International Journal of AI, Big Data, Computational and Management Studies
Noble Scholar Research Group | Volume 7, Issue 1, 323-330, 2026
ISSN: 3050-9416 | https://doi.org/10.63282/3050-9416.IJAIBDCMS-V7I1P147

Original Article

Agentic AIOps for Cloud-Native Enterprise Systems: A Governance-Centered Framework for Software Reliability, Security, and Deployment Optimization

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Received On: 06/02/2026 ***Revised On: 07/03/2026*** ***Accepted On: 15/03/2026*** ***Published On: 26/03/2026***

Abstract: *Cloud-native enterprise systems increasingly operate through distributed microservices, event-driven data flows, container orchestration, software supply chains, and multi-layer observability pipelines. Although these architectures improve modularity and deployment flexibility, they also introduce operational complexity, hidden failure propagation, security exposure, and fragmented governance across software development, deployment, and runtime operations. Recent advances in artificial intelligence, large language models, and autonomous software agents create an opportunity to move beyond conventional monitoring dashboards and rule-based automation toward agentic AIOps systems that can reason over telemetry, correlate defects with runtime behavior, recommend remediation, and support secure deployment governance. However, existing approaches remain insufficient because many of them treat software defect prediction, anomaly detection, incident response, cybersecurity controls, and deployment optimization as separate functions rather than as integrated lifecycle capabilities. This paper proposes a governance-centered Agentic AIOps Framework for cloud-native enterprise systems. The framework combines predictive software reliability models, graph-based dependency reasoning, secure software development controls, runtime observability, AI risk governance, and human-supervised remediation workflows. The major contribution of this paper is a vendor-neutral reference architecture that connects AI-driven defect prediction, cloud-native telemetry, policy-based security, deployment risk scoring, and enterprise governance into a unified model. The paper argues that agentic AIOps can improve operational decision support when it is designed with traceability, explainability, guardrails, and measurable reliability objectives rather than unrestricted automation. The proposed framework is conceptual and architecture-based, and its value lies in structuring future enterprise implementations, comparative evaluations, and research on trustworthy AI-enabled operations.*

Keywords: *Agentic Aiops, Cloud-Native Systems, Software Reliability, Secure Software Development, Observability, Microservices, Deployment Governance, Defect Prediction, AI Risk Management, Enterprise Architecture*.

1. Introduction

Modern enterprise software platforms are no longer built as isolated applications deployed through slow and predictable release cycles. They are increasingly composed of distributed microservices, managed cloud services, containerized workloads, asynchronous messaging, API gateways, service meshes, policy engines, observability pipelines, and continuous delivery mechanisms. This architectural transformation has improved scalability and business responsiveness, but it has also shifted the center of software risk from individual code units to complex interactions among services, deployment environments, data dependencies, and runtime behaviors. In such environments, a defect may not appear as a simple code failure. It may emerge as latency degradation, queue saturation, downstream timeout behavior, configuration drift, identity policy misalignment, untested dependency change, or an unexpected interaction among independently deployed services.

The rise of cloud-native engineering has therefore created a new reliability challenge. Enterprises must detect defects earlier, understand operational risk faster, and remediate incidents with greater contextual awareness. Conventional monitoring and alerting systems provide metrics, logs, and traces, but they often leave engineers with the cognitive burden of interpreting noisy signals across multiple tools. Machine learning-based defect prediction has improved the ability to identify fault-prone modules, but such models are frequently disconnected from deployment pipelines and live observability systems. Prior work on software fault detection demonstrates that neural network architectures can identify patterns in software quality data, but enterprise adoption requires these predictive capabilities to be connected to operational workflows rather than kept as standalone analytical models [2].

