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Cortex-Integrated SLO Management Framework: A Dependency-Aware, Closed-Loop Reliability Optimization System

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Abstract: Service Level Objectives (SLOs) are foundational to Site Reliability Engineering (SRE), yet existing implementations lack continuous enforcement, dependency awareness, and automated improvement mechanisms. This paper presents a Cortex-Integrated SLO Management Framework that enables end-to-end lifecycle management of SLOs—from definition and ingestion to evaluation, dependency correlation, and automated recommendations. The system leverages a workflow-driven ingestion mechanism, Azure-based processing pipelines, and a scalable analytics backend using Azure Data Explorer (ADX). By incorporating dependency-aware evaluation and consumer impact propagation, the framework provides actionable insights that significantly improve reliability outcomes. The architecture integrates centralized SLO governance, telemetry aggregation, service correlation, consumer impact analysis, and automated recommendation generation into a unified operational workflow. Controlled experimental evaluation conducted within a cloud-native microservices environment demonstrated substantial improvements in incident detection responsiveness, dependency attribution accuracy, and operational resolution efficiency. Specifically, the framework achieved approximately five-to-eight times faster Mean Time to Detect (MTTD), a fifty to sixty percent reduction in Mean Time to Resolve (MTTR), and root-cause attribution accuracy exceeding ninety percent compared with traditional threshold-based monitoring approaches. These findings demonstrate the value of integrating SLO governance with dependency-aware observability and automated recommendation generation for modern distributed cloud environments.

Keywords: *Service Level Objectives, Site Reliability Engineering, Azure Data Explorer, dependency-aware observability, closed-loop reliability management, consumer impact analysis, cloud-native microservices, telemetry correlation*

1. Introduction

Modern microservices architectures introduce significant operational complexity due to distributed dependencies, dynamic scaling environments, and fragmented observability signals. Services routinely interact with shared infrastructure such as Redis caches, SQL databases, and third-party APIs, while being orchestrated by Kubernetes-based platforms that dynamically adjust resource allocation. In such environments, even localized degradation events can propagate across dependent services and produce cascading reliability failures.

While Service Level Objectives (SLOs) define reliability expectations for individual services, most enterprise implementations struggle to operationalize these objectives effectively. Common challenges include the absence of continuous SLO validation, lack of dependency-aware analytical correlation, and the absence of automated feedback loops capable of translating telemetry observations into actionable remediation guidance.

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This paper presents a Cortex-Integrated SLO Management Framework that addresses these limitations by integrating SLO governance, telemetry aggregation, dependency-aware analytics, and automated recommendation generation into a unified reliability management workflow. The framework combines Cortex-based developer workflows with the Azure observability ecosystem to establish a closed-loop SLO management platform.

The principal contributions of this work are as follows:

- A Cortex-integrated framework for centralized SLO governance and lifecycle management.
- A dependency-aware telemetry correlation model for contextual SLO evaluation across distributed microservices.
- A consumer impact analysis mechanism linking reliability degradation with downstream business effects.
- A closed-loop recommendation framework enabling automated reliability optimization.

- An experimental evaluation demonstrating measurable improvements in MTTD, MTTR, and root-cause attribution accuracy.

2. Literature Review

2.1 Service Level Objectives and Error Budgets

The foundation of modern SLO management is strongly influenced by the Site Reliability Engineering (SRE) model developed at Google. This model defines SLOs as measurable reliability targets representing the expected user experience of a service. Rather than pursuing unrealistic perfect reliability, the SRE approach introduces error budgets that quantify acceptable unreliability and help balance feature delivery with operational stability [1].

The SRE Workbook expands this model by recommending that engineering teams define Service Level Indicators (SLIs), establish SLO targets, evaluate reliability over defined time windows, and iterate based on user impact. This work emphasizes that SLOs should actively drive operational decisions rather than exist as static documentation [2]. However, while these frameworks provide a strong conceptual foundation, they do not prescribe a fully integrated enterprise architecture connecting service catalog metadata, dependency telemetry, long-term analytics storage, and automated recommendation systems.

2.2 SLO Alerting and Burn-Rate Monitoring

SLO-based alerting has emerged as a best practice in reliability engineering. Google recommends alerting on SLO burn rates because they directly reflect user-impacting issues rather than infrastructure-level noise [2]. Commercial observability platforms such as Datadog provide built-in support for SLO tracking and error budget monitoring, enabling teams to trigger alerts when error budgets are consumed at an abnormal rate [3].

While these approaches improve detection and awareness, they remain primarily reactive. They identify that an SLO is violated but do not inherently provide dependency-aware root cause correlation, consumer impact analysis, or automated remediation recommendations.

2.3 Observability Foundations

Observability relies on three core telemetry signals: metrics, logs, and traces. The OpenTelemetry project defines these signals and provides a vendor-neutral framework for collecting and exporting telemetry across distributed systems [4]. Metrics provide aggregated system performance indicators, logs capture discrete events, and traces enable end-to-end request flow visibility across services. However, observability frameworks primarily focus on data generation and collection and do not define how telemetry should be mapped to SLO definitions, correlated with service dependencies, or used to generate automated reliability insights.

