

Research Article

Agentic AI for Autonomous Cloud Infrastructure Management: A Multi-Agent Framework for Fault Detection, Root-Cause Analysis, and Self-Healing

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Abstract

The increasing complexity of cloud-native infrastructure, characterized by distributed microservices, dynamic workloads, and heterogeneous computing environments, has exposed limitations in conventional fault-management systems. Existing approaches frequently suffer from fragmented fault detection, inaccurate root-cause localization, delayed incident response, and limited autonomous recovery capabilities, compromising infrastructure reliability and operational efficiency. This study proposes an Agentic AI-based Multi-Agent Autonomous Cloud Management Framework (AIC-MAC) to enhance intelligent fault detection, root-cause analysis, and autonomous self-healing in Kubernetes-based cloud environments. The framework integrates six specialized agents responsible for infrastructure monitoring, anomaly detection, root-cause diagnosis, remediation planning, policy enforcement, and recovery verification. It incorporates multivariate telemetry analysis, dependency-aware causal reasoning, evidence-grounded decision-making, and risk-constrained remediation. A controlled experimental methodology is designed using Kubernetes-hosted microservices, observability tools, and fault-injection scenarios. The proposed evaluation assesses fault detection precision, recall, F1-score, root-cause localization accuracy, mean time to detect, mean time to recover, and remediation success rates against conventional monitoring and AIOps baselines. Experimental findings remain pending implementation and validation. AIC-MAC establishes a structured foundation for coordinated, explainable, and safety-aware cloud infrastructure management, with the potential to improve operational resilience and autonomous fault recovery.

Keywords: Agentic AI; Autonomous Cloud Infrastructure; Multi-Agent Systems; Fault Detection; Root-Cause Analysis; Self-Healing; AIOps; Kubernetes.

Introduction

Background and Research Context

Cloud computing has evolved from centralized virtualized infrastructure into highly distributed, cloud-native ecosystems characterized by containerization, microservices, and automated resource orchestration. This transformation has enhanced application scalability, deployment flexibility, and resource utilization while introducing considerable operational complexity. Kubernetes has emerged as a widely adopted orchestration platform that enables automated deployment, scaling, and management of containerized applications. However, its dynamic operating environment, characterized by heterogeneous workloads, interconnected microservices, and fluctuating resource demands, presents substantial challenges for maintaining infrastructure reliability and service continuity.

The distributed nature of cloud-native applications increases their vulnerability to cascading failures, resource contention, network disruptions, and service dependency conflicts. A localized infrastructure fault may propagate across multiple services, complicating fault identification and increasing recovery time. Traditional infrastructure management approaches, which predominantly rely on predefined monitoring thresholds, manual intervention, and rule-based remediation, often lack the contextual intelligence required to address these interconnected failures effectively (Liu et al., 2021; Lee et al., 2023). Artificial Intelligence for IT Operations (AIOps) has consequently gained prominence as an approach to improving infrastructure observability, anomaly detection, and incident management. Advanced machine learning models can identify complex patterns within operational telemetry, while intelligent diagnostic

systems support fault localization through multi-source data analysis (Tuli et al., 2022; Zhang et al., 2025). More recently, Agentic Artificial Intelligence has introduced autonomous decision-making capabilities through intelligent agents that perform specialized tasks, exchange contextual information, and interact with operational environments. Chen et al. (2025) and Shetty et al. (2024) highlight the potential of AI agents to support autonomous cloud operations, establishing opportunities for coordinated fault diagnosis and infrastructure recovery.

Problem Statement

Despite advances in cloud monitoring and AIOps, achieving reliable autonomous infrastructure management remains challenging. Conventional rule-based systems frequently generate excessive alerts, struggle to recognize unfamiliar failure patterns, and provide limited capabilities for distinguishing observable symptoms from underlying causes. In complex microservice environments, service dependencies and fault propagation further complicate accurate root-cause localization (Liu et al., 2021; Pham et al., 2025).

Furthermore, existing approaches frequently separate anomaly detection, root-cause analysis, and remediation into independent operational processes, creating coordination gaps and increasing incident resolution time. Although large language model-based agents have demonstrated potential for automated diagnostic reasoning, their application introduces concerns regarding decision reliability, contextual accuracy, and uncontrolled infrastructure modifications (Roy et al., 2024; Shetty et al., 2024). Autonomous recovery mechanisms must therefore incorporate operational safeguards, verifiable decision processes, and continuous feedback to prevent incorrect interventions from worsening infrastructure failures.

These challenges establish the need for an integrated, safety-aware multi-agent framework capable of coordinating intelligent fault detection, evidence-based diagnosis, and controlled self-healing within cloud-native environments.

Research Aim and Objectives

This study aims to develop an Agentic AI-based Multi-Agent Autonomous Cloud Management Framework (AIC-MAC) for intelligent fault detection, root-cause analysis, and autonomous self-healing in Kubernetes-based cloud infrastructure.

The specific objectives are to:

- Design a modular multi-agent architecture integrating cloud monitoring, anomaly detection, fault diagnosis, remediation planning, policy enforcement, and recovery verification.
- Develop an intelligent fault detection and dependency-aware root-cause localization mechanism using

multivariate infrastructure telemetry.

- Establish a coordinated, risk-constrained autonomous remediation process that preserves operational safety and service reliability.
- Evaluate the proposed framework against conventional monitoring, Kubernetes-native recovery, and established AIOps approaches using measurable performance indicators.

Research Questions and Hypotheses

The study addresses four research questions:

- RQ1: How can specialized AI agents coordinate fault detection, diagnosis, and remediation in distributed cloud environments?
- RQ2: Can intelligent anomaly detection and dependency-aware reasoning improve fault detection and root-cause localization accuracy?
- RQ3: How effectively can policy-constrained autonomous remediation reduce infrastructure recovery time?
- RQ4: To what extent can the proposed multi-agent framework improve cloud service availability and operational reliability compared with existing approaches?

Accordingly, four testable hypotheses are proposed:

- H1: AIC-MAC achieves significantly higher fault detection F1-scores than conventional threshold-based monitoring.
- H2: Dependency-aware multi-agent diagnosis achieves significantly higher root-cause localization accuracy than telemetry-only diagnostic approaches.
- H3: Policy-constrained autonomous remediation significantly reduces mean time to recover compared with conventional incident response.
- H4: AIC-MAC achieves significantly higher service availability than the evaluated baseline infrastructure management approaches.

