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Article

Artificial Intelligence–Based Incident Detection, Response, and Recovery in Cloud-Native Computing Environments: An Intelligent Framework for Autonomous Cyber Resilience

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Abstract

Cloud-native computing has transformed the deployment and operation of digital services through microservices, containers, Kubernetes orchestration, distributed applications, and dynamically scalable infrastructure. Although these technologies improve flexibility, availability, and deployment speed, they also increase operational complexity. Failures can emerge across interconnected services, containers, networks, databases, configurations, and security controls, making incident detection, diagnosis, response, and recovery more difficult. Conventional monitoring approaches often rely on static thresholds, fragmented dashboards, and manually coordinated response processes. These approaches can generate excessive alerts, provide limited contextual understanding of incidents, and delay the restoration of affected services.

This study proposes an artificial intelligence-based framework for autonomous cyber resilience in cloud-native computing environments. The framework integrates telemetry collection and analysis, anomaly detection, incident classification, distributed root-cause analysis, risk-aware response orchestration, recovery validation, and continuous learning. It combines operational data from logs, metrics, traces, Kubernetes events, and security alerts to identify abnormal behaviour and determine probable causes across distributed microservice environments. The response layer applies predefined policies and confidence thresholds to recommend or execute remediation actions, including pod restart, workload scaling, traffic rerouting, deployment rollback, service isolation, and security escalation. High-risk actions remain subject to human approval and governance controls.

The study adopts a design-science and experimental evaluation methodology. The proposed framework will be assessed in a Kubernetes-based cloud-native testbed using simulated operational and cybersecurity incident scenarios, including resource exhaustion, service failures, network latency, configuration errors, database disruptions, and suspicious access events. Performance will be evaluated using detection accuracy, precision, recall, F1-score, root-cause localisation accuracy, mean time to detect, mean time to respond, mean time to recover, recovery success rate, and service availability. The study contributes an integrated and policy-governed approach to intelligent incident management that aims to improve detection speed, reduce recovery time, strengthen service continuity, and support safer automated remediation in complex cloud-native environments.

Keywords: Artificial intelligence; AIOps; cloud-native computing; Kubernetes; autonomous cyber resilience; incident response; root-cause analysis.

Introduction

Background

Cloud-native computing has become widely adopted because it supports flexible, scalable, and faster application deployment. Organisations now use microservices, containers, Kubernetes orchestration, service meshes, APIs, and distributed workloads to build applications that can be updated and scaled independently. These technologies improve agility and service availability, but they also increase operational complexity. In a distributed cloud-native system, a single request may pass through several services, databases, APIs, and infrastructure layers. As a result, a failure in one service can quickly affect connected services and reduce overall application availability.

Problem Statement

Traditional incident management often depends on threshold-based alerts, separate monitoring dashboards,

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and manual investigation. However, cloud-native environments generate large volumes of logs, metrics, traces, Kubernetes events, and security alerts. This can overwhelm operations teams and delay effective response. Conventional tools may detect visible symptoms, such as high latency or service failure, but they often struggle to identify the actual root cause or recommend safe remediation actions. Delayed manual response can increase downtime, cyber risk, financial loss, and reputational damage.

Research Aim

The aim of this study is to develop and evaluate an artificial intelligence-based framework that supports autonomous incident detection, response, recovery, and continuous learning in cloud-native computing environments.

Research Objectives

The objectives of this study are to:

- Identify the limitations of conventional incident-management approaches in cloud-native systems.
- Design an AI-enabled framework for anomaly detection, root-cause analysis, automated response, and recovery.
- Develop a risk-aware decision mechanism for selecting remediation actions.
- Evaluate the framework using controlled incident scenarios in a cloud-native testbed.
- Assess the framework's contribution to autonomous cyber resilience.

Research Questions

This study addresses the following research questions:

- How can AI improve incident detection in cloud-native environments?
- How can machine learning and intelligent reasoning support root-cause analysis across distributed microservices?
- Which automated remediation actions can safely improve incident response and recovery?
- How does the proposed framework perform compared with conventional monitoring and rule-based automation?
- What governance and human-oversight mechanisms are required for trustworthy autonomous cyber resilience?

Research Contributions

This study contributes:

- A unified AI-based framework integrating detection, diagnosis, response, recovery, and learning.
- A policy-governed model for safe autonomous remediation.
- A cloud-native incident taxonomy for evaluating operational and cyber incidents.
- An experimental evaluation approach using Kubernetes-based fault injection and service telemetry.
- Practical recommendations for organisations implementing AI-enabled incident management.

Literature Review

Cloud-Native Computing and Operational Complexity

Cloud-native computing refers to the design and deployment of applications using technologies that support scalability, flexibility, automation, and resilience in dynamic cloud environments. It commonly relies on microservices, containers, Kubernetes orchestration, serverless functions, distributed databases, APIs, and service-based communication. These technologies allow organisations to deploy applications faster, scale services independently, and improve resource efficiency.

Microservices divide applications into smaller services that can be developed and deployed separately. Containers package each service with its dependencies, while Kubernetes manages deployment, scaling, scheduling, and recovery across clusters. Serverless systems reduce infrastructure-management responsibility, and API-driven architectures support communication among services and external systems. Although these technologies improve agility, they also create operational complexity. A single transaction may depend on several services, databases, networks, and infrastructure layers. Therefore, a fault in one service can spread to connected services and cause wider application degradation. This creates challenges related to fault propagation, observability, configuration drift, service dependencies, and dynamic scaling.

Incident Detection in Cloud Environments

Incident detection in cloud environments traditionally depends on monitoring tools, threshold-based alerts, rule-based systems, log analysis, and event correlation. Metrics-based monitoring identifies abnormal conditions when values such as CPU usage, memory consumption, latency, packet loss, error rate, or disk usage exceed predefined limits. Rule-based systems extend this approach by triggering alerts or responses when specific conditions occur. Logs provide details about system behaviour, application errors, failed requests, and security events, while event correlation links related alerts across services and infrastructure components.

However, conventional approaches have several limitations. Static thresholds may generate false positives during normal workload changes or miss incidents that develop gradually. Rule-based systems are often limited to known conditions and may fail when incidents are complex or previously unseen. In large cloud-native

systems, logs, metrics, traces, Kubernetes events, and security alerts can be produced in high volume, creating alert fatigue for operations teams. Monitoring tools may also operate in isolation, making it difficult to understand the full incident context. As a result, traditional approaches often detect visible symptoms but struggle to identify root causes or recommend suitable remediation actions.

Artificial Intelligence and AIOps

Artificial Intelligence for IT Operations, known as AIOps, involves the use of machine learning, analytics, and automation to improve IT operations and incident management. AIOps is relevant to cloud operations because cloud-native environments generate large volumes of operational and security telemetry that cannot be effectively analysed manually. AI can assist by detecting abnormal patterns, grouping related alerts, classifying incidents, predicting failures, and supporting response decisions.

Several AI techniques are useful in this context. Supervised learning can classify known incident types when labelled training data is available. Unsupervised learning can detect unknown or unusual events by learning normal system behaviour and identifying deviations. Deep learning can process complex time-series telemetry and large-scale log data. Natural language processing can interpret log messages, alerts, and incident reports. Graph analytics can model service dependencies and support root-cause analysis across interconnected systems. Reinforcement learning may support response selection by learning which actions produce better recovery outcomes, although it must be controlled carefully in operational environments. Together, these techniques support anomaly detection, alert prioritisation, predictive maintenance, and operational decision-making.

Root-Cause Analysis in Distributed Systems

Root-cause analysis is difficult in distributed cloud-native systems because the service showing an error may not be the component that caused the incident. A visible failure in an application service may originate from a database issue, network delay, failed dependency, configuration error, overloaded container, or security event. This makes manual diagnosis slow and uncertain.

Dependency graphs, service topology analysis, distributed tracing, causal inference, and AI-supported event correlation can improve root-cause analysis. Dependency graphs show the relationships among services, databases, APIs, containers, and infrastructure components. Distributed traces reveal how requests move across services and where delays or failures occur. Causal analysis helps distinguish between correlated symptoms and likely causes. AI-supported event correlation can combine metrics, logs, traces, and Kubernetes events to identify the most probable source of disruption. Explainable AI is also important because engineers must understand why a system classified an incident or selected a root cause before trusting its recommendation.

Automated Incident Response and Recovery

Automated response and recovery involve the use of runbooks, self-healing systems, orchestration tools, autoscaling, rollback mechanisms, traffic routing, and workload isolation to restore normal service operation. Kubernetes already supports some self-healing functions, such as restarting failed containers, rescheduling workloads, and maintaining desired application states. Runbook automation can also execute predefined actions, such as restarting a pod, scaling a service, rolling back a deployment, or sending alerts to engineers.

Despite these benefits, fully autonomous remediation can be risky. An incorrect action may worsen an incident, interrupt critical services, hide useful forensic evidence, or create new security and availability problems. For example, restarting a service may not solve a database-related issue, while isolating a production node may disrupt important workloads. Therefore, automated response must include confidence thresholds, approval workflows, policy controls, audit logs, and human oversight. Low-risk actions may be automated, but high-risk actions should require approval from authorised personnel.