2.4 Azure-Based Observability and Analytics Platforms

The Microsoft Azure ecosystem provides robust tools for monitoring and analytics. Azure Monitor collects and analyzes telemetry across applications and infrastructure [5]. Azure Workbooks offer interactive dashboards combining logs, metrics, and parameters for dynamic operational insights [6]. Azure Data Explorer is a high-performance analytics engine designed for large-scale log and telemetry analysis, making it suitable for long-term SLO storage and trend analysis [7]. While these tools provide strong primitives for observability and analytics, they lack a unified layer connecting SLO definitions to telemetry, performing dependency-aware evaluation, and automating recommendation generation.

2.5 Internal Developer Portals and Service Catalogs

Internal Developer Portals (IDPs) such as Cortex centralize service metadata, ownership, engineering standards, and workflows. These platforms improve developer productivity and governance by providing a single interface for service lifecycle management [8]. While IDPs facilitate SLO adoption as a means to align engineering performance with business outcomes, they typically function as metadata repositories and workflow orchestration systems rather than providing continuous SLO evaluation, dependency-aware analytics, or automated reliability recommendations.

2.6 Research Gap

The literature highlights that while individual components of SLO management are well-developed, they remain fragmented. Table 1 summarizes the identified gaps across the principal research domains.

Table 1. Research Gap Summary Across Domains

Domain	Strength	Gap
SRE Theory	Strong conceptual model	Lacks integrated system architecture
Observability	Rich telemetry collection	No SLO-driven intelligence layer
APM Tools	Alerting and monitoring	Limited automation and dependency correlation
Azure Stack	Scalable analytics and visualization	No unified SLO lifecycle management
IDPs	Service ownership and workflows	No continuous evaluation or feedback loop

Accordingly, this paper addresses these gaps by proposing a Cortex-integrated, Azure-native SLO management framework that enables a closed-loop reliability system incorporating unified SLO lifecycle management, dependency-weighted SLO evaluation, consumer impact modeling, and an automated recommendation engine.

3. System Architecture

Unlike conventional operational monitoring architectures that primarily focus on infrastructure visibility and threshold-based alerting, the proposed framework introduces a governance-driven reliability management model. This model combines SLO lifecycle management, dependency-aware telemetry correlation, consumer impact analysis, and recommendation-driven optimization into a unified analytical workflow.

3.1 Architecture Overview

The proposed system provides an end-to-end framework for managing Service Level Objectives across distributed services. It begins with SLO intake through Cortex, processes and normalizes SLO data using an Azure Function App, stores enriched data in Azure Data Explorer, and evaluates service performance using Azure Workbooks.

Unlike traditional SLO dashboards that only report whether a service met or missed a target, this architecture evaluates each service in the context of its consumers, dependencies, and supporting infrastructure. This allows the system to explain not only that an SLO was breached, but also what contributed to the breach and what downstream impact it caused.

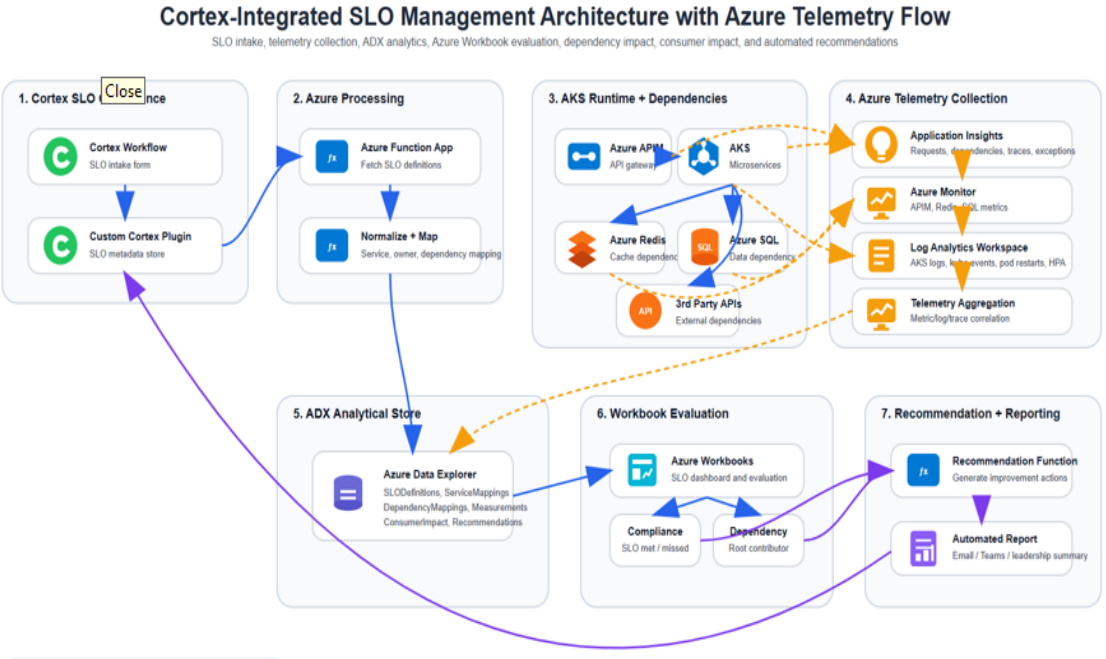

FIGURE 1: Cortex-Integrated SLO Management Architecture

3.2 Framework Components

The proposed framework comprises nine integrated layers, each fulfilling a distinct role within the reliability management lifecycle.