Research Contributions and Article Organization

This study contributes a unified multi-agent architecture integrating intelligent monitoring, hybrid anomaly detection, dependency-aware root-cause analysis, autonomous remediation planning, and independent safety enforcement. Its principal novelty lies in coordinating these capabilities through evidence-grounded agent interactions and closed-loop recovery verification rather than treating fault management activities as isolated functions.

The remainder of the article is organized as follows. Section 2 critically reviews related studies and identifies research gaps. Section 3 presents the proposed AIC-MAC architecture and mathematical formulations. Section 4 describes the experimental methodology and evaluation metrics. Section 5 presents the performance evaluation framework and, following implementation, experimental findings. Section 6 discusses implications and limitations,

while Section 7 concludes the study and outlines future research directions.

Related Work and Research Gap

AI-Based Cloud Infrastructure Monitoring

Cloud infrastructure monitoring has evolved from conventional threshold-based mechanisms toward intelligent observability systems capable of analyzing complex operational patterns. Traditional monitoring relies on predefined thresholds, system logs, and resource utilization metrics to detect abnormal conditions. Although these techniques provide essential infrastructure visibility, their effectiveness diminishes in dynamic cloud-native environments characterized by heterogeneous workloads, fluctuating resource demands, and interconnected microservices. Static thresholds frequently produce false alarms during legitimate workload variations while failing to recognize subtle multivariate anomalies (Zhang et al., 2025).

Machine learning and deep learning techniques have expanded fault detection capabilities through automated pattern recognition and temporal analysis. Tuli et al. (2022) introduced TranAD, a transformer-based architecture for detecting anomalies in multivariate time-series data, demonstrating the relevance of contextual relationships in anomaly identification. Similarly, Xu et al. (2021) proposed the Anomaly Transformer, which identifies abnormal temporal associations within time-series observations. However, detecting anomalous behavior does not necessarily establish its underlying cause, highlighting the need for integrating monitoring with intelligent diagnostic mechanisms.

Agentic AI and Multi-Agent Systems in Cloud Operations

Agentic artificial intelligence represents an advancement beyond conventional AIOps by enabling autonomous reasoning, tool execution, contextual decision-making, and interaction with operational environments. Unlike isolated predictive models, agentic architectures coordinate sequential activities through intelligent agents capable of gathering evidence, evaluating alternatives, and executing authorized actions. Wu et al. (2023) demonstrated multi-agent collaboration through AutoGen, while Yao et al. (2022) introduced ReAct, integrating reasoning and action within language-model-driven decision processes.

In cloud operations, Shetty et al. (2024) investigated architectural requirements and challenges associated with developing AI agents for autonomous infrastructure management. Chen et al. (2025) subsequently introduced AIOpsLab, an experimental framework supporting cloud fault injection, telemetry acquisition, agent interaction, and incident-management evaluation. These contributions establish important foundations for

autonomous cloud operations. Nevertheless, practical deployment requires reliable coordination among specialized agents, structured operational evidence, controlled infrastructure access, and verification of corrective actions. Wang et al. (2024) further identified planning, memory, and tool utilization as fundamental capabilities influencing autonomous agent effectiveness.

Intelligent Fault Detection Techniques

Intelligent fault detection employs statistical learning, unsupervised anomaly detection, and deep neural architectures to identify deviations from expected infrastructure behavior. Statistical methods assess variations in resource utilization and service performance, while Isolation Forest and autoencoder-based approaches identify unusual observations through feature isolation and reconstruction errors, respectively.

Advanced temporal models capture relationships across successive observations, improving the representation of complex operational conditions. TranAD incorporates attention mechanisms for multivariate anomaly detection (Tuli et al., 2022), whereas the Anomaly Transformer examines association discrepancies to identify unusual temporal dependencies (Xu et al., 2021). Additionally, Guo et al. (2021) developed LogBERT, applying bidirectional transformer representations to log anomaly detection. Despite their contributions, these techniques primarily identify suspicious patterns rather than determine causal relationships or appropriate remediation actions. Their integration with dependency-aware diagnosis and recovery planning therefore remains an important research direction.

Root-Cause Analysis in Distributed Cloud Systems

Root-cause analysis (RCA) seeks to identify the originating component or condition responsible for service degradation. In distributed microservices, failures frequently propagate through service dependencies, making symptom-based diagnosis unreliable. Liu et al. (2021) proposed MicroHECL, which uses dynamically constructed service call graphs and anomaly propagation analysis to localize probable root causes. Lee et al. (2023) introduced Eadro, combining multiple telemetry sources for end-to-end microservice troubleshooting.

Recent research has explored language-model-assisted diagnosis. Roy et al. (2024) investigated LLM-based agents equipped with retrieval tools for collecting diagnostic evidence, while Tang et al. (2025) proposed MicroRCA-Agent for agent-supported fault investigation. Retrieval-augmented generation provides a foundation for grounding model responses in external information (Lewis et al., 2020). However, retrieved evidence may be incomplete, and temporal correlation does not independently establish causation. Pham et al. (2025) introduced RCAEval to support standardized evaluation

of microservice root-cause localization, emphasizing the importance of reproducible diagnostic benchmarking.

Autonomous Self-Healing Infrastructure

Autonomous self-healing extends fault management from detection and diagnosis to corrective intervention and recovery assessment. Kubernetes provides native mechanisms involving container restarts, health probes, replica management, and deployment rollback. These mechanisms improve operational resilience but generally operate according to predefined health conditions and orchestration policies rather than comprehensive cross-service causal diagnosis.

Agentic AI offers opportunities to extend these capabilities through context-aware remediation planning and coordinated execution. Nevertheless, autonomous infrastructure modification introduces risks associated with incorrect diagnoses, excessive privileges, and unintended service disruptions. Consequently, recovery decisions should incorporate authorization controls, operational constraints, and independent post-remediation verification. The National Institute of Standards and Technology (NIST, 2023) emphasizes risk management, accountability, and reliability as important considerations for trustworthy AI systems.

Critical Research Gaps

The reviewed literature reveals four interconnected research gaps. First, existing methods frequently address anomaly detection, root-cause localization, and remediation as separate operational functions. Second, diagnostic systems do not consistently integrate causal evidence with executable recovery planning. Third, autonomous agents require stronger mechanisms for independent action authorization, rollback, and recovery verification. Fourth, comparative evaluations often emphasize individual diagnostic metrics rather than end-to-end operational outcomes, including recovery time, availability, and intervention safety.