Cyber Resilience and Autonomous Systems

Cyber resilience refers to the ability of a system to prevent, detect, respond to, recover from, and learn from adverse operational or cyber events. It goes beyond traditional cybersecurity because it includes service continuity, recovery capability, and institutional learning. In cloud-native environments, resilience requires the system to maintain or restore essential functions even when services fail, dependencies degrade, configurations change, or security incidents occur.

Autonomous systems can strengthen cyber resilience by reducing detection and recovery time, improving root-cause analysis, and supporting faster response decisions. However, autonomy must be governed to ensure safety, transparency, and accountability. Existing studies address AI-based anomaly detection, root-cause analysis, observability, and automated recovery, but these areas are often treated separately. The research gap is the limited development of integrated frameworks that connect AI-based detection, diagnosis, response, recovery validation, continuous learning, and governance in one cloud-native cyber-resilience model. This study addresses that gap by proposing an intelligent and policy-governed framework for autonomous cyber resilience.

Table 1: Comparison of Conventional and AI-Based Incident Management Approaches

Dimension	*Conventional Monitoring*	*Rule-Based Automation*	*Proposed AI-Based Framework*
Incident detection	Static thresholds	Predefined conditions	Adaptive anomaly detection
Root-cause analysis	Manual investigation	Limited rule matching	AI-assisted causal reasoning
Response speed	Slow to moderate	Moderate	Rapid and context-aware
Recovery approach	Manual intervention	Fixed remediation scripts	Policy-guided adaptive recovery
Learning capability	Minimal	Limited	Continuous learning from incidents
Human oversight	Fully manual	Moderate	Risk-based approval and governance

Conceptual Framework for Autonomous Cyber Resilience

Framework Overview

This study proposes the Intelligent Autonomous Cyber Resilience Framework, a layered framework designed to improve incident detection, diagnosis, response, recovery, and organisational learning in cloud-native computing environments. The framework is intended for distributed applications built on microservices, containers, Kubernetes clusters, APIs, databases, service meshes, and cloud infrastructure. Its central purpose is to transform cloud incident management from a predominantly reactive and manually coordinated process into a more adaptive, evidence-based, and policy-governed resilience process.

The framework combines five connected capabilities: cloud observability, artificial intelligence analytics, intelligent decision-making, automated remediation, and governance. Rather than treating monitoring, incident analysis, response, and recovery as separate operational activities, the proposed framework links them into a continuous lifecycle. It collects telemetry from different cloud-native components, identifies abnormal patterns, analyses the likely source and severity of incidents, recommends or executes appropriate recovery actions, validates whether the system has returned to a stable state, and stores validated outcomes for future improvement.

Cloud observability provides the evidence base for the framework. It includes operational and security data collected from metrics, logs, traces, Kubernetes events, deployment records, and infrastructure monitoring tools. AI analytics then processes this data to identify anomalies, classify known incidents, correlate related alerts, and detect unusual conditions that may not be recognised through conventional threshold-based monitoring. The decision intelligence layer evaluates the incident context, probable root cause, business impact, confidence score, and response risk before selecting an appropriate remediation action.

The framework does not assume that all response actions should be fully automated. Instead, it adopts a risk-aware model in which low-risk actions can be executed automatically, while medium- and high-risk actions require stronger policy checks or human approval. This design reflects the need to balance operational speed with safety, accountability, and business continuity. High-impact decisions, particularly those involving production isolation, access revocation, or critical service shutdowns, should remain subject to explicit governance and professional oversight.

The framework is therefore structured around six connected layers:

- Telemetry and observability layer
- AI-based incident detection layer
- Intelligent root-cause analysis layer
- Risk-aware decision and response layer
- Recovery validation layer
- Continuous learning and governance layer

The relationship among these layers enables the system to move from raw operational data to validated recovery outcomes. This approach is consistent with the broader concept of cyber resilience, which requires systems to detect adverse conditions, withstand their effects, recover essential functions, and improve future performance through learning (Ross et al., 2021).

Telemetry and Observability Layer

The telemetry and observability layer provides the data foundation for the proposed framework. Its main function is to collect, normalise, and integrate operational and security information from cloud-native applications and infrastructure. In distributed microservice environments, a single data source is rarely enough to explain system behaviour. Effective incident detection therefore requires combined analysis of metrics, logs, traces, Kubernetes events, configuration records, and security signals.

Metrics provide continuous numerical evidence of system performance and resource use. Key metrics include CPU utilisation, memory consumption, latency, error rate, throughput, packet loss, disk usage, pod health, and node availability. These indicators help identify resource exhaustion, service degradation, abnormal workload behaviour, and infrastructure instability.

Logs provide textual evidence of system activity and failure conditions. The framework uses application

logs, container logs, system logs, audit logs, Kubernetes logs, deployment logs, and security logs. These records can reveal application exceptions, failed API calls, authentication errors, configuration changes, database connection problems, suspicious access attempts, and policy violations.

Distributed traces show how requests move across services, APIs, databases, queues, and infrastructure components. Trace data is useful for identifying latency bottlenecks, failed service calls, retries, and dependency-related failures. This is important because a visible customer-facing error may originate from an internal dependency that is not immediately obvious from the affected service (Li et al., 2022).

Kubernetes events add orchestration-level context. These events may include failed deployments, pod restarts, image-pull errors, node failures, scheduling errors, autoscaling activities, failed health checks, and resource-limit violations. Although Kubernetes can restart failed containers and reschedule workloads, these actions do not always explain the underlying cause of failure.

Before telemetry is passed to the AI layers, the framework performs cleaning, timestamp alignment, normalisation, correlation, and enrichment. This process removes duplicate records, standardises data formats, links events to services and infrastructure components, and adds context such as namespace, deployment version, workload priority, and asset criticality. The layer also maintains a dynamic service map showing relationships among microservices, containers, APIs, databases, message queues, nodes, and external dependencies. This service map helps the framework understand how incidents may propagate across the cloud-native environment.

AI-Based Incident Detection Layer

The AI-based incident detection layer analyses cloud-native telemetry to identify abnormal behaviour, classify incidents, correlate alerts, and estimate severity. It improves on static threshold monitoring by examining combined patterns across metrics, logs, traces, Kubernetes events, and service dependencies.

The layer uses both supervised and unsupervised learning. Supervised models classify known incidents such as pod crashes, CPU exhaustion, memory leaks, database failures, network degradation, failed deployments, configuration errors, and suspicious access attempts. Unsupervised models detect unknown or rare incidents by learning normal system behaviour and identifying unusual deviations in multivariate telemetry. Prior studies have shown that unsupervised deep learning and recurrent neural networks are useful for detecting anomalies in complex time-series data (Audibert et al., 2020; Su et al., 2019).

Alert correlation groups related alerts into a single incident cluster. For example, API errors, pod restarts, database timeouts, and increased latency may represent one underlying incident rather than separate failures. The framework then assigns a severity score based on affected services, service criticality, user impact, security relevance, confidence level, and estimated business effect. The output of this layer is a structured incident record containing the anomaly score, incident type, affected services, related alerts, severity level, supporting telemetry, timestamp, and confidence score. This record is then passed to the root-cause analysis layer for deeper investigation.

Intelligent Root-Cause Analysis Layer

The intelligent root-cause analysis layer determines the probable source of an incident by analysing service dependencies, telemetry relationships, distributed traces, operational history, and infrastructure context. Its purpose is to distinguish between the symptoms of a failure and the component or condition most likely responsible for the failure.

Root-cause analysis is difficult in microservice systems because services are interconnected through APIs, databases, message queues, authentication mechanisms, shared infrastructure, and network paths. A visible application failure may therefore be only a secondary effect of an underlying issue elsewhere in the system. For example, a payment-service error may be caused by a slow database query, a failed authentication request, network congestion, a misconfigured deployment, or insufficient memory in an upstream service.

The framework uses a service dependency graph to represent cloud-native relationships. Nodes in the graph represent services, containers, pods, databases, APIs, nodes, network components, and external dependencies. Edges represent communication links, data flows, resource dependencies, or service calls. When an incident occurs, the framework evaluates which components showed abnormal behaviour first, how the incident propagated through connected services, and whether trace data supports a causal relationship.

Graph-based analysis helps the system identify likely propagation paths. If several services show elevated latency but only one database service reports resource exhaustion before the others degrade, the database may be identified as a probable root cause. This approach is supported by previous research showing that graph-based methods can improve root-cause analysis in service-oriented and microservice environments (Brandón et al., 2020). CloudRanger similarly demonstrated that performance metrics and dependency relationships can support root-cause identification in cloud-native systems (Wang et al., 2018).

The framework also examines distributed traces to understand how transaction requests moved through the application. Trace data can reveal failed calls, unusual delays, repeated retries, slow dependencies, and broken

communication paths. For example, a trace may show that several affected services are waiting for responses from the same external API or database. This evidence helps the system move from broad incident symptoms toward more precise diagnostic conclusions.