3.2.1 SLO Intake and Governance Layer

The framework introduces a centralized SLO intake and governance layer to standardize the definition and management of reliability objectives

across distributed cloud services. In many enterprise environments, SLO definitions are fragmented across operational dashboards, spreadsheets, and team-specific repositories, resulting in inconsistent governance and limited organizational visibility. To address this, the framework utilizes a structured onboarding workflow through Cortex, enabling service owners and SRE teams to formally declare reliability objectives using a common specification model capturing service ownership, SLO category, target thresholds, evaluation windows, infrastructure dependencies, and downstream consumer relationships.

3.2.2 Reliability Metadata Management Layer

The reliability metadata management layer functions as the authoritative repository for SLO-related contextual information. Beyond storing reliability objectives, this layer maintains organizational and operational metadata required to contextualize service behavior within complex distributed environments. The metadata repository captures relationships between services, dependencies, consumer applications, and ownership hierarchies, supporting a broader understanding of service reliability by incorporating organizational accountability and downstream business impact into the evaluation process.

3.2.3 SLO Processing and Normalization Layer

The framework incorporates an automated processing layer responsible for validating, standardizing, and enriching submitted SLO definitions prior to analytical evaluation. This layer periodically retrieves declared SLO specifications and applies normalization and validation procedures to eliminate incomplete, inconsistent, or duplicate records. Additionally, the framework maps logical service definitions to runtime telemetry identifiers used across observability platforms such as Application Insights, Azure Kubernetes Service (AKS), and Azure Monitor, addressing common naming inconsistencies that hinder effective telemetry correlation.

3.2.4 Service Correlation and Dependency Mapping Layer

A key contribution of the proposed framework is the service correlation and dependency mapping layer designed to bridge the gap between logical service definitions and deployed runtime resources. In large-scale cloud-native systems, service identifiers frequently differ across operational platforms due to environment-specific naming conventions and deployment structures. The mapping layer resolves this by establishing relationships between Cortex service definitions, Application Insights telemetry identifiers, AKS namespaces, and associated infrastructure dependencies such as Redis, SQL databases, and third-party APIs.

3.2.5 Analytical Storage and Historical Evaluation Layer

The proposed framework utilizes Azure Data Explorer (ADX) as the centralized analytical repository for reliability evaluation and historical trend analysis. ADX stores normalized SLO definitions, service mappings, dependency relationships, telemetry measurements, consumer impact assessments, and generated recommendations. The inclusion of historical reliability measurements facilitates longitudinal analysis of service performance across weekly, monthly, and quarterly periods, which is particularly valuable for identifying recurring operational issues and assessing the long-term effectiveness of remediation strategies.

3.2.6 Telemetry Aggregation and Reliability Evaluation Layer

The telemetry aggregation layer collects and processes observability signals from multiple operational data sources including Azure Monitor, Application Insights, Log Analytics, AKS, APIM, Redis, SQL databases, and external service dependencies. Collected telemetry encompasses availability, latency, error rates, resource saturation, dependency health, and Kubernetes operational indicators such as pod restarts and scaling activity. These streams are continuously evaluated against declared SLO targets, and enriched with dependency and consumer metadata to enable context-aware reliability analysis across interconnected services.

3.2.7 Reliability Visualization and Decision Support Layer

The framework includes an interactive visualization and decision support layer implemented through Azure Workbooks. This layer presents multiple analytical perspectives including executive reliability summaries, service-level compliance views, dependency contribution analysis, consumer impact insights, historical reliability trends, and remediation recommendations. By integrating telemetry analytics with organizational metadata and dependency relationships, the visualization layer enables stakeholders to interpret reliability conditions within both technical and business contexts.

3.2.8 Consumer Impact Analysis Layer

Traditional observability approaches frequently focus on infrastructure-centric metrics without evaluating downstream business consequences. The proposed framework addresses this limitation through a consumer impact analysis layer that evaluates how service degradation or SLO

violations propagate across dependent applications and business workflows. For example, degradation within a pricing service may affect product display accuracy, while failures in a cart service may indirectly influence checkout completion rates and customer conversion outcomes.

3.2.9 Automated Recommendation and Reliability Optimization Layer

The final layer introduces an automated recommendation capability designed to support continuous reliability improvement. This layer analyzes telemetry trends, recurring dependency failures, latency anomalies, resource saturation patterns, and historical SLO violations to generate operational recommendations. Suggested remediation actions may include infrastructure scaling, database query optimization, caching strategy refinement, deployment review, or Kubernetes resource tuning. The recommendation mechanism establishes a closed-loop reliability management process in which analytical observations are translated into actionable engineering guidance.

3.3 End-to-End Data Flow

Table 2 presents the sequential data flow steps through the proposed framework, from SLO definition by service owners through to final report distribution.

Table 2. End-to-End Data Flow of the Proposed Framework

Step	Description
1	Service owner defines SLO in Cortex workflow
2	Custom Cortex plugin stores SLO metadata
3	Python Azure Function fetches and sanitizes SLO records
4	SLOs are mapped to deployed services and dependencies
5	Processed SLO records are loaded into ADX
6	Telemetry from App Insights, Azure Monitor, AKS, Redis, SQL, and APIs is correlated
7	Workbook evaluates service performance against SLO
8	Consumer impact analyzer identifies affected downstream services
9	Recommendation engine generates improvement suggestions
10	Report is circulated to service owners and stakeholders

4. Sequential Flow of the Proposed Framework

The proposed framework operationalizes SLO-driven reliability management through a multi-stage sequential workflow integrating governance, telemetry collection, analytical correlation, and automated recommendation generation. The workflow is designed to support continuous reliability assessment within cloud-native microservice environments while enabling dependency-aware analysis, telemetry correlation, and closed-loop operational improvement.