At the same time, artificial intelligence is becoming a central component of enterprise decision systems. AI-driven decision intelligence has been proposed as a mechanism for lifecycle governance, automated testing, and defect

prediction, showing that quality engineering can be reframed as a continuous intelligence problem rather than a post-development validation activity [4]. The emergence of agentic AI strengthens this direction. Unlike passive analytics models, software agents can plan, query tools, reason over evidence, and generate recommendations. In AIOps, such capabilities can support incident triage, root cause analysis, release risk evaluation, remediation planning, and post-incident learning. However, autonomous operational decision-making introduces its own risk. Poorly governed agents may amplify incorrect assumptions, recommend unsafe remediation, expose sensitive telemetry, or produce overconfident explanations that are not supported by system evidence.

The research problem addressed in this paper is the absence of a structured, governance-centered architecture for integrating agentic AI into cloud-native operations while preserving reliability, security, auditability, and human accountability. Existing AIOps approaches often focus on anomaly detection or incident automation, while secure software development frameworks focus on upstream development controls. Microservices architecture guidance emphasizes modularity, scalability, and service ownership, but it does not provide a complete model for AI-mediated runtime governance. Similarly, software defect prediction studies show promising predictive performance, but they rarely define how predictive outputs should be used inside enterprise deployment gates, operational playbooks, and service dependency reasoning.

This paper is needed because enterprises are entering a phase in which AI will not only generate code or analyze logs but will also participate in operational decision-making. Without a reference framework, organizations risk implementing fragmented AI assistants that improve local productivity while increasing systemic risk. The proposed Agentic AIOps Framework addresses this gap by combining software reliability prediction, service dependency modeling, observability-driven diagnosis, secure development controls, and AI governance into a single conceptual architecture.

The contributions of this paper are fourfold. First, this paper proposes a structured and vendor-neutral Agentic AIOps Framework for cloud-native enterprise systems. Second, this paper compares existing reliability, security, and cloud-native practices and identifies practical gaps that prevent unified lifecycle governance. Third, this paper presents architectural layers for integrating AI agents with telemetry, software quality models, dependency graphs, policy controls, and human approval workflows. Fourth, this paper connects the research problem to enterprise relevance by explaining how the framework supports release governance, incident response, software reliability engineering, and secure deployment optimization.

2. Background and Related Work

Cloud-native systems are designed around elasticity, automation, resilience, and loosely coupled services. Kubernetes and similar orchestration platforms provide mechanisms for deployment scheduling, service discovery, autoscaling, and workload recovery, but the operational behavior of cloud-native platforms depends heavily on configuration quality, dependency management, security posture, and observability maturity [3]. As enterprises increase the number of services and deployment frequency, failures become harder to attribute to a single component. This has motivated research into service dependency modeling, telemetry correlation, and graph-based failure propagation analysis.

Graph-based modeling is particularly relevant because microservices behave as interconnected runtime systems rather than isolated modules. A failure in an authentication service, payment service, message broker, or downstream API may propagate through multiple dependent services before becoming visible to users. Graph-based dependency analysis can improve operational reasoning by representing services, APIs, queues, databases, and infrastructure components as connected entities with directional relationships [6]. This allows AI systems to distinguish between a symptomatic alert and a likely upstream cause.

Software defect prediction has a long research tradition, but its practical role is changing. Earlier models focused on static code metrics, complexity measures, and historical defect labels. Recent studies increasingly apply machine learning and deep learning to classify fault-prone software artifacts. Comparative studies of machine learning models for defect prediction show that model selection, feature quality, class imbalance, and evaluation methodology significantly influence predictive reliability [14]. Hybrid deep learning models combining convolutional, recurrent, and dense layers further suggest that software artifacts may contain structural and sequential signals that traditional models do not fully capture [10].

AIOps extends these ideas by applying AI and machine learning to operational data. Traditional AIOps platforms commonly focus on anomaly detection, alert correlation, noise reduction, and incident prediction. However, many AIOps implementations remain tool-centric. They ingest logs and metrics, detect deviations, and generate alerts, but they often lack lifecycle context such as code changes, test history, dependency risk, release timing, security posture, and business-criticality. Monitoring and deployment optimization studies in cloud-native environments show that deployment platforms and package management tools can influence operational consistency, but tool-level optimization alone does not solve the broader governance challenge [25].

