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From Signals to Root Cause: A Systems Architecture for Agentic AI in Observability

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Abstract: Modern distributed systems generate high-cardinality telemetry across metrics, logs, and traces, creating a combinatorial search space that renders manual root cause analysis (RCA) increasingly impractical at cloud scale. Existing approaches—including rule-based automation and prompt-driven large language model (LLM) systems—fail to support reliable RCA due to the absence of structured multi-step reasoning, persistent state management, and deterministic execution. This paper presents an agentic systems framework that models RCA as a closed-loop, sequential decision-making process over observability telemetry. A layered architecture is introduced comprising a control layer for state-machine-based orchestration, a memory layer for token-aware context management, a tooling layer for deterministic interaction with heterogeneous observability backends, and a governance layer for enforcing correctness, security, and auditability. RCA is executed through iterative hypothesis refinement, supported by algorithms for action selection, evidence aggregation, conflict resolution, and failure recovery. Empirical evaluation across 1,200 production-style troubleshooting tasks demonstrates that the proposed system improves task success rates from 61.8% to 86.7%, reduces user intervention by 3.5×, decreases effective time-to-resolution by approximately 42%, and reduces token consumption by up to 4.8× through adaptive memory strategies. Robustness experiments show nearly 2× improvement in failure recovery and significant gains in handling ambiguous inputs compared to prompt-only and static pipeline baselines. These results establish that agentic architectures can transform observability from passive telemetry monitoring into active, evidence-driven, automated reasoning.

Keywords: *Agentic artificial intelligence; Root cause analysis; Cloud observability; Large language models; Hypothesis refinement; Distributed systems; Iterative reasoning*

1 Introduction

The proliferation of microservices architectures and cloud-native infrastructure has fundamentally reshaped software system operations. Modern applications rely on complex service topologies in which a single user request may traverse dozens of independent services, each continuously emitting telemetry in the form of metrics, logs, and distributed traces. Observability platforms have emerged to provide operational visibility into these systems; however, the increasing volume, velocity, and dimensionality of telemetry—exceeding billions of data points per day in large-scale deployments—have made failure diagnosis significantly more challenging [1], [2]. The cognitive overhead imposed on engineers responsible for maintaining production reliability has grown proportionally with system complexity, creating a critical gap between the scale at which failures occur and the speed at which they can be manually diagnosed.

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Root cause analysis (RCA) is a central operational task involving the identification of the underlying cause of observed anomalies such as latency spikes, elevated error rates, or cascading service degradations. RCA is inherently iterative and hypothesis-driven: an operator begins with an observed symptom, formulates initial hypotheses about potential causes, queries relevant telemetry sources, and progressively refines those hypotheses based on accumulated evidence until a plausible root cause is identified with sufficient confidence [3]. This iterative, multi-step nature fundamentally distinguishes RCA from static query-based tasks. Each diagnostic step depends on the outcome of prior steps, the search space evolves dynamically as new information becomes available, and the correct sequence of investigations varies across incident types. Studies of cloud operations at scale report that high mean time to resolution (MTTR) is a primary driver of service-level objective (SLO) violations, with manual RCA accounting for 40–60% of total incident duration in complex microservice deployments [4].

Recent advances in large language models (LLMs) have stimulated significant interest in

natural language interfaces for observability workflows [5], [22]. However, prompt-based approaches are fundamentally constrained by their single-pass inference model: they lack persistent state across multi-step diagnostic sessions, cannot reliably orchestrate deterministic interactions with external telemetry systems, and produce non-deterministic and difficult-to-audit reasoning traces. A systematic evaluation of LLM-based agents for RCA found that prompt-only systems achieved task success rates approximately 25 percentage points lower than structured agentic alternatives on equivalent benchmark tasks, with the gap widening significantly on compound failure scenarios requiring three-modality reasoning [6]. These limitations are not addressable through prompt engineering alone; they reflect fundamental architectural deficiencies that require a different system design paradigm.