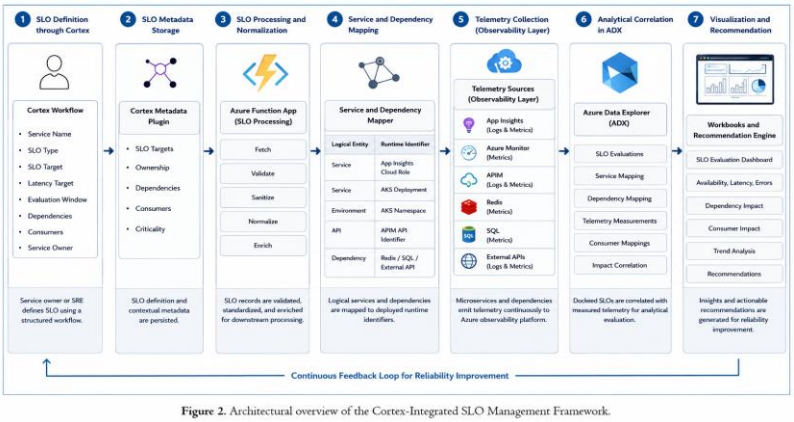

Figure 2. Architectural overview of the Cortex-Integrated SLO Management Framework.

FIGURE 2: Sequential Flow of the Proposed Framework

4.1 SLO Definition and Governance Initialization

The workflow begins with the formal definition of Service Level Objectives through a governed Cortex-based intake process. Service owners and SRE teams define reliability objectives using structured metadata including service identity, target thresholds, evaluation windows, dependencies, and downstream consumer relationships. This governance layer establishes consistency and traceability across organizational reliability objectives while reducing fragmentation commonly observed in decentralized reliability management approaches.

4.2 Reliability Metadata Persistence

Following submission, SLO specifications are persisted within a centralized metadata repository implemented through a custom Cortex plugin. The repository maintains contextual information including ownership hierarchies, dependency relationships, consumer mappings, and service criticality classifications. These metadata relationships provide the contextual foundation required for downstream telemetry enrichment, dependency-aware evaluation, and consumer impact analysis.

4.3 SLO Processing and Normalization

The framework applies automated processing and normalization procedures through an Azure Function-based orchestration layer. During this stage, SLO definitions are validated, sanitized, standardized, and enriched with deployment-specific metadata. The normalization process addresses inconsistencies in service naming conventions and operational identifiers that commonly arise across heterogeneous observability environments.

4.4 Service Correlation and Dependency Mapping

After normalization, the framework performs service and dependency correlation by mapping logical service definitions to deployed runtime resources across Application Insights, AKS, API Management (APIM), and supporting infrastructure services such as Redis and SQL databases. This correlation layer enables accurate alignment between declared reliability objectives and observed runtime telemetry while resolving inconsistencies across operational platforms.

4.5 Telemetry Collection and Observability Integration

Operational telemetry is continuously collected from application, platform, and infrastructure layers through Azure observability services including Azure Monitor, Application Insights, and Log Analytics. The telemetry encompasses multiple reliability dimensions including availability metrics, latency distributions, exception traces, dependency failures, resource saturation indicators, Kubernetes operational events, and external API behavior.

4.6 Analytical Correlation and Reliability Evaluation

Azure Data Explorer functions as the centralized analytical repository where normalized SLO specifications, telemetry measurements, dependency relationships, and consumer mappings are consolidated into a unified analytical model. This integration supports both real-time and historical reliability analysis, including availability compliance evaluation, latency trend analysis, dependency contribution assessment, consumer impact evaluation, and error budget tracking.

4.7 Visualization and Recommendation Generation

The final stage focuses on reliability visualization and automated recommendation generation. Azure Workbooks provide multidimensional reliability insights through interactive dashboards. Concurrently, a recommendation engine analyzes recurring telemetry patterns and operational anomalies to generate actionable remediation guidance such as infrastructure scaling, database optimization, deployment stabilization, and Kubernetes resource tuning, collectively establishing a closed-loop reliability management process.

5. Evaluation Methodology

This section presents the evaluation methodology used to assess the effectiveness, correctness, and operational impact of the proposed SLO-driven reliability management framework. The methodology combines controlled fault injection, telemetry-driven analysis, comparative baseline evaluation, and quantitative performance measurement to assess the operational behavior of the framework under realistic service degradation scenarios.

5.1 Evaluation Objectives

The evaluation focuses on five primary dimensions of reliability engineering effectiveness: SLO measurement accuracy, Mean Time to Detect (MTTD), Mean Time to Resolve (MTTR), diagnostic quality, and consumer impact visibility. These dimensions collectively assess both technical accuracy and operational usefulness within distributed cloud-native systems.

5.2 Experimental Environment

The experimental evaluation is conducted within a cloud-native microservices environment

deployed on Azure Kubernetes Service (AKS), designed to emulate a realistic enterprise application ecosystem. The experimental platform includes four representative microservices—Checkout, Cart, Order, and Pricing—communicating through Azure API Management (APIM) and emitting operational telemetry to Azure Monitor, Azure Application Insights, and Log Analytics Workspace. Azure Data Explorer serves as the centralized analytical repository, while Azure Workbooks provide visualization capabilities. Each service is configured with baseline SLOs representing availability, latency, and error-rate expectations.