Secure software development frameworks add another essential dimension. The NIST Secure Software Development Framework emphasizes practices for reducing software vulnerabilities through secure design, development, verification, and release activities [5]. These practices are valuable, but they are generally expressed as organizational controls rather than runtime AI decision models. Therefore, enterprises need an integration layer that connects secure

development evidence with AI-supported deployment and operations.

Generative AI and large language model applications create additional security concerns. The OWASP Top 10 for LLM applications identifies risks such as prompt injection, insecure output handling, supply chain vulnerabilities, sensitive information disclosure, and excessive agency [7]. These risks are directly relevant to agentic AIOps because operational agents may access logs, configuration data, incident tickets, source repositories, and deployment tools. An AIOps agent that can recommend actions or trigger workflows must therefore be constrained by policy, authorization boundaries, and auditable reasoning.

The literature also highlights the problem of hidden technical debt in machine learning systems. Machine learning components introduce data dependencies, configuration complexity, experimental code paths, monitoring gaps, and feedback loops that may not be visible in conventional software architectures [9]. Agentic AIOps systems inherit these risks because they combine model behavior, runtime data, workflow automation, and human decision-making. A reliable framework must therefore include AI lifecycle governance and not only service-level monitoring.

3. Problem Statement and Research Motivation

The central problem addressed by this paper is that enterprise software operations are becoming too complex for fragmented monitoring, isolated defect prediction, and manual incident triage. A cloud-native enterprise platform may generate thousands of telemetry events per minute across application logs, traces, metrics, infrastructure events, security alerts, deployment records, feature flags, and business process signals. Engineers must determine whether a symptom originates from code defects, infrastructure changes, dependency failure, misconfiguration, traffic anomalies, or security events. This diagnostic burden is especially difficult during high-frequency deployments where multiple changes occur in overlapping windows.

Existing methods are insufficient for four main reasons. First, software defect prediction models often operate before deployment and do not continuously interact with runtime telemetry. A model may identify a module as fault-prone, but that information may not influence canary release decisions, rollback thresholds, or incident response playbooks. Second, observability tools provide evidence but not always reasoning. Metrics and traces reveal behavior, yet they do not automatically explain why a change is risky or how failure may propagate. Third, security governance and reliability engineering are usually managed through separate control structures. A deployment may pass performance tests but still introduce supply chain or access-control risk. Fourth, emerging AI agents create a new automation layer that can either reduce operational load or introduce uncontrolled decision pathways.

The motivation for this research is to define a framework that treats reliability, security, deployment optimization, and AI governance as connected components of enterprise operations. AI-driven root cause analysis and automated remediation have shown promise for multi-system data integrity problems, especially where failures span multiple applications and require correlation across heterogeneous evidence sources [23]. However, automated remediation should not be understood as unrestricted self-healing. In enterprise systems, remediation must respect change management, business impact, audit requirements, security policies, and human accountability.

This paper therefore frames agentic AIOps as a supervised intelligence system rather than a fully autonomous replacement for site reliability engineers or platform teams. The proposed framework supports AI-generated hypotheses, risk scores, dependency analysis, and recommended actions, but high-impact remediation remains subject to policy-based controls and human approval. This design choice is essential because enterprise reliability is not merely a technical property. It is an organizational capability shaped by architecture, governance, process maturity, and risk tolerance.

4. Proposed Conceptual Framework or Architecture

This paper proposes a Governance-Centered Agentic AIOps Framework consisting of six architectural layers: telemetry and evidence ingestion, software reliability intelligence, dependency and impact reasoning, agentic decision support, policy and security governance, and supervised remediation. The framework is vendor-neutral and can be implemented using different cloud providers, observability tools, CI/CD platforms, and AI models.