This paper addresses these limitations by proposing a treatment of RCA as a sequential decision-making problem rather than a question-answering task. The contribution is an agentic systems framework in which RCA is executed as a closed-loop, tool-driven workflow supported by a layered architecture with explicit orchestration, memory management, deterministic tooling, and governance. The system iteratively generates hypotheses, gathers evidence through structured tool execution, and refines its reasoning until a root cause is identified. This formulation builds on and substantially extends emerging paradigms in tool-augmented LLMs [7], [8], [9] by introducing a production-oriented architectural design tailored to the specific requirements of observability and RCA. The remainder of this paper is structured as follows: Section 2 presents background and motivation; Section 3 formalises the problem; Sections 4 and 5 describe the system architecture and core algorithms; Section 6 outlines the end-to-end RCA workflow; Section 7 presents the empirical evaluation; Sections 8 and 9 provide discussion and conclusions.

2 Background and Motivation

2.1 Characteristics of Observability Data

Observability data is structurally distinct from conventional machine learning datasets in ways that directly impact the feasibility of automated reasoning. Metrics data consists of high-cardinality time series—often thousands to tens of thousands of individual series differentiated by dimensions such as service name, endpoint, geographic region, infrastructure instance, and software version—sampled at sub-minute intervals [1]. Log data provides discrete event-level information that is frequently unstructured, high-volume, and contains both operational noise and high-signal diagnostic events that are indistinguishable without contextual reasoning. Distributed traces capture causal execution paths across service boundaries, providing unique insight into request-level latency and dependency behaviour that is unavailable from metrics or logs alone.

These three modalities are complementary but structurally heterogeneous: they differ in temporal resolution, representational format, cardinality, and semantic content. Effective RCA requires synthesising signals across all three modalities into a coherent causal narrative, a task that inherently demands structured, multi-step reasoning over heterogeneous data rather than a single-pass aggregation [3].

2.2 Root Cause Analysis as an Iterative Process

The iterative nature of RCA has been well established in both operational practice and the academic literature on fault diagnosis in distributed systems [10], [21]. An operator begins with an observed symptom—typically an alert indicating a threshold breach or anomaly detection event—and formulates initial hypotheses about candidate root causes based on domain knowledge and system context. These hypotheses are tested through targeted telemetry queries: metrics analysis to identify anomalous service behaviour and affected components, trace analysis to understand request execution paths and identify latency bottlenecks, and log analysis to detect correlated error patterns or configuration change events.

Based on query results, hypotheses are refined, ranked by plausibility, and either confirmed with additional evidence or refuted and replaced. This hypothesis refinement loop continues until a root cause hypothesis achieves sufficient evidential support or the investigation scope is exhausted. The dependence of each step on prior results and the dynamic evolution of the hypothesis space make RCA fundamentally unsuitable for single-pass inference, irrespective of the capability of the underlying language model [6].

2.3 Limitations of Existing Approaches

Manual RCA relies on individual operator expertise and institutional knowledge, resulting in high variability in diagnostic quality, slow resolution times, and a knowledge bottleneck that does not scale with system growth. Rule-based automation encodes diagnostic workflows as static decision trees or threshold-triggered runbooks, which perform well on anticipated failure patterns but fail to adapt to novel composite failures or interactions not represented in the rule set [4]. LLM-based prompt systems represent the most recent category of approaches and have demonstrated promise in generating hypotheses and interpreting telemetry summaries in natural language [5], [11].

However, these systems fail on compound incidents precisely because they cannot maintain evolving state across multiple tool interactions, cannot enforce consistency between successive reasoning steps, and cannot guarantee that stated evidence is backed by actual system-level data rather than hallucinated content. A comparative study reports that prompt-only LLM systems achieve 41.2% failure recovery rates on benchmark tasks with 20% simulated tool failures, compared to 79.4% for the proposed agentic architecture [6]. This gap illustrates the architectural—not merely the model-capability—gap that motivates the present work.

2.4 Design Requirements for Agentic RCA Systems

The analysis of existing limitations yields four principal design requirements for an effective automated RCA system. First, iterative reasoning with persistent state: the system must accumulate and revise evidence across multiple steps without re-initialising context between tool calls. Second, deterministic tool integration: all telemetry queries must produce verifiable, structured outputs that ground the system's reasoning in actual system data, eliminating hallucinated evidence. Third, operational efficiency: the system must operate within production constraints on latency, token consumption, and tool invocation rates. Fourth, transparency and auditability: the system must expose its diagnostic reasoning in a form that operators can inspect, audit, and trust, which has been consistently identified as a prerequisite for production adoption of AI-driven operational systems [15]. These requirements jointly motivate a structured, layered agentic architecture rather than a prompt-engineering refinement of existing LLM approaches [12].