To address these limitations, the proposed Agentic AI-based Multi-Agent Autonomous Cloud Management Framework (AIC-MAC) integrates specialized monitoring, detection, diagnosis, planning, safety, and verification agents within a coordinated incident-management architecture. Its intended contribution is a unified, evidence-grounded, and safety-constrained approach to autonomous cloud operations, subject to experimental validation.

Proposed Agentic AI Multi-Agent Framework

Framework Design and Architectural Principles

This study proposes the Agentic AI-based Multi-Agent Autonomous Cloud Management Framework (AIC-MAC), a modular architecture designed to integrate intelligent fault detection, root-cause analysis, and

autonomous self-healing within Kubernetes-based cloud environments. The framework adopts an event-driven, closed-loop operational model in which specialized agents collaboratively monitor infrastructure conditions, diagnose failures, formulate corrective actions, and verify service recovery. Its design draws on autonomous cloud management principles proposed by Shetty et al. (2024) and agent-based operational evaluation approaches developed by Chen et al. (2025).

AIC-MAC comprises six functional agents: Monitoring, Fault Detection, Root-Cause Analysis, Remediation Planning, Policy and Safety, and Recovery Verification. Each agent performs a distinct operational responsibility while communicating through a centralized incident-state coordination service. This coordination model maintains diagnostic evidence, incident identifiers, operational decisions, and execution histories, reducing inconsistencies between autonomous processes. Multi-agent collaboration is informed by the conversational coordination mechanisms described by Wu et al. (2023). Unlike unrestricted autonomous systems, AIC-MAC implements bounded autonomy, whereby infrastructure modifications require explicit policy validation before execution.

Monitoring and Data Acquisition Agent

The Monitoring Agent continuously acquires operational telemetry from Kubernetes clusters, including CPU utilization, memory consumption, request latency, error rates, network throughput, and container restart events. OpenTelemetry provides standardized collection and correlation of metrics, logs, and distributed traces across interconnected services (OpenTelemetry, 2025). The acquired data undergo timestamp synchronization, missing-value treatment, normalization, and service-level correlation before transmission to downstream agents. This process establishes a consistent representation of infrastructure conditions and supports fault identification across heterogeneous workloads.

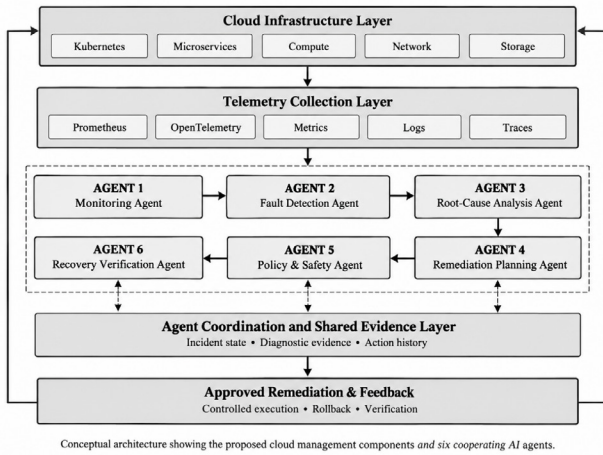
Intelligent Fault Detection Agent

The Fault Detection Agent employs a hybrid anomaly detection mechanism combining statistical indicators with deep learning-based temporal analysis. An autoencoder reconstructs multivariate telemetry observations, while deviations between observed and reconstructed values indicate potential abnormal behavior. Transformer-based anomaly detection research demonstrates the relevance of temporal dependencies in identifying complex system deviations (Tuli et al., 2022; Xu et al., 2021).

Adaptive thresholds are calibrated against validation data to account for changing workload conditions. Detected anomalies are classified according to severity, affected services, and persistence, producing structured incident records for diagnosis. Severity classification incorporates

Table 1: Comparative Review of Existing Research and Identified Gaps

Study	Research approach	Key contribution	Limitation relative to this study	Identified gap
Liu et al. (2021)	Dependency-graph-based RCA	MicroHECL for efficient fault localization	Does not establish an integrated autonomous recovery architecture	Diagnosis-to-remediation integration
Tuli et al. (2022)	Transformer-based anomaly detection	TranAD for multivariate anomaly identification	Does not address operational remediation	Fault detection and recovery coordination
Lee et al. (2023)	Multi-source deep learning	Eadro for end-to-end microservice troubleshooting	Focuses on troubleshooting rather than autonomous recovery execution	Closed-loop self-healing
Roy et al. (2024)	LLM-based diagnostic agents	Tool-assisted root-cause investigation	Does not provide comprehensive recovery authorization and verification	Safe autonomous intervention
Shetty et al. (2024)	Agentic cloud architecture	Design principles for autonomous cloud agents	Broad architectural focus rather than the proposed six-agent integration	Specialized operational coordination
Chen et al. (2025)	Agentic AIOps evaluation	AIOpsLab for evaluating autonomous cloud agents	Evaluation platform rather than a fully validated AIC-MAC implementation	Integrated remediation framework
Pham et al. (2025)	RCA benchmarking	RCAEval for reproducible microservice diagnosis	Does not implement autonomous infrastructure recovery	End-to-end operational evaluation
Proposed AIC-MAC	Multi-agent, safety-constrained AIOps	Integrated fault detection, RCA, planning, execution control, and verification	Empirical performance remains unvalidated	Unified and experimentally testable self-healing


Figure 1: Conceptual architecture of the proposed AIC-MAC framework, illustrating six specialized agents, shared incident coordination, and controlled infrastructure remediation.

service criticality and observed service-level objective violations rather than anomaly magnitude alone.

Root-Cause Analysis Agent

The Root-Cause Analysis Agent identifies probable fault origins through dependency-aware reasoning and multi-source evidence correlation. It constructs a directed service dependency graph using distributed traces, service metadata, and communication relationships. Candidate components are evaluated according to anomaly severity,

temporal precedence, dependency propagation, and supporting operational evidence. This design builds upon dependency-based localization demonstrated by MicroHECL and multi-source troubleshooting approaches established by Eadro (Liu et al., 2021; Lee et al., 2023).

Retrieval-augmented reasoning incorporates relevant operational runbooks, historical incidents, deployment records, and configuration changes to improve diagnostic contextualization (Lewis et al., 2020; Roy et al., 2024). The agent generates ranked root-cause hypotheses supported by traceable evidence. Importantly, temporal correlation is treated as diagnostic evidence rather than definitive proof of causality.