The root-cause analysis layer considers several possible sources of failure:

- Application code defects or runtime exceptions
- Container crashes or repeated pod restarts
- CPU, memory, disk, or network resource exhaustion
- Database failures or slow queries
- Failed API dependencies
- Misconfigured deployments or environment variables
- Incorrect Kubernetes resource settings
- Service-mesh or network-policy restrictions
- Node failures or scheduling problems
- Suspicious access events or security-policy violations

Explainability is an essential output of this layer. Rather than providing only a root-cause label, the framework should explain why a service, pod, node, configuration, or network component was selected. The explanation may include abnormal metrics, related logs, trace evidence, service-dependency paths, time sequence of events, known incident similarities, and confidence scores. For example, the system may state that a database node was identified as the probable root cause because CPU utilisation increased sharply before related service failures, traces showed delayed database responses, and multiple dependent services experienced timeout errors. Explainable outputs strengthen operational trust because engineers can examine the evidence before accepting or rejecting the recommendation. Explainability is particularly important where the suggested response may affect production services, users, or security controls. Barredo Arrieta et al. (2020) emphasised that explainability and transparency are essential for the responsible use of AI in high-impact operational contexts.

Risk-Aware Decision and Response Layer

The risk-aware decision and response layer converts diagnostic findings into remediation recommendations or controlled automated actions. Its role is not merely to select the fastest possible response, but to select an action that is appropriate for the incident type, system context, confidence level, operational impact, and cybersecurity risk.

The framework classifies remediation actions into low-, medium-, and high-risk categories. The categorisation is based on the potential impact of the action on service continuity, data integrity, security posture, compliance obligations, and customer operations.

Low-risk actions are routine remediation activities that are unlikely to cause wider operational disruption when applied correctly. These may include restarting unhealthy pods, rescheduling failed workloads, scaling service replicas, clearing temporary caches, renewing expired service connections, or restarting a non-critical service instance. Such actions can be executed automatically when the system has high diagnostic confidence and the action falls within approved operational policies.

Medium-risk actions have greater potential to affect service availability or business processes. These actions may include rolling back a deployment, rerouting traffic through alternative service paths, disabling a faulty feature, isolating a non-critical service, changing a scaling policy, or restricting access to a suspected compromised workload. Medium-risk actions should normally require additional policy checks and may require approval from a site reliability engineer, cloud engineer, or designated incident manager.

High-risk actions may significantly affect production systems, customer access, security operations, or critical business functions. Examples include revoking access credentials, isolating infrastructure nodes, disabling production services, blocking major network routes, shutting down a database cluster, or suspending a critical integration. These actions should not be executed autonomously without mandatory human approval, even where the AI model reports high confidence.

The decision engine considers several factors before selecting an action:

- Incident severity and affected business service
- Probable root cause and diagnostic confidence
- Number of affected users or dependent services
- Security implications
- Operational criticality of the affected workload
- Availability of alternative service paths
- Expected recovery benefit
- Possible side effects of the proposed action
- Existing policies, runbooks, and compliance controls

The framework uses confidence thresholds to determine the level of automation. For example, a pod restart may be automatically approved when the detection and root-cause confidence scores are high and no critical dependency is affected. In contrast, a deployment rollback may require confirmation because it could remove important functionality or conflict with another active release. This risk-aware approach prevents the system from treating all incidents as equivalent.

Approval workflows are built into the framework for medium- and high-risk actions. The system should provide a concise response recommendation that includes the proposed action, reason for the recommendation, expected impact, confidence score, supporting telemetry, and possible alternatives. Human approvers can then accept, reject, modify, or escalate the recommendation. All decisions should be recorded in an audit log to support accountability, post-incident review, and future model improvement.

Table 2: Components of the Proposed Autonomous Cyber Resilience Framework

Framework Layer	*Primary Inputs*	*AI or Automation Function*	*Key Output*
Telemetry and observability	Logs, traces, metrics, events	Data collection and normalisation	Unified operational view
Incident detection	Real-time telemetry	Anomaly detection and classification	Incident alert and severity score
Root-cause analysis	Service dependencies and incident data	Causal correlation and diagnosis	Probable root cause
Response orchestration	Incident context and policies	Response recommendation or execution	Remediation action
Recovery validation	Post-action telemetry	Stability and performance verification	Recovery status
Continuous learning	Incident history and outcomes	Model refinement and knowledge updates	Improved future resilience

Recovery Validation and Continuous Learning Layer

The recovery validation and continuous learning layer ensures that a remediation action has genuinely restored normal system operation. Automated action alone should not be considered evidence of successful recovery. A pod restart, traffic reroute, or deployment rollback may appear to resolve an immediate alert while the underlying problem remains active. The framework must therefore validate service health after remediation.

Recovery validation examines post-response telemetry, including latency, error rates, throughput, CPU and memory consumption, pod health, service availability, network performance, transaction success rate, and workload stability. The system compares these values with normal baseline behaviour and determines whether the affected service has returned to an acceptable operational state. For example, a successful recovery may require error rates to fall below an accepted limit, latency to return to normal range, pod restarts to stop, transaction success rates to stabilise, and dependent services to recover.

The framework should also assess whether the remediation introduced unintended effects. A scaling action may reduce latency but create excessive cost or overload a database. A traffic reroute may restore one service while increasing pressure on another region. A rollback may resolve errors but reintroduce a previously corrected security vulnerability. Continuous validation is therefore necessary to ensure that the overall system remains stable after response execution.

Each incident should be stored in a structured incident knowledge repository. The stored record may include the incident category, telemetry evidence, root-cause findings, selected remediation action, approval status, recovery outcome, recovery time, service impact,

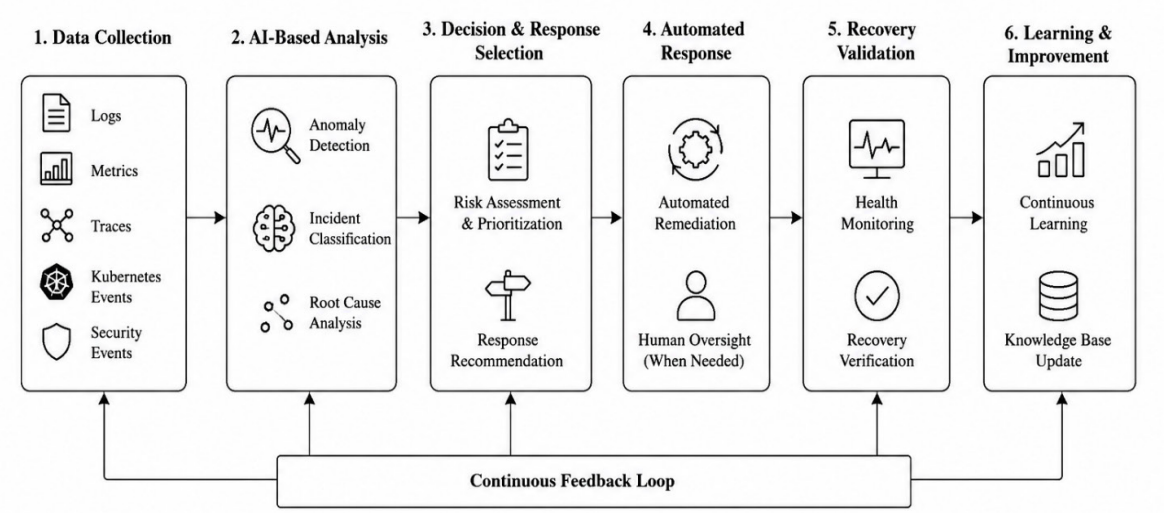

Figure 1: Intelligent Framework for Autonomous Cyber Resilience

and lessons learned. This repository supports both operational learning and model refinement.

Validated incident data can be used to retrain supervised classification models, update anomaly baselines, improve alert-correlation rules, refine risk scores, and enhance response recommendations. Over time, the framework should become more effective at recognising recurring incidents and selecting actions that have previously produced safe and successful recovery outcomes. However, model updates must be controlled through validation procedures to prevent inaccurate or biased learning from being introduced into production decisions.

The continuous learning layer also supports organisational learning. Incident reports can identify recurring weaknesses in architecture, configuration management, deployment processes, access control, capacity planning, or monitoring design. This allows organisations to move beyond repeated recovery actions and address systemic causes of operational and cyber risk.

In summary, the proposed Intelligent Autonomous Cyber Resilience Framework integrates observability, AI analytics, root-cause analysis, risk-aware remediation, recovery validation, and continuous learning into a single cloud-native incident-management model. The framework is designed to improve detection speed, diagnostic precision, recovery effectiveness, and service continuity while maintaining human oversight for actions that carry significant operational or security risk.

Research Methodology

Research Design

This study adopts a design-science research approach combined with controlled experimental evaluation. Design science is appropriate because the research does not only examine an existing operational problem; it develops a practical artefact, namely the proposed Intelligent Autonomous Cyber Resilience Framework, and evaluates whether the framework improves incident-management performance in cloud-native environments. The framework is designed to address a practical challenge faced by organisations operating Kubernetes-based microservices: the difficulty of detecting incidents quickly, identifying their real causes across distributed services, selecting safe remediation actions, and validating that recovery has actually occurred. Rather than treating incident management as a sequence of isolated monitoring and response tasks, the proposed framework integrates telemetry collection, AI-based anomaly detection, root-cause analysis, risk-aware response selection, recovery validation, and continuous learning.