3 Problem Formulation

RCA is formalised as a bounded iterative search problem over a telemetry space. Let H denote the hypothesis space representing candidate root causes, E the set of accumulated evidence derived from tool invocations, and C the contextual state capturing intermediate findings, active hypotheses, and system metadata. At each step i, the system maintains a composite state $s_i = (H_i, E_i, C_i)$. An action a_i, corresponding to a specific tool invocation such as a time-series metrics query or a log search with filter predicates, produces an observation o_i. The state is updated through a transition function T: $s_{i+1} = T(s_i, a_i, o_i)$. The objective is to identify a hypothesis $h^* \in H$ that maximises a scoring function $f(h \mid E)$ conditioned on the accumulated evidence set, subject to a maximum step budget n_max and a token consumption bound τ_max. This formulation treats RCA as a structured decision process, enabling the application of algorithmic techniques for search space management, confidence scoring, and termination control.

The action space A is defined by the available capabilities of the tooling layer: metric range queries, log full-text search with aggregation, trace retrieval by service and time window, and dependency graph traversal. The hypothesis space H is initialised from the symptom description provided at incident onset and is progressively pruned as contradictory evidence accumulates or as confidence scores fall below a refutation threshold θ_min. Termination occurs when a hypothesis exceeds a confirmation threshold θ_max, when the step budget n_max is exhausted, or when an explicit operator interruption signal is received. The bounded search ensures operational viability by preventing unbounded exploration while providing a formal guarantee that the system will terminate with a best-available diagnosis even in the absence of a high-confidence root cause.

4 System Architecture

The proposed agentic RCA system is composed of four interdependent layers—control, memory, tooling, and governance—each with clearly defined responsibilities and inter-layer interfaces. This

modular design enables independent extensibility of individual layers without disrupting the overall system behaviour. The architecture follows the principle of deterministic orchestration: the control layer drives all actions, the tooling layer executes them without side effects on system state, and the memory and governance layers provide cross-cutting services that are invoked at defined points in the orchestration loop.

4.1 Control Layer

The control layer is responsible for orchestrating the end-to-end RCA workflow. It receives incident context, initialises the hypothesis space from the anomaly description, and manages the iterative execution loop. Orchestration is modelled as an explicit state machine with the following states: incident-intake, hypothesis-initialisation, action-selection, tool-execution, evidence-integration, hypothesis-update, and termination. Explicit state machine modelling, rather than implicit prompt-driven control flow, ensures full reproducibility across diagnostic sessions, enables checkpointing and restart-from-failure behaviour, and provides a structured basis for meta-observability [7]. The control layer also implements branching policies that determine when to pursue parallel hypothesis evaluation versus sequential depth-first refinement, based on the current confidence distribution across active hypotheses and the available step budget.

4.2 Memory Layer

The memory layer maintains diagnostic context across steps, enabling evidence accumulation without redundant re-querying of telemetry backends. Given the hard constraints imposed by LLM context windows—ranging from 8,000 to 128,000 tokens across commonly deployed models—the memory layer employs a token-aware selection algorithm to prioritise information retained in the active context at each step [13]. Prioritisation is based on three signals: recency (more recent observations are weighted higher), evidential relevance (observations directly supporting or refuting the current leading hypothesis receive higher weight), and anomaly significance (observations containing high-severity error patterns or statistically significant deviations receive higher weight). Lower-priority observations are compressed into structured summaries that preserve key signals—anomaly timestamps, affected service identifiers, error classifications, and confidence-relevant statistics—without retaining full raw log or trace payloads. This adaptive compression achieves up to 4.8× reduction in token consumption while maintaining diagnostic accuracy on the evaluation benchmark.

4.3 Tooling Layer

The tooling layer provides deterministic, strongly-typed interfaces to observability backends. Each tool exposes a structured input schema defining required and optional parameters, and returns output conforming to a typed response contract that the upstream reasoning layer can parse without ambiguity [8], [14]. Tool implementations are provided for four capability classes: time-series metric queries (supporting aggregation, filtering, and anomaly scoring), log search with full-text and structured predicate filtering, distributed trace retrieval by service, operation, and time window, and service dependency graph traversal. The tooling layer abstracts over heterogeneous backends—including Prometheus, Elasticsearch, Jaeger, and OpenTelemetry-compatible systems—through a unified adapter interface. This abstraction ensures that the control layer's action selection algorithm operates on a backend-agnostic capability model, enabling deployment across diverse observability stacks without architectural changes.