Autonomous Remediation Planning Agent

The Remediation Planning Agent translates validated diagnostic hypotheses into candidate corrective actions. Depending on the incident, these actions may include replica scaling, container restart, deployment rollback, configuration restoration, or traffic redistribution. The agent evaluates alternatives according to anticipated recovery time, resource expenditure, and potential service disruption.

A multi-objective decision function selects the lowest-cost permissible action while respecting reliability constraints. Reasoning-and-action principles established by Yao et al. (2022) inform the separation between operational planning, tool invocation, and environmental feedback. Each remediation proposal includes its target resource, supporting diagnosis, predicted impact, execution conditions, and rollback requirements.

Policy Enforcement and Safety Agent

The Policy and Safety Agent provides an independent authorization mechanism for infrastructure modifications. It evaluates remediation proposals against role-based access controls, predefined operational policies, service criticality, and acceptable disruption thresholds. Kubernetes role-based access control supports permission restrictions over infrastructure resources, while the NIST AI Risk Management Framework emphasizes reliability, accountability, and risk governance (National Institute of Standards and Technology, 2023).

Low-risk, explicitly authorized operations may proceed automatically; high-impact interventions require human approval. Actions violating safety constraints are rejected and escalated. This separation prevents diagnostic agents from obtaining unrestricted execution privileges.

Recovery Verification Agent

The Recovery Verification Agent evaluates infrastructure conditions following authorized intervention. Recovery is assessed using service availability, request latency, error rates, workload readiness, and predefined service-level objectives. Successful API execution is not considered sufficient evidence of recovery; operational indicators must demonstrate sustained improvement over a specified observation interval.

If recovery fails, the agent initiates a technically permissible rollback or escalates the incident for human assessment. Post-incident outcomes are recorded to support future model recalibration and evaluation of remediation effectiveness.

Multi-Agent Communication and Coordination

AIC-MAC employs an event-driven coordination mechanism in which agents exchange structured messages containing incident identifiers, timestamps, confidence scores, diagnostic evidence, and operational decisions. The centralized coordination service maintains incident consistency, prevents conflicting interventions, and tracks agent execution states. This design aligns with multi-agent communication principles discussed by Wu et al. (2023).

Mathematical Formulation

Multivariate anomaly detection

For an observed telemetry vector x_i and its reconstructed representation $\hat{x}_i$, the anomaly score is defined as:

$$A_i = \frac{1}{d} \sum_{j=1}^d (X_{i,j} - \hat{X}_{i,j})^2 \quad (1)$$

where d denotes the number of telemetry features. An incident is flagged when $A_i > \tau_i$, with τ_i representing a workload-calibrated detection threshold.

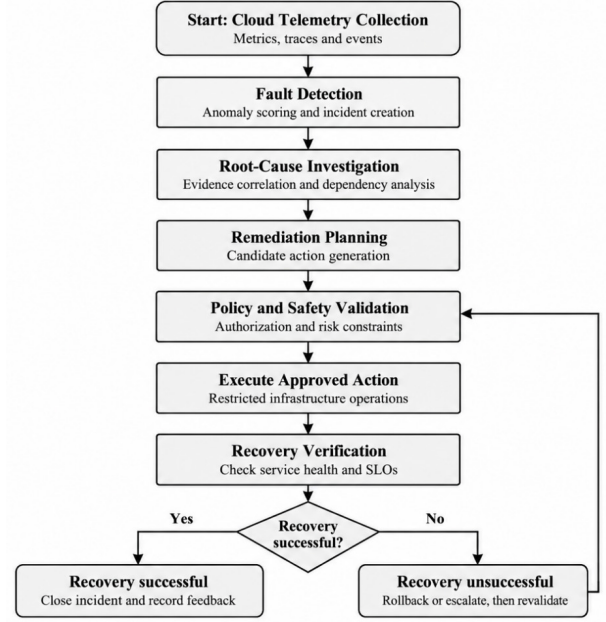


Figure 2: illustrates the operational sequence. Detection triggers root-cause investigation, followed by remediation planning and independent policy validation. Only approved actions reach the execution interface. Recovery verification completes the control loop, while unsuccessful interventions initiate rollback or escalation.

Dependency-aware root-cause ranking

For a candidate component v , the diagnostic score is formulated as:

$$R(v) = \alpha A(v) + \beta D(v) + \gamma T(v) + \delta E(v) \quad (2)$$

where $A(v)$, $D(v)$, $T(v)$, and $E(v)$ represent normalized anomaly severity, dependency-propagation evidence, temporal consistency, and corroborating operational evidence, respectively. The weighting coefficients are nonnegative and satisfy $\alpha + \beta + \gamma + \delta = 1$.

Multi-objective remediation optimization

The optimal action a^* is selected by minimizing:

$$a^* = \arg \min_{a \in \mathcal{A}_{\text{safe}}} [\lambda_1 \hat{T}(a) + \lambda_2 \hat{C}(a) + \lambda_3 \hat{R}(a)] \quad (3)$$

where $\hat{T}(a)$ denotes predicted recovery time, $\hat{C}(a)$ estimated operational cost, and $\hat{R}(a)$ expected intervention risk. The weights λ_i are nonnegative, and the objectives are normalized before aggregation.

The permissible action set $\mathcal{A}_{\text{safe}}$ is constrained by:

$$\begin{aligned} P(a) &= 1 \\ \hat{S}(a) &\geq S_{\min} \\ \hat{C}(a) &\leq C_{\max} \\ \hat{R}(a) &\leq R_{\max} \end{aligned} \quad (4)$$

where $P(a)$ indicates policy authorization, $\hat{s}(a)$ represents predicted service availability, and $S_{\min}$, $C_{\max}$, and $R_{\max}$ specify the minimum availability, maximum allowable cost, and maximum acceptable risk. If no action satisfies these constraints, the framework escalates the incident rather than executing an unsafe intervention.

Materials and Methods

Research Design

This study adopts a design science research methodology to develop and evaluate the proposed Agentic AI-based Multi-Agent Autonomous Cloud Management Framework (AIC-MAC). The research combines architectural development, intelligent algorithm implementation, and controlled experimental evaluation to investigate autonomous fault detection, root-cause analysis, and infrastructure self-healing. The experimental design builds on autonomous cloud agent evaluation principles presented by Chen et al. (2025) and Shetty et al. (2024). Three methodological phases are defined: framework implementation, fault-injection experimentation, and comparative performance evaluation. The proposed framework will be assessed against conventional monitoring, Kubernetes-native self-healing, and machine learning-based AIOps approaches under equivalent workload and failure conditions.