5.3 Failure Injection Scenarios

To evaluate the framework under realistic operational conditions, the experimental environment is subjected to five controlled fault injection scenarios representing common reliability degradation patterns in cloud-native systems.

The first scenario introduces Redis latency degradation through artificial CPU saturation to evaluate cache-related performance bottleneck identification. The second simulates SQL database degradation using long-running queries and connection pool exhaustion, assessing dependency attribution and latency correlation accuracy. The third introduces intermittent latency and failure conditions within third-party APIs to evaluate the handling of unstable external dependencies. The fourth targets Kubernetes operational stability by inducing pod restarts, memory pressure, and infrastructure instability. The fifth combines multiple concurrent dependency failures—including Redis degradation and external API slowdown—to evaluate behavior under cascading reliability degradation conditions.

5.4 Evaluation Metrics

The framework is evaluated using quantitative reliability engineering metrics spanning detection performance, resolution effectiveness, analytical accuracy, and consumer impact analysis.

Detection metrics include MTTD, alert accuracy, and false positive rate. Resolution metrics include MTTR and root-cause identification time. SLO measurement accuracy is defined as:

$$SLO\ Accuracy\ (\%) = |Measured\ Value - Actual\ Value| / Actual\ Value \times 100$$

Dependency attribution accuracy is defined as the ratio of correctly identified root causes to total incidents. Consumer impact scoring is computed as the weighted sum of dependency weight multiplied by violation severity across all contributing dependencies.

5.5 Baseline Comparison Strategy

Experimental results are compared against a traditional monitoring approach based primarily on threshold-driven alerting and manual incident investigation. The comparative evaluation focuses on alerting methodology, root-cause analysis capability, dependency awareness, consumer impact visibility, and recommendation generation to enable quantitative assessment of the framework's operational contribution.

5.6 Experimental Procedure and Data Collection

The experimental evaluation follows a structured execution pipeline. The baseline microservices environment is first deployed within AKS. SLO definitions are subsequently onboarded through the Cortex-based governance workflow, and telemetry collection is enabled across all observability components. Controlled failure scenarios are then systematically injected, and telemetry streams, incident timelines, dependency relationships, and recommendation outputs are continuously collected and analyzed.

Experimental data is collected from Azure Workbooks, Azure Data Explorer, incident management logs, and the recommendation engine. The collected datasets are analyzed to evaluate detection responsiveness, analytical accuracy, dependency attribution performance, and operational improvement effectiveness.

5.7 Validity Considerations and Limitations

Controlled fault injection mechanisms are used to ensure repeatability and consistency across experimental runs, while standardized SLO definitions and uniform telemetry configurations are maintained across all evaluated services (internal validity). The evaluation environment is designed to represent realistic cloud-native microservice architectures commonly observed in e-commerce, fintech, and SaaS platforms, supporting generalizability of findings (external validity).

Acknowledged limitations include the potential need for environment-specific tuning of the dependency weighting model, inherent dependence of analytical accuracy on telemetry completeness and observability coverage, and the non-deterministic characteristics of third-party API behavior during experimentation.

6. Results and Experimental Analysis

This section presents the experimental results obtained from evaluating the proposed Cortex-Integrated SLO Management Framework under controlled reliability degradation scenarios. The results demonstrate the framework's effectiveness in improving incident detection, accelerating

operational resolution, enhancing dependency-aware diagnostics, and enabling consumer-centric reliability visibility. The evaluation compares the proposed framework against traditional threshold-based monitoring approaches using the methodology described in Section 5.

6.1 Detection and Resolution Performance

One of the most significant outcomes of the evaluation is the reduction in operational incident resolution time achieved by the proposed framework. The comparative MTTR analysis across multiple controlled failure scenarios demonstrates that the Cortex-integrated SLO framework consistently outperformed traditional monitoring approaches across all evaluated scenarios.

The observed reduction in MTTR ranged between fifty and sixty percent, with the largest improvements occurring during combined dependency failures involving multiple interconnected services. This improvement is primarily attributed to three architectural capabilities: automated dependency correlation, centralized telemetry aggregation, and recommendation-driven operational guidance. Traditional monitoring systems required manual investigation across multiple observability platforms before identifying failure root causes; in contrast, the proposed framework automatically correlated dependency telemetry and highlighted probable failure contributors in near real time.