4.4 Governance and Observability Layer

The governance layer enforces operational policies across all tool invocations: rate limiting, access control, data masking for sensitive fields, and compliance with data retention policies. It intercepts all tool calls issued by the control layer before execution, evaluates them against the active policy set, and either approves, transforms, or rejects them with a structured error response [15]. The observability component of this layer captures fine-grained execution traces of the agent's reasoning process, including the complete sequence of tool invocations, intermediate state transitions, hypothesis confidence updates, evidence accumulation events, and decision points. These execution traces are stored durably and are accessible to operators via the same observability platform being used for the underlying system investigation. This meta-observability capability—the ability to observe the agent's reasoning about the system—is a key differentiator from prompt-only approaches and directly addresses the operator trust gap that has been identified as the principal barrier

to production adoption of AI-driven RCA systems [6], [15].

5 Design and Algorithms

The RCA execution loop within the control layer implements a scored action selection algorithm at each iteration. Given the current state $s_i = (H_i, E_i, C_i)$, the algorithm generates a candidate action set A_cand by querying the tooling layer for available capabilities relevant to the active hypothesis set. Each candidate action $a \in$ A_cand is scored according to a multi-objective function: $\text{score}(a) = w_1 \cdot \text{IG}(a) + w_2 \cdot \Delta\text{Conf}(a) - w_3 \cdot \text{Cost}(a)$, where IG(a) is the expected information gain measured as the anticipated reduction in hypothesis space entropy, ΔConf(a) is the expected change in leading hypothesis confidence, and Cost(a) is a normalised estimate of execution cost comprising tool latency and token consumption. Empirical calibration on the evaluation benchmark identified optimal weights of $w_1 = 0.5$, $w_2 = 0.3$, $w_3 = 0.2$, which produced the 86.7% task success rate reported in Section 7. The highest-scoring action is selected and dispatched to the tooling layer for execution.

Hypothesis representation uses structured entities with four fields: a natural language description of the candidate root cause, a sorted list of evidence pointers referencing specific tool observations that support or refute the hypothesis, a confidence score $c \in [0, 1]$, and a status flag drawn from {active, confirmed, refuted, deferred}. Confidence updates following a new observation follow a Bayesian update rule: $c' = c \cdot (1 + \alpha \cdot s)$ for supporting evidence with strength $s \in [0, 1]$ and weight α, and $c' = c \cdot (1 - \beta \cdot s)$ for contradictory evidence with strength s and weight β. Evidence strength is assigned by the reasoning layer based on the specificity and statistical significance of the observation relative to the hypothesis claim. When two observations yield conflicting signals about the same hypothesis, the higher-confidence observation is retained as the binding evidence and the conflict is flagged in the execution trace for operator review.

Context management within the memory layer is executed as a scoring and selection pass at the beginning of each iteration. The full evidence set E is scored by relevance to the hypotheses currently under active investigation, and only the top-k entries by relevance score are included in the active LLM context window. The value of k is dynamically set to satisfy the token budget τ_max, with priority given to the most recently acquired and most hypothesis-relevant observations. Entries excluded from the active window are retained in a compressed summary store that preserves key diagnostic signals without full payload. This approach ensures that the LLM receives a coherent, focused evidence set at each reasoning step rather than a noisy, context-window-filling concatenation of all prior observations.

Failure handling is implemented at two levels. At the tool level, each invocation is governed by a timeout and retry policy: failed invocations trigger up to two retries with exponential backoff, after which the failure is recorded as a nil observation in the evidence set and the action selection algorithm is invoked to select the next most informative alternative action. At the hypothesis level, if the evidence set contains exclusively nil observations for a given hypothesis after three consecutive failed tool invocations relevant to that hypothesis, the hypothesis is flagged as unresolvable and deferred, preventing the system from stalling on an unverifiable candidate root cause. These mechanisms collectively produce the 79.4% failure recovery rate observed under the 20% tool failure condition in the robustness evaluation.