The study follows five design-science stages. First, the operational problem is identified through the literature on cloud-native observability, AIOps, distributed fault diagnosis, automated remediation, and cyber resilience. Second, the proposed framework is designed as a layered architecture that connects cloud observability, AI analytics, decision intelligence, remediation automation, governance, and post-incident learning. Third, a Kubernetes-based cloud-native testbed is developed to represent a distributed microservice environment. Fourth, controlled operational and cybersecurity incidents are injected into the testbed. Finally, the framework is evaluated against conventional threshold-based monitoring and rule-based automation approaches. The experimental evaluation uses measurable performance indicators to determine whether the proposed framework provides meaningful improvements. The key indicators include incident-detection accuracy, precision, recall, F1-score, false-positive rate, root-cause localisation accuracy, mean time to detect, mean time to respond, mean time to recover, recovery success rate, and service availability. These measures support a structured comparison between conventional monitoring, rule-based remediation, and the AI-enabled framework.

The research design also incorporates a risk-aware approach to automation. The evaluation does not assume that all remediation actions should be executed autonomously. Instead, actions are categorised as low, medium, or high risk. Low-risk actions may be performed automatically, while medium- and high-risk actions require policy validation, operational approval, or mandatory human oversight. This design reflects the importance of accountability and explainability when AI systems are used to influence cloud operations and cybersecurity decisions (National Institute of Standards and Technology [NIST], 2023).\

Cloud-Native Experimental Environment

The proposed framework will be evaluated in a Kubernetes-based microservices testbed designed to replicate the operational characteristics of a cloud-native application environment. Kubernetes is selected because it provides widely used capabilities for container orchestration, workload scheduling, autoscaling, service discovery, load balancing, self-healing, rolling updates, and resource management (Burns et al., 2016). These functions make Kubernetes suitable for investigating how AI-supported incident detection and recovery can operate in dynamic distributed systems.

The testbed will contain multiple containerised microservices representing a typical transaction-based cloud application. The application may include the following components:

- **User authentication service**, responsible for login requests, user-session validation, and access control.
- **API gateway**, responsible for routing requests to the appropriate backend microservices.

- **Application services**, such as order processing, payment processing, product management, notification delivery, and reporting.
- **Database service**, responsible for transactional and persistent data storage.
- **Message broker or queue service**, supporting asynchronous communication between microservices.
- **Load balancer**, responsible for distributing incoming requests across service replicas.
- **Kubernetes cluster**, containing worker nodes, pods, namespaces, deployments, services, and autoscaling configurations.
- **Monitoring and observability stack**, responsible for collecting metrics, logs, traces, alerts, and Kubernetes events.
- **Security-monitoring component**, responsible for recording authentication events, access attempts, suspicious activity, and policy violations

The Kubernetes environment will be configured with multiple pods and service replicas to reflect the distributed nature of cloud-native applications. Each service will expose health endpoints and performance indicators so that the framework can observe changes in response time, error rate, resource consumption, request volume, and service availability. The environment will also include deployment configurations, service accounts, role-based access controls, resource limits, network policies, and autoscaling rules to represent realistic operational conditions.

A monitoring stack will be used to collect time-series metrics from services, containers, nodes, and infrastructure resources. Relevant telemetry will include CPU utilisation, memory usage, response latency, throughput, network traffic, packet loss, request failure rates, disk usage, queue length, pod status, restart counts, and node health. These metrics provide quantitative evidence of workload behaviour and potential resource-related failures.

A centralised logging infrastructure will collect application logs, container logs, system logs, audit logs, Kubernetes event logs, and security logs. Application logs will capture exceptions, failed requests, transaction errors, database connectivity issues, and internal service failures. Kubernetes events will capture deployment errors, pod restarts, image-pull failures, node conditions, scheduling errors, failed health checks, and autoscaling activities. Audit and security logs will record login attempts, changes to access permissions, suspicious requests, and unauthorised access events.

Distributed tracing will also be included to track requests as they move across the API gateway, microservices, databases, message queues, and external dependencies. Trace data will be used to identify service dependencies, transaction delays, failed service calls, repeated retries, and abnormal request pathways. Distributed tracing is especially important in microservice ecosystems because the component showing an error may not be the component that caused the incident (Mace et al., 2015; Li et al., 2022).

The collected telemetry will be stored in an integrated observability repository. Before analysis, the data will be cleaned, timestamp-aligned, normalised, labelled where possible, and linked to relevant services, pods, nodes, namespaces, deployment versions, and infrastructure resources. This process will allow the AI-enabled framework to analyse multiple telemetry sources together rather than treating metrics, logs, traces, and Kubernetes events as unrelated data streams.

Incident Scenario Development

The framework will be tested using controlled fault-injection and cyber-incident scenarios. Controlled scenarios are necessary because they provide known incident conditions, expected root causes, and measurable recovery outcomes. They also allow the researcher to compare how different monitoring and response approaches perform under the same conditions.

The incident scenarios are designed to represent common operational and cybersecurity disruptions in cloud-native environments. Each scenario will be injected into the Kubernetes testbed while telemetry is collected from the monitoring, logging, tracing, and security systems. The framework will then be assessed according to its ability to detect the incident, classify its severity, identify the probable root cause, recommend or execute an appropriate response, and validate recovery.

The first scenario involves pod failure or repeated container crashes. A service pod may be terminated unexpectedly or forced into repeated restart cycles. This scenario represents failures caused by application exceptions, missing dependencies, incorrect container images, insufficient resources, or failed health checks. The expected response may include restarting the pod, rescheduling the workload, inspecting container logs, or escalating the incident if repeated restarts continue.

The second scenario involves **CPU or memory exhaustion**. Resource-intensive workloads will be introduced to cause elevated CPU usage, increasing memory consumption, slow response times, reduced throughput, and possible service instability. This scenario tests whether the framework can distinguish between temporary workload pressure and sustained resource exhaustion. Expected remediation actions may include horizontal pod scaling, resource-limit adjustment, workload redistribution, or restarting affected services after investigation.

The third scenario involves network latency or packet loss. Artificial delays, dropped packets, or restricted network communication will be introduced between services. This scenario represents common distributed-system problems

that can affect API calls, database connections, service-mesh communication, and transaction completion. The framework will be expected to identify the affected communication path, correlate elevated latency with trace evidence, and recommend actions such as traffic rerouting, service retry management, or network-policy review.

The fourth scenario involves service dependency failure. A supporting service, such as an authentication service, message broker, cache, or external API, will be made unavailable or degraded. This scenario examines whether the framework can recognise that failures in downstream services are secondary effects rather than independent incidents. The expected response may include activating fallback mechanisms, restarting the failed dependency, rerouting traffic, or escalating to an incident manager where the dependency is business critical.

The fifth scenario involves database connection failure. Database access may be interrupted through connection-pool exhaustion, misconfigured credentials, unavailable database nodes, or artificially delayed queries. The resulting symptoms may include application errors, transaction failures, increased latency, and repeated retries. The framework will be expected to identify the database layer as a probable root cause rather than incorrectly attributing the incident to the customer-facing microservice.

The sixth scenario involves a misconfigured deployment. A new application version may be deployed with an incorrect environment variable, unavailable endpoint, faulty service configuration, incompatible container image, insufficient permission, or incorrect network policy. This scenario reflects the operational risk associated with continuous deployment in cloud-native environments. The expected response may include deployment rollback, configuration correction, traffic rerouting to a stable version, or temporary service isolation.

The seventh scenario involves a denial-of-service traffic surge. A large volume of simulated requests will be directed toward a public-facing API or service to create high throughput, increased latency, resource pressure, and elevated error rates. The framework will be expected to distinguish between legitimate traffic growth and suspicious overload behaviour. Potential responses may include autoscaling, rate limiting, traffic filtering, request throttling, or escalation to cybersecurity teams.

The eighth scenario involves a suspicious authentication attempt. Repeated failed login attempts, abnormal access locations, credential-stuffing patterns, or excessive token-validation failures will be generated against the authentication service. The scenario tests whether the framework can combine security logs, access events, and service telemetry to identify a possible security incident. Expected responses may include alert escalation, temporary access restriction, rate limiting, token invalidation, or mandatory human review.

The ninth scenario involves an unauthorised access event. The experiment may simulate attempts to access restricted APIs, modify Kubernetes resources without sufficient permission, access confidential data, or use expired or unauthorised credentials. The framework should detect the event through audit and security logs, identify the affected resources, estimate the risk level, and recommend security controls such as access revocation, workload isolation, or escalation to an authorised security analyst.

The final scenario involves a vulnerability exploit simulation. A controlled and non-destructive exploit pattern may be introduced against a deliberately vulnerable test service. The aim is not to conduct harmful activity, but to observe how the framework identifies suspicious service behaviour, abnormal network activity, unusual process events, or unauthorised resource access. Because this scenario involves elevated security risk, the framework should classify it as a high-risk incident and require mandatory human approval before any disruptive remediation action is taken.

Together, these scenarios provide a broad evaluation set that includes application failures, infrastructure failures, configuration problems, dependency disruptions, performance degradation, network issues, and cybersecurity events. Fault injection is valuable in this context because it enables resilience mechanisms to be tested under controlled adverse conditions rather than assumed to work during real incidents (Basiri et al., 2016).

Data Collection and Processing

The proposed framework requires the collection of multiple forms of cloud-native operational and cybersecurity telemetry. Because incidents in distributed environments rarely appear in only one data source, the study will collect logs, traces, metrics, Kubernetes events, alert histories, and security events from the experimental testbed. These data sources will provide the evidence needed for anomaly detection, incident classification, root-cause analysis, response selection, and recovery validation.