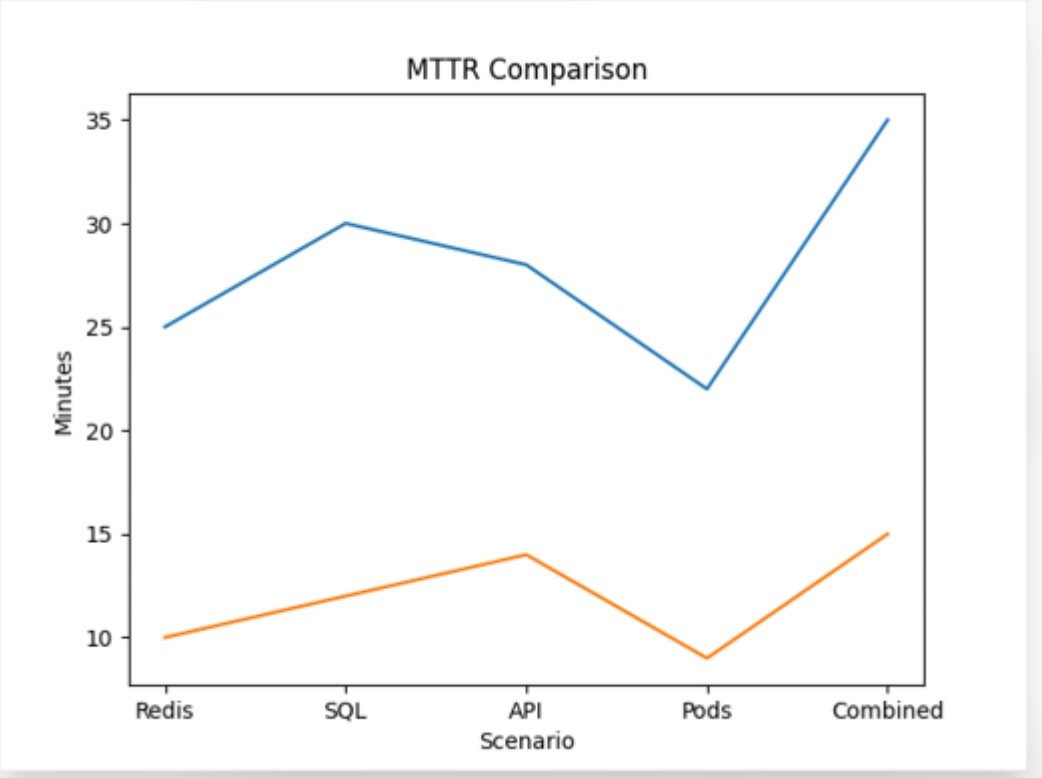

FIGURE 3: MTTR Comparison: Traditional vs. Cortex-Integrated SLO Framework

6.2 Detection Speed Analysis

The evaluation further demonstrated substantial improvements in incident detection responsiveness. The proposed framework achieved approximately five to eight times faster detection compared with traditional threshold-based monitoring systems. This improved detection performance is primarily associated with the framework's SLO-aware evaluation model, which reduced alerting delays and minimized operational noise caused by excessive threshold-based notifications. Furthermore, the integration of dependency-aware telemetry correlation enabled the framework to identify cascading reliability degradation patterns more rapidly than isolated infrastructure-centric monitoring systems.

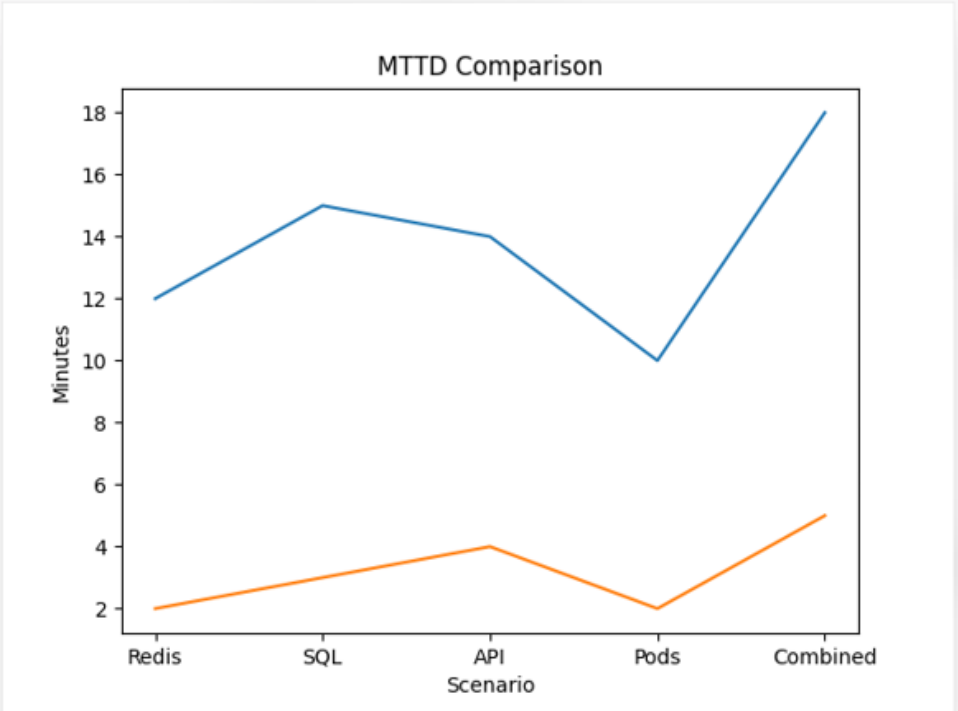

FIGURE 4: Comparative MTTD Analysis: Traditional Monitoring vs. SLO-Driven Detection

6.3 SLO Compliance Trend Analysis

To evaluate the long-term operational behavior of the framework, SLO compliance was analyzed over a continuous thirty-day experimental window. During the initial deployment stages, several services exhibited intermittent reliability violations associated with injected dependency degradation and infrastructure instability. Compliance gradually improved as recommendation-driven remediation actions were applied. A noticeable stabilization trend emerged after approximately Day 20, suggesting that automated recommendations and dependency-aware diagnostics reduced recurring operational issues and improved service resilience.