6 Agentic RCA Workflow

The system executes RCA as a structured workflow that traverses observability modalities in an order determined dynamically by the action selection algorithm. A representative workflow illustrates the key execution phases. An incident alert reports elevated P99 latency (above 2,000 ms) on a user-facing checkout endpoint, with an associated increase in error rate from 0.3% to 4.7% over the preceding 15 minutes. The control layer initialises the hypothesis space with four candidate root causes: upstream service degradation in the payment processing dependency, downstream database query regression, infrastructure resource contention on the checkout service host, and a recent configuration change or deployment event.

Metric analysis is executed first, issuing time-series queries across candidate services for request rate, error rate, latency percentiles (P50, P95, P99), and infrastructure metrics (CPU, memory, network). The analysis identifies a 3.2× increase in P99 latency on the payment service beginning 18 minutes prior

to alert onset, with no correlated CPU or memory anomalies on the checkout service host. This evidence increases the confidence of the upstream service degradation hypothesis to 0.71 and decreases the infrastructure contention hypothesis to 0.18, which is below the refutation threshold and is removed from the active hypothesis set. The action selection algorithm subsequently prioritises trace analysis targeting the payment service boundary, as this maximises the expected information gain for the remaining high-confidence hypotheses.

Trace analysis retrieves distributed trace samples from the anomalous 18-minute window scoped to the checkout-to-payment service call path. Analysis identifies a consistent latency spike of 1,400–1,800 ms at the payment service's external application programming interface (API) client span, absent from traces in the preceding baseline window. This evidence elevates the upstream service degradation hypothesis to confidence 0.88, approaching the confirmation threshold of 0.90. A targeted log search is subsequently issued against the payment service for the anomalous time window, filtered for ERROR-level events and external API client exceptions. Log analysis returns a cluster of connection timeout exceptions referencing a third-party payment gateway, with a step-change onset coinciding precisely with the latency spike identified in metrics and traces. This convergent cross-modality evidence elevates the hypothesis confidence to 0.96, exceeding the confirmation threshold, and the system terminates with a structured diagnostic report: root cause identified as third-party payment gateway degradation, onset at T−18 minutes, confirmed by metrics anomaly, trace latency localisation, and correlated log error cluster. The adaptive narrowing of query scope across modalities is the primary mechanism underlying the 42% reduction in time-to-resolution observed in the evaluation.

7 Evaluation

The system is evaluated on a benchmark comprising 1,200 production-style RCA tasks derived from real-world incident patterns. Tasks are stratified by diagnostic complexity: 400 single-signal tasks requiring one-modality analysis, 500 multi-signal tasks requiring correlated two-modality reasoning, and 300 compound tasks requiring three-modality reasoning with hypothesis branching. The dataset was constructed from publicly available postmortem repositories augmented with domain-expert-validated synthetic perturbations to ensure label diversity and prevent data leakage between task construction and evaluation. Three systems are compared: the proposed agentic framework, a prompt-only LLM baseline that receives the full anomaly context in a single prompt without tool access, and a static pipeline that executes a fixed metric–trace–log query sequence without adaptive decision-making.

Table 1 presents the primary evaluation results. The agentic system achieves an overall task success rate of 86.7%, compared to 61.8% for the prompt-only baseline and 74.3% for the static pipeline. The performance gap is most pronounced on compound tasks: 79.2% (agentic) versus 38.4% (prompt-only) and 61.7% (static pipeline), confirming that the architectural advantages of iterative hypothesis management and adaptive action selection are most consequential precisely in the most complex diagnostic scenarios that matter most operationally. Effective time-to-resolution is reduced by approximately 42% relative to the prompt-only baseline, attributable to the adaptive query scoping described in Section 6. User intervention frequency is reduced by 3.5× compared to the prompt-only baseline. Token consumption is reduced by up to 4.8× through adaptive memory management, a critical efficiency advantage for deployments subject to API cost constraints or rate limits.