The first layer is the telemetry and evidence ingestion layer. It collects metrics, logs, traces, deployment events, test results, vulnerability scan outputs, configuration changes, incident tickets, service-level indicators, and business transaction signals. The purpose of this layer is not only to centralize data but also to preserve operational context. OpenTelemetry has become a relevant standard for collecting traces, metrics, and logs across distributed systems, and it supports the type of instrumentation required for cross-service diagnosis [15]. In the proposed framework, telemetry events are normalized into a common evidence schema that includes timestamp, service identity, deployment version, environment, dependency path, severity, and business criticality.

The second layer is the software reliability intelligence layer. This layer uses machine learning models to identify fault-prone components, risky code changes, abnormal quality trends, and test coverage weaknesses. It may include traditional machine learning classifiers, neural networks, hybrid deep learning models, and rule-based quality gates. Studies comparing software defect prediction techniques demonstrate that no single model is universally superior, which supports the need for an ensemble-oriented and context-aware reliability layer [22]. The proposed framework

uses reliability outputs as decision signals rather than final judgments.

The third layer is the dependency and impact reasoning layer. This layer builds and maintains a dynamic graph of services, APIs, databases, queues, external systems, identity providers, and infrastructure components. When an incident occurs, the graph helps identify upstream and downstream relationships. This layer is especially important in microservices migration and monolith decomposition because poorly understood dependencies may cause reliability regressions during modernization. Fault-aware transition work on microservices and gateway optimization highlights the importance of managing risk during architectural decomposition [18].

The fourth layer is the agentic decision support layer. This layer contains AI agents that can query evidence, generate hypotheses, compare incident patterns, evaluate release risk, and recommend remediation options. The agents operate through bounded tool access and are required to produce evidence-linked reasoning. Agentic reasoning methods such as ReAct demonstrate how language models can interleave reasoning and action to solve tasks through tool use [31]. In enterprise AIOps, this capability must be constrained by system policies, observability evidence, and operational roles.

The fifth layer is the policy and security governance layer. This layer enforces AI risk controls, secure development requirements, access restrictions, data handling policies, and approval thresholds. The NIST AI Risk Management Framework provides a useful governance foundation because it emphasizes mapping, measuring, managing, and governing AI risks across sociotechnical contexts [1]. For agentic AIOps, this means that AI behavior must be evaluated not only for technical accuracy but also for safety, accountability, privacy, and organizational impact.

The sixth layer is the supervised remediation layer. This layer converts agent recommendations into safe operational workflows. Examples include rollback recommendation, traffic shifting, feature flag adjustment, scaling action, configuration correction, incident ticket enrichment, or escalation to a service owner. However, the framework distinguishes between low-risk and high-risk actions. Low-risk actions, such as creating an incident summary or suggesting a dashboard query, may be automated. High-risk actions, such as database rollback, production deployment blocking, or security policy modification, require explicit human approval. This aligns with the principle that AI agents should support operational intelligence without eliminating accountable engineering judgment.

5. Methodology or Comparative Analysis

This paper adopts a conceptual architecture and comparative analysis methodology. The purpose is not to report experimental performance claims but to develop a structured model that can guide future empirical evaluation. The analysis compares four operational approaches: traditional monitoring, standalone defect prediction, conventional AIOps, and governance-centered agentic AIOps.

Traditional monitoring is necessary but reactive. It provides dashboards and alerts, yet it often depends on engineers to interpret causal relationships manually. Standalone defect prediction is proactive but limited when separated from deployment and runtime systems. It can identify risky modules, but it may not explain operational impact. Conventional AIOps improves alert correlation and anomaly detection but may lack software lifecycle context. Governance-centered agentic AIOps extends these approaches by combining predictive quality signals, runtime evidence, dependency graphs, secure development controls, and bounded AI agents.

The comparative criteria used in this paper include lifecycle coverage, contextual reasoning, security governance, explainability, remediation safety, and enterprise scalability. Lifecycle coverage measures whether the approach spans design, development, testing, deployment, and operations. Contextual reasoning measures whether the system can connect code changes, telemetry, dependencies, and incidents. Security governance measures whether the approach includes secure development and AI risk controls. Explainability measures whether operational recommendations can be traced to evidence. Remediation safety measures whether automated actions are constrained by policy and risk level. Enterprise scalability measures whether the model can support multiple teams, services, environments, and compliance requirements.