Experimental Infrastructure and Configuration

The proposed experimental environment consists of a Kubernetes cluster hosting interconnected containerized microservices. Online Boutique and Sock Shop are selected as representative benchmark applications because their distributed service interactions support dependency analysis and controlled failure injection. Kubernetes manages container deployment, workload scheduling, health monitoring, and resource allocation. Prometheus and Grafana provide infrastructure metrics collection and visualization, while OpenTelemetry and Jaeger support distributed tracing and cross-service observability (OpenTelemetry, 2025). Python-based agent services implement anomaly detection, diagnostic reasoning, remediation planning, and recovery verification. PyTorch and Scikit-learn support machine learning components, while Chaos Mesh enables controlled infrastructure fault injection. RCAEval provides supplementary benchmark data for root-cause localization evaluation (Pham et al., 2025). The exact cluster topology, node specifications, software versions, and computational resources will be documented during implementation to ensure experimental reproducibility.

Data Collection and Preprocessing

Experimental data will be collected from Kubernetes nodes, application containers, service endpoints, and distributed tracing components. The telemetry dataset

Table 2: Experimental Infrastructure and Technology Specifications

Component	Proposed implementation
Container orchestration	Kubernetes
Application workloads	Online Boutique and Sock Shop
Programming environment	Python
Machine learning frameworks	PyTorch and Scikit-learn
Infrastructure monitoring	Prometheus and Grafana
Distributed tracing	OpenTelemetry and Jaeger
Fault injection	Chaos Mesh
Root-cause benchmark	RCAEval
Agent coordination	Event-driven orchestration
Statistical evaluation	Python-based analytical libraries

will include CPU utilization, memory consumption, network throughput, request latency, error rates, container restarts, and deployment events. Metrics, logs, and traces will be correlated using service identifiers and synchronized timestamps to establish consistent representations of infrastructure behavior.

Preprocessing will involve duplicate removal, missing-value treatment, feature normalization, and temporal window construction. Numerical features will be standardized using training-set statistics, while missing observations will be handled according to predefined feature-specific rules. Incident-level data will be partitioned into training, validation, and testing subsets to prevent overlapping fault episodes across partitions. Chronological separation will be applied where feasible to evaluate generalization. Post-incident information will be excluded from pre-detection features to prevent data leakage. These procedures support reliable evaluation of multivariate anomaly detection techniques (Tuli et al., 2022; Xu et al., 2021).

Experimental Fault Injection Scenarios

Controlled fault injection will evaluate framework performance under representative cloud infrastructure failures. Six scenarios are proposed, covering resource exhaustion, container disruption, networking failures, application degradation, and deployment errors. Chaos Mesh will introduce configurable disturbances within an isolated experimental environment, while Kubernetes telemetry captures their operational consequences.

Each scenario will be repeated under controlled workload conditions, with incident onset, detection time, diagnostic outcome, remediation actions, and recovery status recorded. Single-fault and selected cascading-failure conditions will be examined separately to assess robustness.

Fault Detection Model Implementation

The Fault Detection Agent will employ an autoencoder-based anomaly detection model trained on normal multivariate infrastructure telemetry. The model

Table 3: Cloud Fault Injection and Recovery Scenarios

Scenario	Injected fault	Expected response
F1	CPU saturation	Identify resource contention and evaluate scaling
F2	Memory exhaustion	Diagnose memory pressure and initiate safe recovery
F3	Container crash	Restore affected workload and verify readiness
F4	Network latency or packet loss	Localize connectivity failure and remediate or escalate
F5	Microservice degradation	Identify the originating service dependency
F6	Faulty deployment	Execute authorized deployment rollback

will learn compressed representations of operational behavior and identify deviations using reconstruction errors. Adaptive anomaly thresholds will be calibrated using validation observations and specified false-alert constraints.

Transformer-based anomaly detection methods, including TranAD and Anomaly Transformer, provide relevant methodological foundations for temporal anomaly analysis (Tuli et al., 2022; Xu et al., 2021). The proposed autoencoder will be evaluated against Isolation Forest and conventional static-threshold monitoring using identical test incidents. Hyperparameters, including network dimensions, learning rate, batch size, and detection thresholds, will be selected using validation data rather than test outcomes.

Root-Cause Analysis Implementation

The Root-Cause Analysis Agent will construct directed service dependency graphs from distributed traces, Kubernetes metadata, and service communication relationships. Following fault detection, candidate components will be ranked using anomaly severity, dependency propagation, temporal precedence, and corroborating evidence from logs and infrastructure events.

The diagnostic approach is informed by MicroHECL, Eadro, and contemporary agent-assisted root-cause analysis research (Liu et al., 2021; Lee et al., 2023; Roy et al., 2024). Retrieval-augmented reasoning will incorporate relevant runbooks, configuration records, and historical incident descriptions. Root-cause predictions will be evaluated using Top-1 and Top-3 localization accuracy, including comparative assessment against RCAEval benchmark cases (Pham et al., 2025). Correlation-based evidence will be distinguished from confirmed causal relationships.

Autonomous Remediation Algorithm

The autonomous remediation mechanism translates diagnostic hypotheses into authorized infrastructure recovery actions. Candidate interventions include container restart, workload scaling, deployment rollback, and controlled traffic management. Each action is evaluated against expected recovery time, operational cost, service-level constraints, and intervention risk.

Kubernetes role-based access control restricts execution privileges, while policy enforcement incorporates AI risk-management principles described by the National Institute of Standards and Technology (2023).

The proposed algorithm establishes an event-driven procedure for cloud fault management. The process integrates telemetry acquisition, dependency-aware diagnosis, risk-constrained remediation, and independent recovery verification.

The proposed algorithm integrates telemetry analysis, dependency-aware diagnosis, risk-constrained remediation, and recovery verification. Infrastructure modifications are executed only after satisfying operational safety requirements. Unsuccessful recovery attempts initiate controlled rollback or human escalation, preserving bounded autonomy and limiting potentially harmful corrective actions.