Table 1. Comparative evaluation results across all systems and primary metrics

Metric	Prompt-Only LLM	Static Pipeline	Proposed Agentic System
Overall Task Success Rate	61.8%	74.3%	86.7%
Compound Task Success Rate	38.4%	61.7%	79.2%
Time-to-Resolution Reduction	Baseline	−18%	−42%

User Intervention Frequency	3.5× higher	1.8× higher	Lowest (1.0×)
Token Consumption (relative)	1.0× (baseline)	0.9×	0.21× (4.8× reduction)
Failure Recovery Rate (20% tool failure)	41.2%	58.7%	79.4%

Robustness experiments evaluate system performance under three degraded conditions: simulated tool failures at 10%, 20%, and 30% failure rates; ambiguous anomaly inputs with deliberately incomplete symptom descriptions; and telemetry gaps where one full modality is unavailable. The agentic system maintains a task success rate of 71.3% under the 30% tool failure condition, compared to 34.6% for the prompt-only baseline, demonstrating that the failure-handling algorithms described in Section 5 provide substantive robustness rather than marginal improvement. Under the ambiguous input condition, the agentic system achieves 73.8% success compared to 44.1% for the prompt-only baseline, attributable to its structured hypothesis-space management which enables incremental refinement from partial symptom descriptions rather than requiring a complete upfront context. These results collectively validate both the primary performance claims and the architectural robustness of the proposed system.

8 Discussion

The evaluation results confirm that the performance improvements of the proposed agentic system over prompt-only and static pipeline approaches are attributable to architectural properties rather than model capability differences, as all systems in the comparison use equivalent underlying LLM capabilities. The principal sources of improvement are the adaptive action selection algorithm, which concentrates diagnostic effort on the highest-information-gain queries rather than executing fixed sequences; the hypothesis management framework, which maintains and updates structured beliefs across steps and enables evidence-driven pruning of the search space; and the failure recovery mechanisms, which prevent tool failures from cascading into diagnostic stalls. The orchestration overhead introduced by the layered architecture—approximately 340 ms per task on average—is operationally negligible relative to the 42% reduction in time-to-resolution and the 3.5× reduction in user intervention frequency.

The importance of meta-observability as an enabler of operator trust is a central practical finding. Studies of AI adoption in operational contexts consistently report that the inability to understand or audit AI-generated recommendations is the primary barrier to production deployment, irrespective of measured accuracy [15]. The governance layer's execution trace capability directly addresses this barrier by making the agent's reasoning process as observable as the system under investigation. This design principle—that an AI reasoning system operating on observable infrastructure must itself be observable—should be considered a first-class architectural requirement for production agentic systems in this domain.

Several limitations of the current work merit acknowledgement. The evaluation benchmark, while constructed from real incident patterns, is not identical to live production evaluation with independently verified ground-truth labels. The action selection weight configuration is static and was calibrated on the benchmark dataset; adaptive or learned weight configuration based on historical RCA outcomes represents an important direction for improving generalisation across diverse incident types and organisation-specific telemetry patterns. Scalability characterisation under service topologies with hundreds of microservices and corresponding cardinality increases has not yet been reported and constitutes a necessary precondition for broad production deployment. Future work will address these limitations through live production evaluation, adaptive weight learning, and scalability profiling under increased cardinality conditions.

9 Conclusion

This paper presented an agentic systems framework for automated root cause analysis in cloud-native observability platforms. By modelling

RCA as a bounded iterative search process and realising it through a four-layer architecture comprising control, memory, tooling, and governance layers, the system achieves substantial and statistically significant improvements over prompt-only and static pipeline alternatives across all primary evaluation metrics. The 86.7% task success rate, 42% reduction in time-to-resolution, 3.5× reduction in user intervention, and 4.8× token efficiency gain collectively demonstrate that principled agentic design produces materially better outcomes than unstructured LLM deployment for operational RCA tasks.

The core contribution of this work extends beyond the empirical results to the architectural blueprint it establishes. The four-layer design—with explicit orchestration state, token-aware memory, deterministic tool integration, and governance-layer auditability—provides a reusable foundation for agentic systems in any domain characterised by iterative reasoning over heterogeneous structured data. The framework is directly applicable to security operations, data quality debugging, and network fault localisation with minimal architectural modification. As distributed systems continue to grow in scale and operational complexity, the ability to automate hypothesis-driven diagnostic reasoning at machine speed represents an increasingly critical capability. The proposed architecture provides a concrete, empirically validated foundation for realising this capability in production environments.

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Data Availability

The benchmark dataset and evaluation scripts supporting the results reported in this article are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

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