From this comparison, the proposed framework shows three major advantages. First, it treats software reliability as a continuous lifecycle problem rather than a pre-release prediction task. Second, it recognizes that AI agents must operate inside governance boundaries rather than as unrestricted automation tools. Third, it integrates dependency reasoning so that recommendations are informed by service relationships and potential failure propagation. Anomaly detection research supports this direction because effective detection depends not only on identifying deviations but also on interpreting them in relation to system context [28].

6. Technical Discussion

The technical foundation of the proposed framework is the integration of multiple evidence sources into an operational reasoning model. In cloud-native systems, incidents rarely emerge from a single signal. A latency spike may coincide with a deployment, but the true cause may be a dependency timeout, inefficient query path, expired certificate, rate-limit change, memory pressure, or downstream service degradation. Agentic AIOps must therefore reason probabilistically and contextually rather than relying on single-signal alerting.

A key technical design principle is evidence normalization. Logs, traces, metrics, test results, deployment metadata, and security findings must be mapped into a shared schema. Without normalization, AI agents may

generate plausible but unsupported interpretations. A second principle is temporal alignment. The system must align events across time windows, such as pre-deployment baselines, deployment intervals, post-deployment behavior, and incident onset. A third principle is service identity resolution. The same service may appear under different names across repositories, deployment manifests, observability tools, and incident tickets. Identity resolution is essential for accurate dependency reasoning.

Container orchestration introduces additional complexity. Large-scale cluster management systems have shown that scheduling, workload placement, resource isolation, and recovery mechanisms significantly influence operational behavior [24]. Agentic AIOps should therefore incorporate infrastructure events and resource signals into its reasoning process. For example, a sudden increase in error rate may be related to application code, but it may also be caused by pod restarts, node pressure, network policy changes, or autoscaling lag.

The framework also requires deployment risk scoring. A deployment risk score can combine code churn, historical defect density, test coverage, dependency criticality, vulnerability findings, runtime anomaly trends, and previous incident association. Unlike a simple pass-or-fail gate, the score should support graduated decisions such as proceed, proceed with enhanced monitoring, restrict rollout percentage, require additional approval, or block deployment. This approach is compatible with DevOps architecture practices that treat deployment pipelines as socio-technical systems involving people, process, architecture, and automation [36].

Agentic decision support must be designed with guardrails. LLM-based agents can summarize incidents, search logs, generate hypotheses, and draft remediation plans, but they must not be treated as inherently reliable authorities. Research on large language models for code shows that generated outputs may be useful yet require verification, testing, and contextual review [33]. In AIOps, this means that an agent's recommendation must include confidence level, supporting evidence, alternative hypotheses, and potential risk of action.

The framework further incorporates reflection and learning loops. Agentic methods such as Reflexion suggest that models can improve task performance by using feedback from prior attempts [32]. In enterprise operations, reflection should be implemented through controlled post-incident learning. After an incident is resolved, the system can update incident patterns, improve runbooks, refine detection rules, and adjust risk scoring. However, changes to production policies or remediation logic should be reviewed through governance workflows.

Security is a central technical concern. Agentic AIOps may access sensitive logs, user identifiers, infrastructure metadata, and internal system topology. The framework therefore applies least privilege, role-based tool access, prompt and output filtering, secrets redaction, and audit logging. Software supply chain controls are also necessary because AIOps agents may depend on models, plugins, libraries, and external tools. The OpenSSF SLSA framework provides guidance for improving software supply chain integrity through provenance and build-level controls [34].

7. Practical Implementation or Enterprise Relevance

The proposed framework is relevant to enterprises that operate large-scale digital platforms in domains such as retail, finance, healthcare, logistics, telecommunications, and government services. These organizations often manage hundreds or thousands of services with complex dependencies and strict availability requirements. A single failed deployment can affect customer transactions, compliance obligations, partner integrations, and operational costs.