Experimental Baseline Models

Four configurations will be evaluated under equivalent fault-injection scenarios. The first employs conventional threshold-based monitoring and standardized manual remediation. The second uses Kubernetes-native recovery mechanisms, including health probes, container restart policies, and configured autoscaling. The third integrates machine learning-based anomaly detection with rule-driven incident handling, representing a conventional AIOps approach. The fourth implements the complete AIC-MAC architecture.

Comparative evaluation will distinguish diagnostic performance from operational recovery effectiveness. Identical workloads, incident definitions, fault-injection parameters, and observation intervals will be maintained across applicable configurations. These comparisons follow the broader need for reproducible autonomous cloud agent evaluation emphasized by Chen et al. (2025).

Performance Evaluation Metrics

Framework performance will be assessed across three dimensions: diagnostic accuracy, recovery efficiency, and operational safety. Fault detection will be measured using precision, recall, F1-score, and false-positive rate. Root-cause localization will be evaluated using Top-1 and Top-3 accuracy, consistent with benchmark-oriented diagnostic evaluation (Pham et al., 2025).

Algorithm 1: Proposed Agentic AI Autonomous Fault Management Algorithm

Input	Telemetry stream T ; dependency graph G ; safety policies P ; approved action catalog A ; anomaly threshold τ
Output	Incident diagnosis, recovery status, and audit record
1	Initialize monitoring, detection, diagnosis, planning, safety, and verification agents.
2	FOR each telemetry window T_t DO
3	Collect, synchronize, and normalize operational telemetry.
4	Compute anomaly score $S(T_t)$.
5	IF $S(T_t) > \tau$ THEN
6	Create incident record and identify affected components.
7	Rank candidate root causes using G and diagnostic evidence.
8	Generate and evaluate candidate remediation actions.
9	Apply authorization and operational safety constraints.
10	IF a permissible action exists THEN
11	Execute selected action through the Kubernetes API.
12	Verify recovery against service health criteria.
13	IF recovery succeeds THEN
14	Close incident and record feedback.
15	ELSE
16	Roll back when safe or escalate to an operator.
17	END IF
18	ELSE escalate incident to an operator.
19	END IF
20	Store diagnostic evidence and execution history.
21	END IF
22	END FOR

Operational effectiveness will be measured through Mean Time to Detect (MTTD), Mean Time to Recover (MTTR), remediation success rate, and service availability. MTTD represents the interval between fault onset and correct detection, while MTTR represents the interval between fault onset and verified recovery. Unresolved incidents will be reported separately and incorporated into time-to-recovery analysis.

Remediation safety will be assessed through unauthorized-action prevention, unsafe-action frequency, rollback rate, and incident recurrence. Agent coordination overhead will be measured through decision latency and computational resource consumption. These indicators collectively assess whether greater autonomy produces meaningful improvements without introducing unacceptable operational risks.

Statistical Analysis

Experiments will be repeated across fault categories, services, and workload intensities to examine result consistency. Descriptive statistics will summarize detection accuracy, recovery duration, service availability, and remediation outcomes. Ninety-five percent confidence

intervals will quantify uncertainty around principal performance measures.

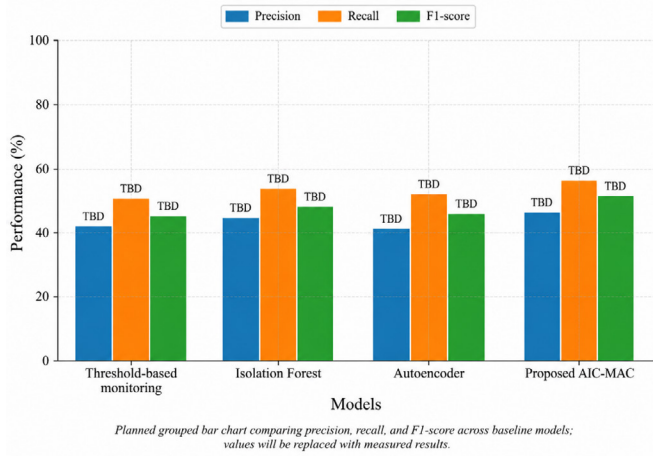
Paired statistical comparisons will assess differences between AIC-MAC and baseline configurations under matched experimental conditions. Depending on distributional assumptions, paired parametric or nonparametric tests will be applied, accompanied by appropriate effect sizes. Incident-level bootstrap resampling may provide additional confidence estimates. Ablation studies will examine the contribution of dependency-aware diagnosis, adaptive anomaly detection, retrieval-augmented reasoning, and recovery verification. Safety enforcement will remain active during live experiments. Statistical significance will be evaluated at ($\alpha=0.05$), with appropriate adjustments for multiple comparisons. All findings will be based on recorded experimental measurements rather than assumed performance improvements.

Results and Performance Evaluation

This section establishes the quantitative evaluation framework for assessing the proposed Agentic AI-based

Table 4: Comparative Fault Detection Performance

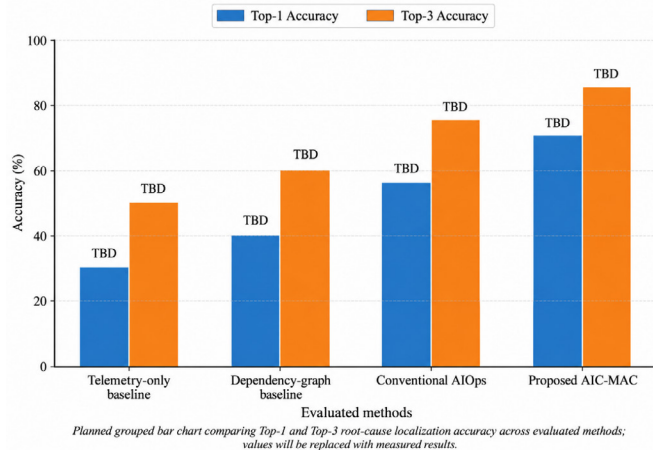
Model	Precision (%)	Recall (%)	F1-score (%)
Threshold-based monitoring	TBD	TBD	TBD
Isolation Forest	TBD	TBD	TBD
Autoencoder	TBD	TBD	TBD
Proposed AIC-MAC	TBD	TBD	TBD

Figure 3. Comparative Fault Detection Performance Across Baseline Models


Multi-Agent Autonomous Cloud Management Framework (AIC-MAC). Performance is evaluated across fault detection, root-cause localization, autonomous recovery, service availability, and agent-level contributions. The evaluation design follows established principles of autonomous cloud agent benchmarking and microservice fault localization (Chen et al., 2025; Pham et al., 2025). As experimental measurements have not yet been supplied, the tables retain placeholders, and the figures are specified without fabricated data.