The first data source consists of system and application logs. These logs will include application exceptions, failed API calls, database errors, timeout messages, container logs, deployment logs, authentication records, and infrastructure messages. Log data is particularly useful because it captures detailed descriptions of abnormal behaviour and failure conditions. However, logs are usually unstructured or semi-structured, highly repetitive, and generated in large volumes. Therefore, they require preprocessing before they can be used effectively by machine-learning models.

The second data source consists of operational metrics

collected from the Kubernetes cluster, microservices, infrastructure nodes, and network environment. Relevant metrics will include CPU utilisation, memory consumption, latency, response time, error rate, throughput, disk usage, network traffic, packet loss, request count, pod restart frequency, queue length, and node status. These metrics provide time-series evidence of workload behaviour and are especially important for detecting resource exhaustion, performance degradation, traffic anomalies, and service instability.

The third data source consists of distributed trace. Trace records will capture the path of user requests as they move through the API gateway, application services, databases, message queues, and external dependencies. Each trace will include information such as service names, request duration, transaction status, failed calls, retries, parent-child service relationships, and timestamps. Trace data is useful for identifying where a request failed or slowed down and for understanding the relationship between affected services.

The fourth data source includes Kubernetes events and cluster records. These may include failed deployments, image-pull errors, pod evictions, container restarts, unschedulable workloads, failed liveness or readiness checks, node failures, autoscaling events, resource-limit violations, and service-account errors. Kubernetes events provide important context because they connect application-level symptoms with orchestration and infrastructure conditions.

The fifth data source includes alert histories and incident records. These records will capture alert timestamps, alert severity, affected services, triggered monitoring rules, escalation status, and response outcomes. Historical alert information will support event correlation and help identify whether multiple alerts relate to the same underlying incident.

The final data source consists of security events. These will include failed authentication attempts, unusual login behaviour, unauthorised access attempts, suspicious API requests, access-control violations, abnormal privilege changes, network-policy violations, and simulated exploit indicators. Security events are necessary because the proposed framework is intended to address both operational failures and cyber-related disruptions.

Before analysis, the collected data will undergo a structured preprocessing process. The first step will involve data cleaning. Duplicate events, incomplete records, corrupted entries, irrelevant messages, and inconsistent fields will be removed or corrected. For example, duplicate monitoring alerts generated from the same event may be merged, while incomplete log records may be flagged for exclusion or further review.

The next step will involve normalisation. Metrics collected from different services may use different scales and units. CPU usage may be recorded as a percentage, memory usage in megabytes, latency in milliseconds, and throughput in requests per second. Normalisation will convert these values into comparable ranges to support machine-learning analysis. Standardisation techniques may also be used to ensure that variables with larger numerical values do not dominate the model.

Timestamp alignment will be applied to connect related events across different telemetry sources. Logs, metrics, traces, Kubernetes events, and security records may be generated by separate tools with different timestamps or collection intervals. The study will align these records within a common time window so that events associated with the same incident can be examined together. For example, an increase in CPU usage, a pod restart, elevated latency, and database errors occurring within the same time period may be linked as part of one incident sequence.

The study will also perform feature extraction. From metrics, features may include average CPU use, maximum memory consumption, error-rate changes, latency variation, request volume, and pod restart counts. From logs, useful features may include error keywords, exception categories, message frequency, unusual log sequences, and semantic patterns. From traces, features may include request duration, number of failed service calls, retry counts, dependency paths, and bottleneck locations. From Kubernetes events, features may include deployment status, pod lifecycle transitions, node condition changes, and autoscaling activity.

Where possible, incidents will be assigned labels to support supervised learning. Event labelling will classify examples into known categories such as pod failure, CPU exhaustion, memory leak, database connection failure, network latency, deployment misconfiguration, service dependency failure, traffic surge, suspicious authentication activity, unauthorised access, and vulnerability exploit simulation. Labels will be based on the controlled scenario introduced into the testbed and validated using the recorded telemetry evidence.

Class balancing will be applied where incident categories are unevenly distributed. In practical systems, normal operational records may greatly outnumber failure events, while some high-risk incidents may occur only rarely. This imbalance can affect model performance by causing the classifier to favour common classes. The study may use methods such as controlled sampling, oversampling of minority incident types, undersampling of dominant normal records, or class-weight adjustment during model training.

For supervised learning tasks, the prepared dataset will be divided into training, validation, and test sets. The training dataset will be used to build the incident-classification model. The validation dataset will be used to tune model parameters, select thresholds, and reduce the risk of overfitting. The test dataset will be reserved

for final performance evaluation and will not be used during model development. A possible split may be 70% for training, 15% for validation, and 15% for testing, although the final allocation may be adjusted according to the size and diversity of the collected incident data.

For unsupervised anomaly detection, normal operational telemetry will be used to establish baseline behaviour. The model will learn expected patterns across metrics, traces, and event sequences. Incident scenarios will then be introduced to determine whether the model can identify deviations from this baseline. This approach is important because some future incidents may not match any previously labelled category.

AI and Analytical Techniques

The proposed framework uses a combination of artificial intelligence and analytical techniques to detect, classify, diagnose, and respond to cloud-native incidents. Since some incidents are known and repeatable while others are rare or previously unseen, the framework combines unsupervised anomaly detection, supervised incident classification, graph-based root-cause analysis, natural language processing, and rule-guided response selection.

Unsupervised anomaly detection is used to identify abnormal behaviour that may not appear in labelled incident data. The model analyses multivariate telemetry such as CPU usage, memory consumption, latency, error rates, throughput, packet loss, disk activity, pod restarts, and service availability. It learns normal operational patterns and flags unusual deviations. This is useful for detecting unknown failures, unusual workload behaviour, and emerging threats that may not trigger conventional threshold-based alerts.

Supervised incident classification is applied to known incident types using labelled data from the controlled testbed scenarios. The classifier distinguishes incidents such as pod crashes, CPU or memory exhaustion, database connection failure, network latency, deployment misconfiguration, denial-of-service traffic surge, suspicious authentication attempts, and unauthorised access events. It produces an incident category, severity level, and confidence score. The confidence score supports response decisions by helping the framework determine whether to automate a low-risk action, request approval, or escalate the incident for manual investigation.

Graph-based root-cause analysis is used to identify service dependencies and trace the likely source of an incident across distributed microservices. The cloud-native environment is represented as a dependency graph, where nodes represent services, pods, databases, APIs, nodes, and external dependencies, while edges represent communication and dependency relationships. When an incident occurs, the framework analyses service topology, trace paths, alert patterns, metric changes, and log evidence to separate root causes from secondary symptoms. The output includes the probable root cause, affected services, confidence level, and supporting evidence.

Natural language processing is used to interpret logs, alerts, and error messages. Since logs often contain unstructured technical information, NLP helps extract error categories, exception types, service names, configuration references, security indicators, and recurring message patterns. Log messages such as "connection timeout," "authentication failed," "permission denied," or "out of memory" can help identify database, access-control, or resource-related incidents. NLP also improves explainability by showing the key log evidence that contributed to the diagnosis.

For response selection, the framework uses rule-guided logic and, where appropriate, reinforcement-learning principles. Rule-guided logic is applied to well-understood and low-risk actions, such as restarting unhealthy pods, scaling workloads, or rescheduling failed services. Reinforcement-learning principles may support decision improvement by learning from previous recovery outcomes, such as whether scaling, rerouting, rollback, or restart actions produced the best result. However, response automation remains controlled by policy constraints, confidence thresholds, and human approval. High-risk actions, including credential revocation, node isolation, service shutdown, and access-policy changes, remain subject to mandatory human oversight.

Evaluation Metrics

The performance of the proposed framework will be evaluated using detection, diagnosis, response, recovery, and resilience metrics. These measures will allow comparison between conventional threshold-based monitoring, rule-based automation, and the proposed AI-enabled framework.

Accuracy

Accuracy measures the proportion of all correctly classified observations out of the total number of observations. In this study, it will indicate how often the framework correctly distinguishes between normal and abnormal conditions or correctly assigns incidents to their intended categories.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- **TP** = True Positives
- **TN** = True Negatives
- **FP** = False Positives
- **FN** = False Negatives

Precision

Precision measures the proportion of detected incidents that are genuinely correct. High precision is important because it reduces the number of false alerts that may contribute to alert fatigue.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall

Recall measures the proportion of actual incidents that are successfully detected by the framework. High recall is important because missing a critical incident may result in prolonged downtime, undetected security exposure, or service degradation.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score

The F1-score provides a balanced measure of precision and recall. It is especially useful where incident classes are unevenly distributed.

$$\text{F1-Score} = 2 \text{ x } \frac{Precision \ x Recall}{Precion \ x Recall}$$

False-Positive Rate

The false-positive rate measures how often the framework incorrectly identifies normal behaviour as an incident. A lower false-positive rate indicates that the system is less likely to generate unnecessary alerts or trigger inappropriate responses.

$$False\text{-}Positive\ Rate = \frac{FP}{FP + TN}$$

Root-Cause Localisation Accuracy

Root-cause localisation accuracy measures how often the framework correctly identifies the component, service, configuration, database, node, network path, or dependency responsible for an incident.

$$Root\text{-}Cause\ Localisation\ Accuracy = \frac{Correctly\ Identified\ Root\ Causes}{Total\ Case\ Incidents}\ x\ 100$$

This metric is particularly important because a framework may detect an incident correctly but still recommend an ineffective remediation action if it identifies the wrong source of failure.