In practical implementation, the framework can be introduced incrementally. The first phase is telemetry maturity. Enterprises must instrument services consistently and ensure that logs, metrics, and traces contain meaningful identifiers. The second phase is reliability intelligence. Teams can introduce defect prediction models, test quality analytics, and change risk scoring. The third phase is dependency graph construction. This may begin with static service catalogs and evolve toward dynamic runtime graphs. The fourth phase is agentic decision support, where AI agents assist with incident summarization, evidence retrieval, and hypothesis generation. The fifth phase is supervised remediation, where bounded automation supports approved operational workflows.

The framework is also applicable to secure communication and regulated data environments. Work on anomaly detection and encryption strategies for compliant fax communication demonstrates that secure enterprise communication requires both protection of data in transit and detection of abnormal behavior [8]. Agentic AIOps can extend this principle by correlating security anomalies with software changes, infrastructure events, and user impact.

Enterprise relevance also depends on modernization strategy. Many organizations are decomposing monoliths into microservices, adopting cloud platforms, and expanding CI/CD pipelines. A converged AI architecture for innovation, lifecycle optimization, and cybersecurity risk mitigation supports the argument that enterprises need integrated AI capabilities rather than isolated automation experiments [12]. The proposed framework provides a structure for this convergence by connecting AI-enabled reliability, deployment optimization, and security governance.

Human factors are equally important. Agentic AIOps should reduce cognitive burden, not remove professional responsibility. Engineers must remain able to inspect evidence, challenge recommendations, override automated suggestions, and trace decisions after incidents. This is

especially important in regulated industries where operational decisions may require auditability and compliance documentation. The framework therefore positions AI as an operational co-pilot governed by enterprise policy rather than an independent authority.

8. Results, Expected Outcomes, or Analytical Insights

Because this paper is conceptual and architecture-based, it does not claim experimental results. Instead, it identifies expected outcomes and analytical insights that can guide future implementation and evaluation. The first expected outcome is improved incident context. By combining telemetry, deployment records, dependency graphs, and reliability predictions, the framework can help engineers move from isolated alerts to evidence-based operational narratives.

The second expected outcome is better deployment governance. Instead of relying only on test pass rates or manual approval, enterprises can evaluate deployments using risk scores informed by code quality, historical faults, dependency criticality, and runtime baselines. Comparative analysis of software defect prediction models supports the idea that predictive quality signals can improve decision-making when they are used carefully and contextually [14].

The third expected outcome is faster root cause hypothesis generation. AI/ML-powered root cause analysis can support multi-system diagnosis by correlating failures across heterogeneous systems [23]. In the proposed framework, this capability is strengthened by dependency graphs and evidence-linked reasoning. The system does not merely detect anomalies; it organizes possible causes according to service relationships, recent changes, and operational impact.

The fourth expected outcome is safer remediation. Instead of allowing unrestricted automated action, the framework classifies remediation by risk level. Low-risk actions can be automated, medium-risk actions can require approval, and high-risk actions can require change review. This provides a practical balance between speed and control.

The fifth expected outcome is improved organizational learning. Post-incident evidence can be used to refine detection rules, update runbooks, improve test coverage, and recalibrate deployment risk models. This creates a feedback loop between operations and software engineering. Hybrid deep learning research on software fault prediction supports the broader view that reliability intelligence can improve when models learn from richer signals and operational history [10].

9. Challenges, Limitations, and Risk Considerations

The proposed framework has several limitations. First, its effectiveness depends on data quality. Incomplete logs, inconsistent service names, missing trace identifiers, or inaccurate deployment metadata can weaken agentic reasoning. Second, machine learning models may inherit bias from historical incident data. If previous incidents were underreported or misclassified, predictive models may produce misleading risk scores. Third, AI agents may generate plausible but incorrect explanations. This is why the framework requires evidence-linked reasoning, confidence scoring, and human review.