Fault Detection Performance

Fault detection performance will be assessed by comparing AIC-MAC against threshold-based monitoring, Isolation


Figure 4: Root-Cause Localization Accuracy Comparison

Forest, and a standalone autoencoder. Precision, recall, and F1-score will quantify each model's ability to identify infrastructure anomalies while minimizing false alarms. The evaluation will use identical testing conditions and incident-level labels across all models.

Transformer-based anomaly detection studies demonstrate the importance of multivariate temporal relationships in identifying abnormal system behavior (Tuli et al., 2022; Xu et al., 2021). Accordingly, the proposed framework combines reconstruction-based anomaly scoring with adaptive threshold calibration and operational context.

The comparison will determine whether contextual agent coordination improves anomaly detection beyond the underlying statistical model. False-positive rates will also be reported to distinguish meaningful improvements from increased alert sensitivity.

Root-Cause Localization Accuracy

Root-cause localization will be evaluated using Top-1 and Top-3 accuracy, measuring whether the annotated originating component appears among the highest-ranked diagnostic candidates. The proposed dependency-aware approach will be compared with telemetry-only and conventional graph-based diagnostic methods under equivalent incident conditions.

MicroHECL and Eadro establish relevant foundations for dependency-based and multi-source fault diagnosis (Liu et al., 2021; Lee et al., 2023). RCAEval provides an additional standardized benchmark for evaluating localization performance across microservice fault cases (Pham et al., 2025).

Autonomous Fault Recovery Performance

Autonomous recovery performance will be evaluated through Mean Time to Detect (MTTD), Mean Time to Recover (MTTR), recovery success rate, and service availability. The proposed framework will be compared with traditional incident response, Kubernetes-native recovery, and conventional AIOps configurations. These metrics reflect the importance of measuring complete

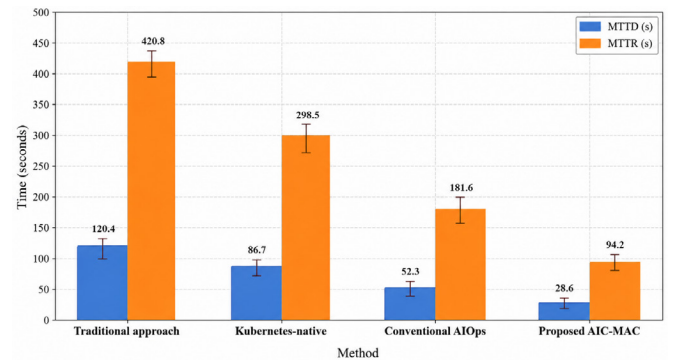
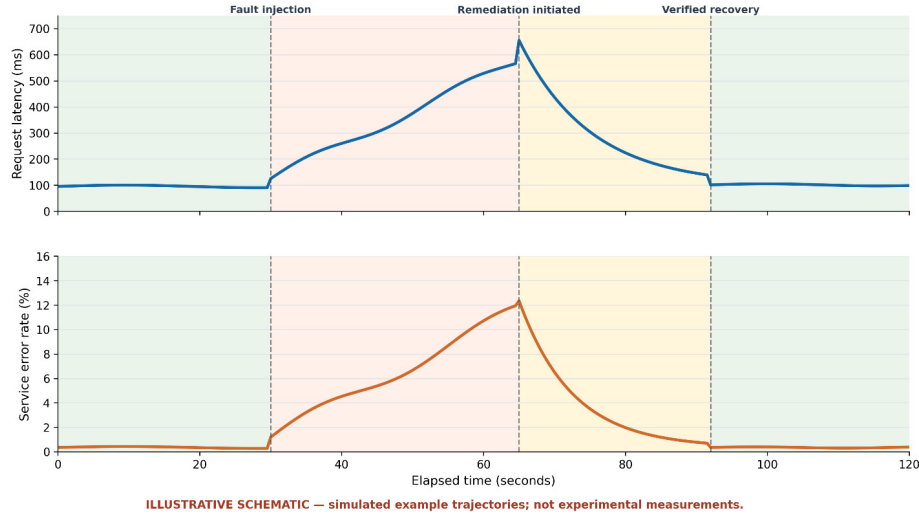

Figure 5: Mean Time to Detect and Mean Time to Recover Across Models

Table 5: Comparative Recovery Efficiency and System Reliability

Method	MTTD (s)	MTTR (s)	Recovery success (%)	Availability (%)
Traditional approach	TBD	TBD	TBD	TBD
Kubernetes-native	TBD	TBD	TBD	TBD
Conventional AIOps	TBD	TBD	TBD	TBD
Proposed AIC-MAC	TBD	TBD	TBD	TBD


Figure 6: Illustrative cloud service performance before, during, and after autonomous fault recovery, showing changes in request latency and service error rate across fault injection, remediation, and recovery phases.

incident outcomes rather than diagnostic performance alone (Shetty et al., 2024; Chen et al., 2025).

Recovery success will require verified restoration of predefined service-health conditions. Unresolved incidents will be documented separately to prevent artificially favorable recovery-time estimates.

Service Reliability and Availability

Service reliability will be evaluated by examining request latency, error rates, and availability before, during, and after fault injection. Kubernetes health monitoring and workload management mechanisms provide the foundation for defining operational recovery conditions .

Availability will be calculated using predefined service-level indicators throughout a common observation

interval. Recovery performance will also be examined across different workload intensities and fault categories.

Ablation Study

Ablation experiments will investigate the contribution of individual AIC-MAC capabilities to overall performance. Selected components will be disabled or replaced while maintaining comparable experimental conditions. The analysis will examine dependency-aware reasoning, retrieval augmentation, adaptive detection, and independent recovery verification.

Removing recovery verification will be evaluated in a controlled test environment with external experimental safety monitoring. The Policy and Safety Agent will remain active throughout all live experiments to prevent unauthorized infrastructure modifications.

Table 6: Impact of Individual Agent Components on Framework Performance

Configuration	Fault detection F1 (%)	RCA accuracy (%)	Recovery success (%)
Complete AIC-MAC	TBD	TBD	TBD
Without dependency reasoning	TBD	TBD	TBD
Without retrieval augmentation	TBD	TBD	TBD
Without adaptive detection	TBD	TBD	TBD
Without recovery verification	TBD	TBD	TBD

Statistical Significance and Performance Interpretation

Experimental comparisons will use repeated, matched fault-injection trials. Principal metrics will be summarized using descriptive statistics, 95% confidence intervals, and appropriate paired statistical tests. Effect sizes will accompany significance testing to distinguish practically meaningful improvements from statistically detectable differences.