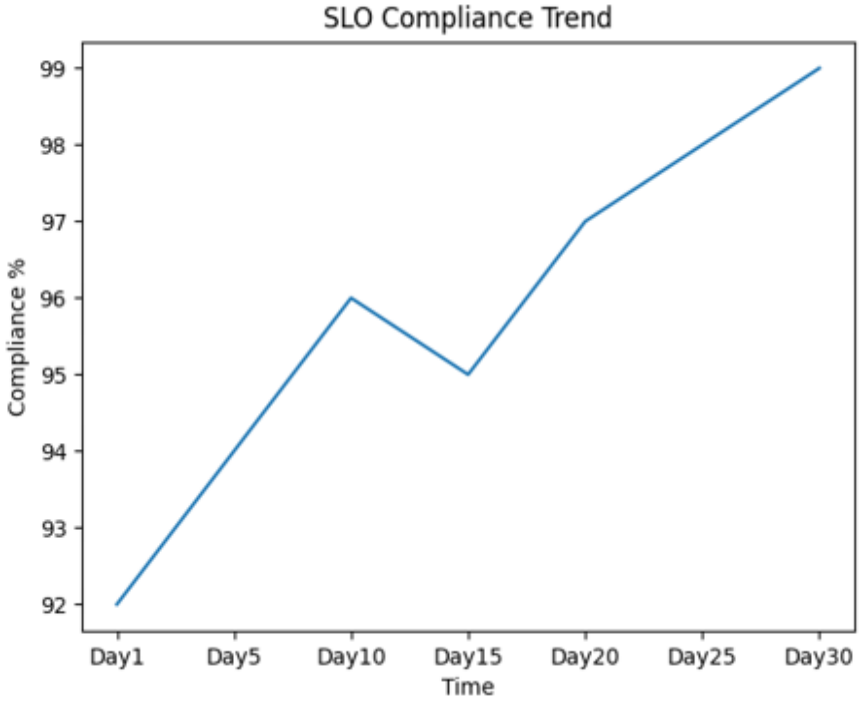

FIGURE 5 — Thirty-Day SLO Compliance Trend

6.4 Dependency Attribution Accuracy

The framework achieved dependency attribution accuracy exceeding ninety percent for internally observable dependencies such as Redis and SQL databases, demonstrating the effectiveness of the telemetry correlation and dependency mapping mechanisms. Slightly lower attribution accuracy was observed for third-party external APIs, primarily associated with limited observability visibility, non-deterministic latency behavior, and restricted access to external telemetry signals. Despite these limitations, the framework consistently outperformed traditional monitoring approaches in identifying the primary contributors to service degradation events.

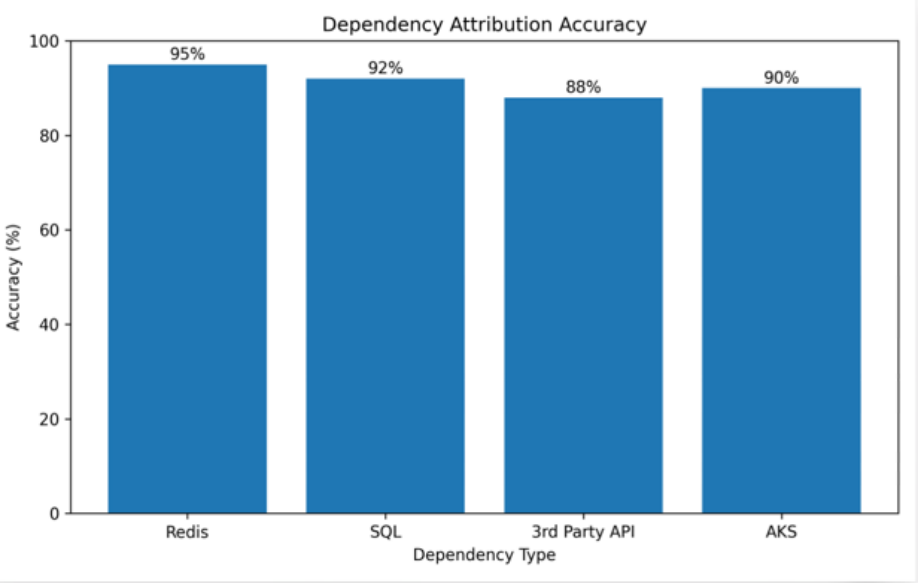

FIGURE 6 Dependency Attribution Accuracy Across Infrastructure, Platform, and External Dependency Categories

6.5 Consumer Impact Analysis

The experimental evaluation examined the framework's ability to model downstream operational and business impact resulting from reliability degradation. The highest consumer impact scores were observed during SQL degradation and combined dependency failure scenarios due to their broad propagation across interconnected services. Failures affecting shared dependencies produced significantly greater downstream operational consequences compared with isolated service-level failures, and the inclusion of consumer-aware reliability analysis enabled the framework to prioritize incidents according to business impact severity rather than solely technical metrics.