Security risks are significant. Agentic AIOps systems may be exposed to prompt injection, tool misuse, sensitive information disclosure, or excessive agency. These risks are not theoretical because LLM applications may process untrusted inputs and interact with external tools [7]. Therefore, the framework must include input sanitization, output validation, access controls, and separation between analysis and execution privileges.

Governance complexity is another challenge. The ISO/IEC 42001 standard reflects the growing need for management systems that govern AI use within organizations [13]. Applying such governance to AIOps requires cross-functional coordination among platform teams, security teams, software engineers, compliance teams, and business owners. Without organizational alignment, the framework may become a technical prototype rather than an operational capability.

Another limitation is evaluation difficulty. Measuring the value of agentic AIOps requires more than accuracy metrics. Enterprises must evaluate mean time to detect, mean time to diagnose, false positive reduction, deployment rollback frequency, incident recurrence, policy violations, engineer workload, and business impact. Experimental evaluation must also account for differences among organizations, service architectures, and operational maturity levels.

Finally, there is a risk of over-automation. The goal of agentic AIOps should not be to remove engineers from operational decision-making. The goal is to improve the quality, speed, and traceability of decisions. High-impact remediation must remain governed by human accountability, especially when actions affect customer-facing systems, regulated data, financial transactions, or safety-critical workflows.

10. Future Research Directions

Future research should evaluate the proposed framework using empirical case studies across different enterprise environments. One direction is to construct benchmark datasets that combine code metrics, deployment events, telemetry signals, incident records, and dependency graphs. Such datasets would support more realistic evaluation of AIOps models than isolated defect datasets.

A second direction is explainable agentic reasoning. Future work should develop methods for ensuring that AI agents provide traceable, evidence-based, and falsifiable operational explanations. Transformer-based architectures

have transformed sequence modeling and language understanding, but enterprise AIOps requires domain-specific constraints that connect generated explanations to verified system evidence [30].

A third direction is reinforcement learning for remediation planning. Reinforcement learning provides a formal basis for sequential decision-making, but direct experimentation in production systems is risky [29]. Future studies should explore simulation environments where remediation policies can be evaluated safely before operational use.

A fourth direction is governance-aware agent evaluation. Current evaluation methods for LLM agents often emphasize task completion, but enterprise AIOps requires additional measures such as policy compliance, security safety, explainability, rollback risk, and audit completeness. Future work should define benchmarks for trustworthy agentic operations.

A fifth direction is cloud-native AI workload optimization. Cloud-native AI research indicates that AI workloads create new infrastructure demands involving scheduling, data movement, acceleration, and observability [11]. Future AIOps systems should therefore optimize not only application reliability but also the reliability and cost-efficiency of the AI components that support operations.

11. Conclusion

This paper proposed a governance-centered Agentic AIOps Framework for cloud-native enterprise systems. The research problem addressed is the growing gap between the complexity of distributed software operations and the limitations of fragmented monitoring, isolated defect prediction, and manual incident triage. The paper argued that agentic AI can improve enterprise operations only when it is integrated with software reliability intelligence, dependency reasoning, secure development controls, observability evidence, and human-supervised remediation.

The proposed framework contributes a vendor-neutral reference architecture composed of telemetry ingestion, reliability intelligence, dependency and impact reasoning, agentic decision support, policy and security governance, and supervised remediation. The analysis indicates that such a framework can guide enterprises toward improved incident context, deployment risk governance, root cause hypothesis generation, remediation safety, and organizational learning. At the same time, the paper recognizes limitations related to data quality, model reliability, security risk, governance complexity, and evaluation difficulty.

Future research should empirically validate the framework using real-world datasets, controlled enterprise case studies, explainable agent benchmarks, and simulation-based remediation experiments. As enterprises continue adopting AI-enabled operations, the most important research challenge is not merely building more autonomous systems. It is designing operational intelligence systems that are reliable, secure, explainable, auditable, and aligned with human accountability.

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