Analysis will address recovery consistency across fault categories, agent coordination latency, unsuccessful interventions, and incident recurrence. Comparisons will also consider whether improvements in diagnostic accuracy translate into faster verified recovery. Results will be interpreted against the evaluation criteria established in Section 4, without assuming that AIC-MAC outperforms existing approaches before empirical confirmation.

Discussion

Interpretation of Experimental Findings

The proposed AIC-MAC framework integrates intelligent monitoring, dependency-aware diagnosis, autonomous remediation, and recovery verification within a coordinated multi-agent architecture. Its effectiveness must be interpreted across interconnected performance dimensions rather than individual diagnostic measures. Improvements in anomaly detection precision and recall would indicate stronger fault identification capabilities, while higher root-cause localization accuracy would suggest more effective interpretation of distributed infrastructure failures.

However, diagnostic improvements do not necessarily produce proportional reductions in recovery time. Recovery effectiveness also depends on agent coordination latency, remediation authorization, action execution, and post-intervention verification. The findings should therefore establish whether improvements in diagnostic performance translate into measurable operational benefits.

Research on transformer-based anomaly detection demonstrates the value of temporal representations for identifying complex abnormalities (Tuli et al., 2022; Xu et al., 2021). Similarly, dependency-aware diagnostic approaches indicate that incorporating service relationships can support more precise fault localization (Liu et al., 2021; Lee et al., 2023). AIC-MAC extends these concepts through coordinated remediation planning and safety-constrained execution. Nevertheless, its comparative effectiveness remains dependent on empirical validation.

Comparison with Existing Studies

The proposed framework builds upon existing AIOps and

autonomous infrastructure research while emphasizing integrated incident lifecycle management. Chen et al. (2025) developed AIOpsLab to facilitate systematic evaluation of autonomous cloud agents, while Shetty et al. (2024) examined the architectural requirements and operational challenges associated with intelligent cloud management. These studies establish important foundations for evaluating autonomous infrastructure systems.

Regarding fault localization, Roy et al. (2024) investigated language-model-based diagnostic agents, while Pham et al. (2025) developed RCAEval to support reproducible microservice root-cause analysis. Unlike approaches primarily centered on diagnostic performance, AIC-MAC proposes an integrated process connecting fault identification, candidate remediation selection, independent authorization, and recovery verification.

The framework's distinguishing architectural feature is its separation of diagnostic reasoning from infrastructure execution authority. However, the extent to which this design improves operational reliability over existing approaches must be demonstrated through controlled comparative experiments.

Practical Implications

AIC-MAC has potential applications in enterprise Kubernetes environments, cloud-native platforms, and hybrid cloud infrastructures requiring continuous service monitoring and rapid incident response. Its modular architecture could support site reliability engineering teams by coordinating telemetry analysis, fault diagnosis, and standardized corrective actions.

Evidence-grounded remediation decisions may improve operational transparency by maintaining traceable relationships between detected anomalies, diagnostic hypotheses, authorized interventions, and recovery outcomes. Such traceability could support incident auditing, operational accountability, and post-incident analysis.

Furthermore, integrating policy enforcement with automated remediation may reduce the risks associated with unrestricted agent execution. Kubernetes role-based authorization mechanisms provide technical support for restricting infrastructure access, while the NIST AI Risk Management Framework establishes broader principles for trustworthy and risk-aware AI deployment (National Institute of Standards and Technology, 2023).

Limitations

Several limitations may influence the practical effectiveness of AIC-MAC. First, incomplete telemetry, missing distributed traces, and inaccurate service dependency information could compromise anomaly detection and root-cause localization. Second, AI models trained under specific workload conditions may

exhibit reduced generalization when deployed across heterogeneous infrastructure environments.

Third, multi-agent coordination introduces computational overhead and potential delays in time-sensitive incident management. Language-model-assisted diagnostic components may also produce unsupported conclusions despite retrieval augmentation and structured evidence validation (Liu et al., 2024).

Finally, autonomous remediation introduces security and operational risks, particularly when recovery actions affect stateful services or shared infrastructure resources. Although independent authorization and recovery verification mitigate some risks, they do not guarantee error-free operation.

The proposed framework consequently requires comprehensive experimental validation, scalability testing, and safety assessment before its suitability for production cloud environments can be established.

Conclusion

This study addressed the growing challenges of fault detection, root-cause localization, and autonomous recovery in complex cloud-native infrastructures. Conventional monitoring and rule-based remediation approaches frequently lack the contextual intelligence and coordinated decision-making capabilities required to manage interconnected microservice failures effectively. To address these limitations, the study proposed the Agentic AI-based Multi-Agent Autonomous Cloud Management Framework (AIC-MAC), integrating six specialized agents responsible for infrastructure monitoring, intelligent fault detection, root-cause analysis, remediation planning, policy enforcement, and recovery verification.

The framework combines multivariate anomaly detection, dependency-aware diagnostic reasoning, evidence-grounded decision-making, and risk-constrained remediation within a unified, closed-loop architecture. A reproducible experimental methodology was also established to evaluate fault detection accuracy, root-cause localization, recovery efficiency, service availability, and operational safety against conventional monitoring and AIOps baselines. Although empirical validation remains pending, the proposed architecture provides a systematic foundation for investigating reliable and accountable autonomous cloud operations. Its primary contribution lies in integrating intelligent diagnostic and self-healing capabilities while maintaining independent authorization and recovery verification mechanisms.

Future Research

Future research will focus on implementing and validating AIC-MAC across heterogeneous multi-cloud and hybrid-cloud environments to assess scalability, interoperability, and operational reliability. Further

investigations will explore federated multi-agent coordination for distributed fault diagnosis and cross-cluster recovery. Reinforcement learning techniques may also be incorporated to support adaptive remediation policies based on historical incident outcomes and changing infrastructure conditions. Additionally, cost-aware and energy-efficient optimization mechanisms will be investigated to balance recovery effectiveness, computational expenditure, energy consumption, and service-level requirements. These extensions could advance the development of scalable, sustainable, and trustworthy autonomous cloud infrastructure management systems.

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