Mean Time to Detect

Mean Time to Detect measures the average duration between the occurrence of an incident and its detection by the monitoring or AI system.

$$MTTD = \frac{\sum Detection\ Time}{Number\ of\ \ Incidents}$$

A lower Mean Time to Detect indicates that the framework can identify harmful conditions more quickly.

Mean Time to Respond

Mean Time to Respond measures the average time between incident detection and the initiation of a response action.

$$MTTR_{Response} = \frac{\sum Response\ Initiation\ Time}{Number\ of\ \ Incidents}$$

This metric reflects the efficiency of alert correlation, diagnosis, decision-making, and approval workflows.

Mean Time to Recover

Mean Time to Recover measures the average time required to restore the affected service or workload to an acceptable operational state after an incident occurs.

$$MTTR_{Recovery} = \frac{\sum Recovery\ Duration}{Number\ of\ \ Incidents}$$

Recovery will be considered successful when key operational indicators, such as latency, error rate, throughput, availability, pod health, and workload stability, return to acceptable thresholds.

Recovery Success Rate

Recovery success rate measures the percentage of remediation actions that successfully restore normal service operation without causing significant secondary effects.

$$Recovery\ Success\ Rate = \frac{Successful\ Recovery\ Actions}{Total\ Recovery\ Actions}\ x\ 100$$

This measure is important for evaluating whether the selected automated or semi-automated actions are safe and effective.

Service Availability

Service availability measures the proportion of time that an application or service remains operational and accessible to users.

$$Service\ Availability = \frac{Total\ Operational\ Time}{Total\ Scheduled\ Time}\ x\ 100$$

High availability indicates that the framework supports operational continuity and limits the impact of incidents on end users.

Together, these metrics will provide a comprehensive evaluation of the proposed framework. They will show not only whether the framework detects incidents

Table 3: Cloud-Native Incident Scenarios for Experimental Evaluation

Incident ID	*Incident Type*	*Affected Component*	*Expected System Impact*	*Expected Response*
I1	Pod crash	Kubernetes workload	Service interruption	Restart or reschedule pod
I2	CPU exhaustion	Application container	High latency and failures	Scale workload or limit resources
I3	Memory leak	Microservice instance	Repeated restarts	Restart pod and analyse memory usage
I4	Network latency	Service communication path	Slow transaction completion	Reroute traffic or investigate network path
I5	Database failure	Data service	Transaction errors	Failover or reconnect service
I6	Deployment misconfiguration	Application deployment	Service instability	Roll back deployment
I7	Suspicious access event	API gateway or identity service	Cybersecurity risk	Restrict access and notify analyst
I8	Traffic surge	Public-facing application	Availability degradation	Autoscale or activate traffic controls

Table 4: Evaluation Metrics for the Proposed Framework

Metric	*Description*	*Relevance*
Precision	Proportion of detected incidents that are genuine	Reduces false alerts
Recall	Proportion of actual incidents detected	Measures detection coverage
F1-score	Balance between precision and recall	Overall detection performance
Root-cause accuracy	Correct identification of incident origin	Measures diagnostic reliability
Mean Time to Detect	Average time from incident occurrence to detection	Measures monitoring efficiency
Mean Time to Respond	Average time from detection to response action	Measures response effectiveness
Mean Time to Recover	Average time to restore normal operation	Measures resilience
Recovery success rate	Percentage of successful remediation actions	Measures automation reliability
Service availability	Percentage of time service remains operational	Measures business continuity

accurately, but also whether it identifies root causes correctly, initiates suitable responses quickly, restores services effectively, and supports higher levels of cloud-native cyber resilience.

Results and Analysis

Incident Detection Performance

This section evaluates the incident-detection performance of three approaches: conventional threshold-based monitoring, rule-based automation, and the proposed AI-based autonomous cyber resilience framework. The comparison focuses on five indicators: Accuracy, Precision, Recall, F1-score, and False-Positive Rate. These metrics were selected because they assess not only the ability to identify incidents correctly, but also the ability to minimise unnecessary alerts and avoid missed operational or cybersecurity events.

Conventional threshold-based monitoring was used as the baseline approach. This method generated alerts when predefined limits for CPU utilisation, memory consumption, latency, error rate, packet loss, pod restart frequency, or other operational indicators were exceeded. Rule-based automation extended this baseline by correlating selected alert conditions with predefined response rules. The proposed AI framework combined multivariate anomaly detection, supervised incident classification, alert correlation, severity scoring, and telemetry-based contextual analysis.

Table 5 presents the comparative incident-detection performance of the three approaches.

The results show that the proposed AI-based framework achieved the strongest detection performance across all major indicators. It recorded the highest Accuracy, Precision, Recall, and F1-score, indicating that it was better able to identify genuine incidents and detect a larger proportion of actual failures. Its low False-Positive Rate also suggests that the framework reduced unnecessary alerts more effectively than conventional monitoring and rule-based automation.

Conventional threshold-based monitoring produced the weakest results because it relied mainly on static

Table 5: Incident Detection Performance Comparison

Approach	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*	*False-Positive Rate (%)*
Conventional threshold-based monitoring	72.3	68.1	66.5	67.3	24.7
Rule-based automation	83.6	81.2	80.3	80.7	12.6
Proposed AI-based framework	93.4	91.6	92.1	91.8	4.3

alert limits and isolated metrics. Rule-based automation improved performance by applying predefined conditions and response rules, but it remained less effective for complex or multi-service incidents. Overall, the proposed AI-based framework provided a more accurate and context-aware incident-detection capability by analysing logs, metrics, traces, Kubernetes events, alert histories, and security signals together.

Root-Cause Analysis Performance

The root-cause analysis evaluation examined the ability of the proposed AI-based framework to distinguish visible service symptoms from the actual source of an incident. This capability is particularly important in cloud-native environments because microservices, containers, APIs, databases, and infrastructure resources are tightly interconnected. A failure observed in one service may be caused by an upstream dependency, an overloaded database, a network problem, a configuration error, or a cybersecurity event occurring elsewhere in the environment.

Unlike conventional monitoring approaches, which often report the component where an error becomes visible, the proposed framework combines service dependency graphs, distributed traces, telemetry correlation, Kubernetes events, log evidence, and contextual analysis. This enables the framework to identify probable root causes rather than only reporting secondary service failures. The evaluation considered five main incident categories: application failures, infrastructure and resource failures, network-related incidents, deployment and configuration errors, and cybersecurity events.

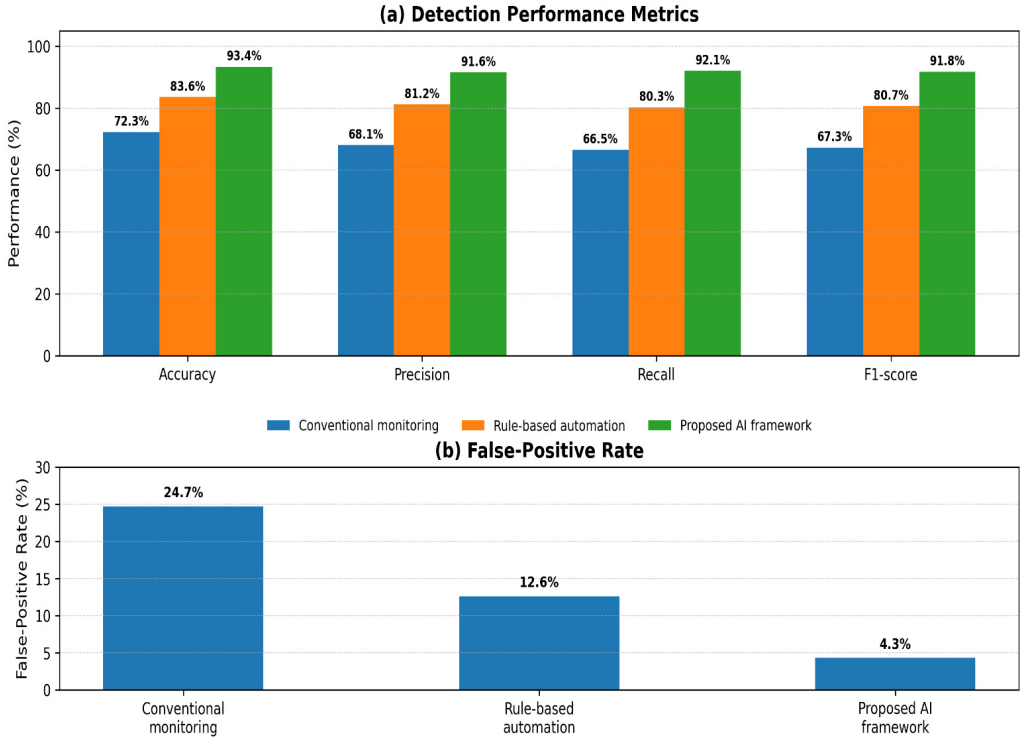

Figure 2: Incident Detection Performance of Conventional Monitoring, Rule-Based Automation, and the Proposed AI Framework

Table 6: Root-Cause Localisation Performance Across Incident Categories

Incident Category	*Number of Test Cases*	*Correctly Localised Cases*	*Root-Cause Accuracy (%)*	*Incident Category*
Application failure	20	18	90.0	Application failure
Resource exhaustion	20	17	85.0	Resource exhaustion
Network anomaly	15	13	86.7	Network anomaly
Configuration error	15	13	86.7	Configuration error
Security event	20	16	80.0	Security event
Overall	90	77	85.6	Overall

The results show that the proposed AI-based framework achieved an overall root-cause localisation accuracy of 85.6% across 90 controlled incident cases. The highest accuracy was recorded for application failures, where telemetry patterns were clearer and easier to trace. Security events recorded the lowest accuracy because suspicious access behaviour and exploit indicators often overlapped with normal authentication and network activities. Overall, the findings suggest that combining logs, metrics, traces, Kubernetes events, and dependency graphs improves the framework's ability to identify the likely source of incidents across distributed cloud-native services.

