, 5:11:55 PM	Open
single_eval_1755702681107_0xkayir8r	0315d07c-755c-4b1a-8cf1-f553199c6b99	Single	65.0%	1	7s	8/20/2025, 5:11:21 PM	Open
single_eval_1755702649079_ypeahns0h	0315d07c-755c-4b1a-8cf1-f553199c6b99	Single	65.0%	1	10s	8/20/2025, 5:10:50 PM	Open
batch_eval_1755702069834_ooh3utrlo	0315d07c-755c-4b1a-8cf1-f553199c6b99	Batch	32.9%	24	264s	8/20/2025, 5:01:19 PM	Open
batch_eval_1755701590075_e6nfqbdcb	cb7f52c9-4f1a-41e2-bfdf-aaf04e84cc87	Batch	53.2%	30	263s	8/20/2025, 4:53:24 PM	Open
batch_eval_1755701069954_bgkmh9bi3	cb7f52c9-4f1a-41e2-bfdf-aaf04e84cc87	Batch	91.1%	14	107s	8/20/2025, 4:46:49 PM	Open
single_eval_e5408ef6-a798-49a9-bb7a-25a07602ee2c	datascientist_fr_assistant_ia_agent	Batch	65.0%	100	1769s	8/20/2025, 4:46:49 PM	Open

Figure 5: End-to-end dual-agent execution in the production interface: negotiated schemas, synchronized task dispatch, streaming responses, judge scoring, and aggregated reporting.