The results indicate that the proposed AI-based framework reduced detection, response, and recovery time compared with the two baseline approaches. The improvement was mainly due to AI-based alert prioritisation, root-cause localisation, and automated execution of low-risk remediation actions such as pod restart, workload scaling, and cache clearing.

Human approval was still required for medium- and high-risk actions, including deployment rollback, service isolation, credential revocation, and production node isolation. This ensured that automation improved response speed without removing operational oversight from decisions that could affect service availability or security. Overall, the proposed framework demonstrated faster recovery, higher recovery success, and stronger support for autonomous cyber resilience in cloud-native environments.

Incident Distribution

The incident-distribution analysis presents the relative frequency of operational and cybersecurity incidents introduced into the Kubernetes-based microservices testbed. This analysis is important because cloud-native environments are exposed to different forms of disruption, including application errors, infrastructure instability, network degradation, configuration failures, dependency problems, and security-related events. A balanced incident dataset enables the proposed framework to be evaluated across a broad range of realistic conditions rather than being tested only on common resource or application failures.

The evaluation dataset was organised into six major incident categories: application failures, infrastructure and resource failures, network anomalies, deployment and configuration errors, service dependency and database failures, and cybersecurity incidents. Each category contained controlled scenarios designed to represent common cloud-native operational risks. The scenarios were generated through fault injection, workload manipulation, configuration changes, simulated access violations, and controlled service disruptions.

Application and infrastructure-related incidents are expected to account for a substantial proportion of the evaluation cases because pod instability, application exceptions, resource exhaustion, and service failures are common causes of cloud-native disruption. These incidents are useful for assessing whether the framework can recognise abnormal workload behaviour and distinguish local failures from faults that affect dependent services.

Network anomalies are included because latency, packet loss, connection instability, and network-policy restrictions can affect multiple microservices at the same

Table 7: Response and Recovery Time Comparison

Approach	*Mean Time to Detect (min)*	*Mean Time to Respond (min)*	*Mean Time to Recover (min)*	*Recovery Success Rate (%)*
Conventional threshold-based monitoring	6.8	11.4	29.6	72.2
Rule-based automation	3.9	5.2	18.4	81.1
Proposed AI-based framework	1.7	2.1	9.8	91.1

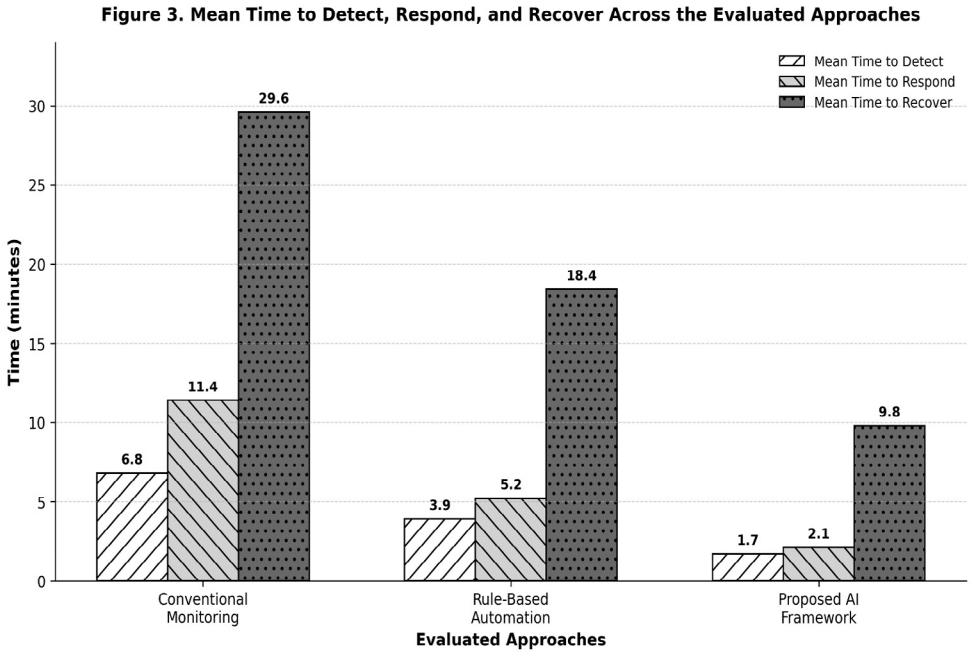

Figure 3: Mean Time to Detect, Respond, and Recover Across the Evaluated Approaches

time. These incidents test the framework's ability to use distributed traces and service-dependency information to determine whether the problem originates from a shared communication path rather than from the individual services displaying errors.

Deployment and configuration incidents are also important because cloud-native systems are frequently updated through continuous integration and continuous deployment processes. An incorrect configuration, unavailable secret, invalid endpoint, incompatible container image, or insufficient permission can quickly affect application availability. Including these cases allows the framework to evaluate the relationship between deployment history, Kubernetes events, service health, and incident occurrence.

Cybersecurity incidents are represented by suspicious authentication patterns, unauthorised access attempts, abnormal traffic behaviour, and simulated exploit indicators. Although these incidents may occur less frequently than routine operational failures, they are important because they often require more cautious response decisions. The framework must determine whether the event represents a genuine security threat, assess its potential impact, and ensure that high-risk remediation actions remain subject to human approval.

The distribution of incident categories supports a comprehensive assessment of the proposed AI-based framework. It ensures that detection, root-cause analysis, response selection, and recovery validation are evaluated across routine operational failures as well as higher-risk cybersecurity events. This broad incident coverage strengthens the relevance of the experimental evaluation and supports the proposed framework's objective of improving autonomous cyber resilience in cloud-native environments.

Contribution to Autonomous Cyber Resilience

The proposed framework contributes to autonomous cyber resilience by supporting early detection, adaptive response, verified recovery, and continuous learning in cloud-native environments. In this study, resilience goes beyond incident prevention. It includes the ability to detect disruptions, reduce their impact, restore affected services, confirm recovery, and improve future response. The framework improves proactive detection by analysing metrics, logs, traces, Kubernetes events, and security signals together. This enables the early identification of abnormal patterns such as rising latency, repeated retries, increasing error rates, resource exhaustion, pod instability, or suspicious authentication activity. By detecting these signals early, the framework reduces the risk of cascading failure across connected microservices.

Its adaptive value comes from combining supervised learning, unsupervised anomaly detection, graph-based analysis, and distributed traces. Supervised learning helps recognise known incident types, while unsupervised detection identifies unusual or previously unseen behaviours. Dependency graphs and traces support root-cause analysis by linking symptoms to affected services, containers, databases, nodes, or network paths.

Table 8: Distribution of Incident Categories in the Evaluation Dataset

Incident Category	*Illustrative Incident Examples*	*Number of Cases*	*Relative Frequency (%)*
Application failures	Pod crash, container restart loop, application exception, failed API request	24	20.0
Infrastructure and resource failures	CPU exhaustion, memory leak, node failure, storage limitation	24	20.0
Network anomalies	Packet loss, elevated latency, routing disruption, network-policy restriction	18	15.0
Deployment and configuration errors	Incorrect environment variable, invalid image, failed deployment, access-permission error	18	15.0
Service dependency and database failures	Database connection failure, unavailable message queue, failed external API dependency	18	15.0
Cybersecurity incidents	Suspicious authentication attempt, unauthorised access, abnormal traffic, exploit indicator	18	15.0
Total	—	120	100.0

A key contribution is recovery validation. The framework does not assume that an incident is resolved simply because a response action has been executed. It checks post-response telemetry such as latency, error rate, throughput, pod health, transaction success rate, workload stability, and service availability. This ensures that recovery is based on actual service restoration.

Continuous learning further strengthens resilience. Each incident record stores the incident type, affected components, telemetry evidence, root-cause result, selected response, approval status, recovery outcome, and lessons learned. These records can improve anomaly baselines, classification models, response rules, and service-dependency maps. They can also reveal repeated weaknesses in deployment, configuration, access control, monitoring, and service design.

Governance, Explainability, and Human Oversight

Autonomous incident management can reduce response time, but not all remediation actions should be fully automated. Cloud-native systems often support critical services, customer transactions, sensitive data, and production infrastructure. An incorrect automated action

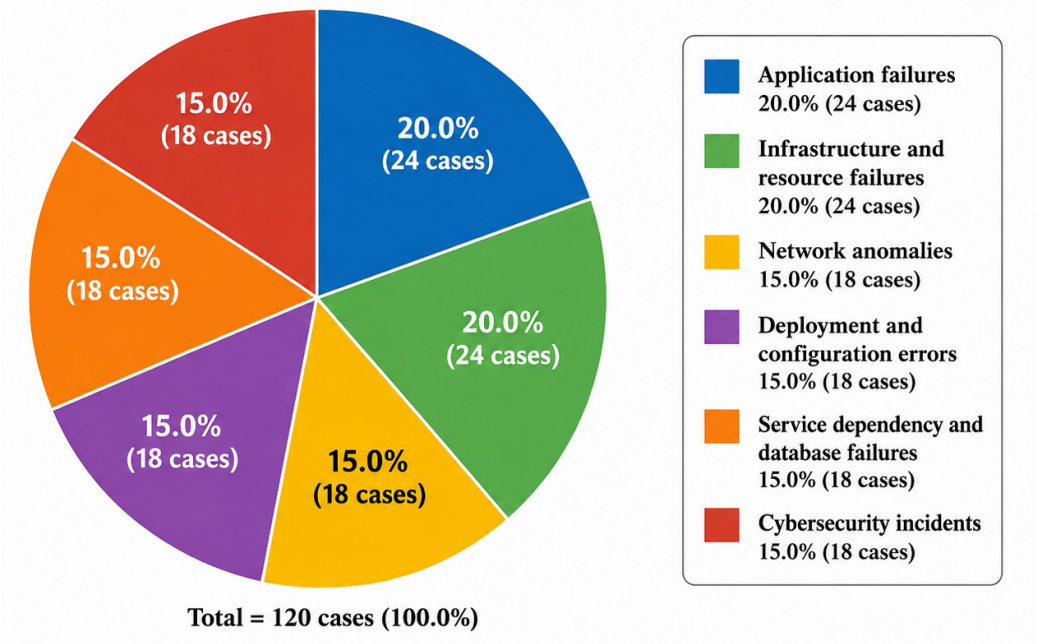

Figure 4: Distribution of Cloud-Native Incident Categories in the Evaluation Dataset

may disrupt operations, increase cyber risk, or affect compliance.

The proposed framework uses a risk-aware governance model. Low-risk actions, such as restarting unhealthy pods, scaling replicas, rescheduling workloads, or clearing temporary caches, may be automated when confidence is high. Medium-risk actions, such as deployment rollback, traffic rerouting, service isolation, or temporary access restriction, should require policy checks and may require operational approval. High-risk actions, including credential revocation, node isolation, disabling production services, or blocking critical network routes, should require mandatory human approval.

Confidence thresholds determine the level of autonomy. If evidence is incomplete, uncertain, or linked to unfamiliar incident patterns, the framework should escalate the case for human review. If confidence is high and the action is low risk, automated execution may be allowed, provided that the action is logged and recovery is validated.

Explainability supports trust. The framework should show why an incident was detected, why a root cause was selected, and why a response action was recommended. Evidence may include abnormal metrics, log messages, trace paths, dependency relationships, event sequences, confidence scores, and similar past incidents. Audit logs should also record the incident identifier, selected action, approval status, execution time, recovery outcome, and side effects.

Practical Implications

The framework is useful for cloud engineers, DevOps teams, cybersecurity analysts, site reliability engineers, and enterprise leaders. For cloud engineers, it supports Kubernetes workload monitoring, service-dependency analysis, resource management, and configuration stability. For DevOps teams, it strengthens post-deployment monitoring and supports evidence-based rollback decisions. For cybersecurity analysts, it connects security alerts with operational telemetry to distinguish routine failures from possible security incidents.

For site reliability engineers, the framework can reduce alert fatigue, group related alerts, identify probable root causes, and recommend response actions based on severity, confidence, and risk. For enterprise leaders, it provides measurable resilience indicators, including Mean Time to Detect, Mean Time to Respond, Mean Time to Recover, service availability, recovery success rate, and incident recurrence.

The framework can be implemented gradually with existing tools. Kubernetes can support remediation actions such as restart, scaling, rollback, and rescheduling. Observability platforms can supply metrics, logs, traces, and service maps. SIEM tools can provide security alerts and audit records. CI/CD tools can provide deployment history, while incident-management systems can support escalation, approval, and documentation. This allows organisations to begin with AI-assisted recommendations before adopting controlled automation for low-risk incidents.

Limitations

This study has several limitations. First, the framework is evaluated in a controlled Kubernetes-based testbed. Although the environment reflects common cloud-native conditions, it may not fully represent the scale, diversity, and organisational complexity of large enterprise systems operating across multiple clouds, regions, services, and regulatory contexts.

Second, the framework depends on the quality and representativeness of available data. The experimental dataset includes controlled operational and cybersecurity scenarios, but it may not cover every rare failure, emerging attack method, zero-day vulnerability, unusual workload pattern, or complex multi-stage incident. Models trained on limited scenarios may perform less effectively when exposed to unfamiliar conditions.

Third, AI models can still produce false positives, false negatives, incorrect classifications, or inaccurate root-cause recommendations. A false positive may create unnecessary investigation, while a false negative may allow a genuine incident to continue. Incorrect diagnosis may lead to a response that treats symptoms without resolving the real cause. These risks justify the use of confidence thresholds, explainability, policy controls, recovery validation, and human approval for medium- and high-risk actions.

Fourth, the framework assumes reliable telemetry. In practice, some organisations may have incomplete logs, missing traces, inconsistent timestamps, weak audit records, or limited service-dependency visibility. Poor observability can reduce the quality of anomaly detection, root-cause analysis, and response selection.

Finally, implementation requires operational maturity. Organisations need clear incident policies, service ownership, access controls, approved runbooks, escalation procedures, and governance mechanisms. Without these foundations, automation may increase confusion rather than resilience. Therefore, the framework should be introduced gradually, beginning with observability improvement and AI-assisted decision support before expanding to automated remediation.

Conclusion

Cloud-native computing environments require more intelligent and adaptive approaches to incident management because modern applications depend on distributed microservices, containers, Kubernetes clusters, APIs, databases, and dynamic workloads.

Although these technologies improve scalability, flexibility, and deployment speed, they also increase operational complexity. A failure in one service can quickly affect connected services and reduce overall application availability.

This study proposed the Intelligent Autonomous Cyber Resilience Framework to improve incident detection, response, recovery, and continuous learning in cloud-native environments. The framework integrates cloud observability, AI-based anomaly detection, incident classification, alert correlation, service-dependency analysis, root-cause identification, risk-aware response selection, recovery validation, and continuous learning. By analysing metrics, logs, traces, Kubernetes events, deployment records, alert histories, and security events together, the framework provides a broader and more reliable view of incidents than isolated monitoring tools.

A key contribution of the framework is its ability to distinguish visible symptoms from probable root causes. In microservice systems, an incident observed in one service may originate from another dependency, such as a database, API gateway, network path, authentication service, Kubernetes node, or configuration setting. The framework addresses this challenge through dependency graphs, trace analysis, telemetry correlation, and explainable outputs that support operational decision-making.

The framework also supports safer movement toward autonomous cyber resilience. Low-risk remediation actions, such as restarting unhealthy pods, scaling workloads, or clearing temporary caches, can be automated when confidence is high. Higher-risk actions, including rollback, traffic rerouting, workload isolation, credential revocation, or production service shutdown, remain subject to policy controls and human approval. This ensures that automation improves response speed without removing accountability.

Recovery validation further strengthens the framework by confirming whether remediation has restored normal service operation. The system evaluates post-response latency, error rates, throughput, pod health, workload stability, and service availability. It also records incident evidence, response decisions, recovery outcomes, and lessons learned to improve future detection and response. Overall, the study concludes that AI can improve cloud-native incident management by reducing alert fatigue, improving root-cause analysis, accelerating recovery, and supporting safer automated remediation. However, AI should support rather than replace cloud engineers, DevOps teams, site reliability engineers, and cybersecurity analysts.

Future Research

Future research should evaluate the framework using large-scale enterprise datasets from real cloud-native environments. While controlled testbeds support structured evaluation, real systems may involve thousands of services, multi-region deployments, hybrid infrastructure, changing workloads, and more complex security requirements.

Further studies should also examine the framework in multi-cloud and hybrid-cloud environments, where incidents may span public clouds, private infrastructure, edge systems, and on-premises data centres. Federated learning is another promising direction because it may allow incident models to learn from distributed telemetry without exposing sensitive logs, traces, or security records.

Future work may also explore reinforcement learning for adaptive remediation selection, especially for determining when to scale workloads, roll back deployments, reroute traffic, or isolate services. However, such methods should first be tested in simulations or isolated environments to avoid operational risk.

Explainability and trust should receive further attention. Future studies should examine which explanations are most useful for engineers and cybersecurity analysts, including abnormal telemetry patterns, ranked dependencies, trace paths, key log messages, confidence scores, and expected response impact. The security of AI-based incident-management systems should also be studied, particularly against adversarial telemetry manipulation, poisoned training data, misleading logs, concept drift, and attempts to influence automated remediation decisions.

Finally, future research should investigate cost-benefit outcomes and organisational adoption. AI-enabled incident management may reduce downtime and manual effort, but organisations must consider the cost of telemetry storage, model development, integration, governance, and maintenance. Wider adoption will depend not only on technical performance but also on whether teams trust the system, understand its recommendations, and accept its role in operational decision-making.

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