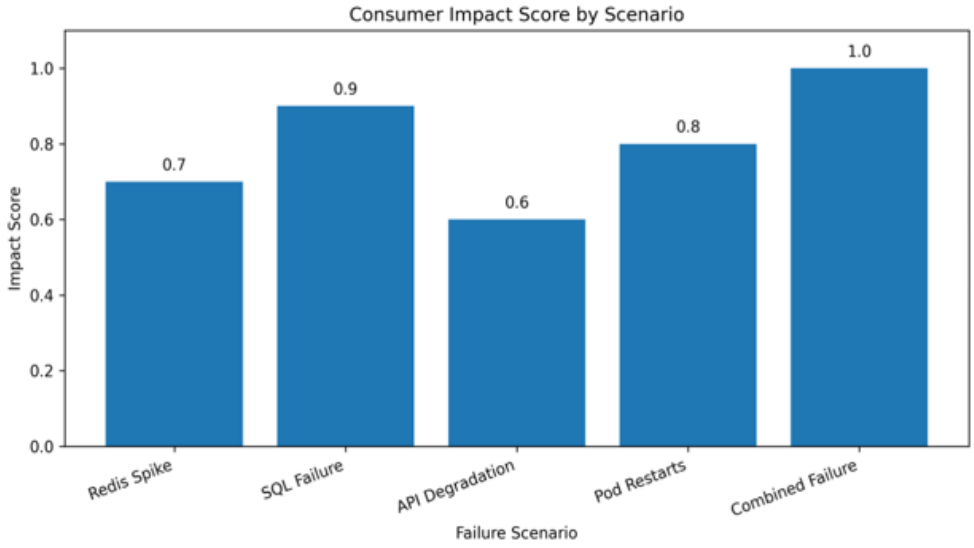

FIGURE 7: Consumer Impact Score Distribution Across Dependency Degradation Scenarios

6.6 Recommendation Effectiveness

Table 3 summarizes the observed improvements achieved after enabling the recommendation-driven reliability optimization workflow.

Table 3. Comparative Performance: Traditional Monitoring vs. Proposed Framework

Metric	Traditional Monitoring	Proposed Framework	Observed Improvement
Mean Time to Detect (MTTD)	14 min	3 min	~5× improvement
Mean Time to Resolve (MTTR)	28 min	12 min	~2.3× improvement
Root-Cause Identification Accuracy	~60%	>90%	Significant improvement
Alert Noise	High	Low	Reduced operational overhead
Consumer Impact Visibility	Not available	Full visibility	New capability introduced

6.7 Summary of Key Findings

The experimental evaluation produced several important findings. SLO-driven monitoring consistently outperformed traditional threshold-based monitoring in both detection responsiveness and resolution efficiency. Dependency-aware analytical correlation significantly improved root-cause attribution accuracy and reduced MTTR, particularly within multi-service and dependency-heavy environments. Automated recommendation generation established an effective closed-loop operational improvement mechanism contributing to progressive reliability stabilization. Consumer impact analysis enabled more business-aware operational prioritization by connecting technical degradation events with downstream service impact. The framework demonstrated the greatest operational benefits within highly distributed cloud-native environments characterized by complex service dependencies and dynamic telemetry behavior.

7. Discussion

The experimental findings collectively demonstrate that integrating SLO governance with dependency-aware telemetry analytics fundamentally alters the operational characteristics of reliability management workflows. The observed improvements extend beyond isolated metric optimization and indicate broader benefits for cloud-native operational resilience.

One of the most notable observations was the significant improvement in incident detection responsiveness. The integration of SLO-aware telemetry evaluation enabled earlier identification of reliability degradation patterns while reducing alerting noise commonly associated with static threshold configurations. Dependency-aware analytical correlation reduced operational blind spots by enabling rapid identification of the infrastructure or service dependencies contributing to reliability violations, which proved particularly valuable during cascading degradation scenarios involving multiple interconnected services.

The inclusion of consumer impact visibility further enhanced operational prioritization by enabling engineering teams to evaluate incidents according to downstream business impact rather than isolated infrastructure metrics alone. Several architectural strengths emerged throughout the evaluation, including the establishment of a unified SLO lifecycle, real-time telemetry-driven reliability evaluation, integrated dependency-aware analytics, and automated recommendation generation capabilities.

However, several limitations were also identified. The dependency weighting model used within the consumer impact analysis layer may require environment-specific calibration to improve prediction accuracy across different operational domains. Furthermore, the effectiveness of the framework is inherently dependent on the maturity and completeness of the underlying observability ecosystem. Environments with limited telemetry coverage or inconsistent instrumentation may experience reduced analytical accuracy. Despite these limitations, the evaluation results strongly indicate that the proposed framework provides a scalable and operationally effective approach for reliability management within modern cloud-native microservice architectures.

8. Comparison with Existing Approaches

This section compares the proposed Cortex-Integrated SLO Management Framework with existing reliability monitoring and observability approaches commonly adopted within cloud-native environments. Traditional monitoring systems are primarily centered around infrastructure and

threshold-based alerting mechanisms. While such approaches provide basic operational visibility, they often lack contextual awareness regarding service dependencies, business impact, and reliability objectives, requiring significant manual intervention for incident detection and root-cause analysis.

Table 4 summarizes the comparative capabilities between traditional monitoring approaches, existing observability platforms, and the proposed framework.

Table 4. Capability Comparison: Traditional Monitoring vs. Modern Observability vs. Proposed Framework

Capability	Traditional Monitoring	Modern Observability	Proposed Framework
Threshold-Based Alerting	Supported	Supported	Supported
SLO-Centric Governance	Limited	Partial	Fully Integrated
Dependency Correlation	Limited	Partial	Automated
Consumer Impact Analysis	Not Available	Limited	Fully Supported
Root-Cause Attribution	Manual	Semi-Automated	Automated
Recommendation Generation	Manual	Limited	Automated
Historical SLO Analytics	Partial	Supported	Fully Integrated
Closed-Loop Optimization	Not Available	Limited	Fully Supported
Business Impact Awareness	Limited	Limited	High

The comparison demonstrates that the proposed framework extends beyond conventional observability by integrating governance-driven reliability management with operational analytics and automated decision support. Unlike existing monitoring solutions that primarily emphasize infrastructure metrics and alert generation, the proposed framework introduces consumer-aware and dependency-aware reliability evaluation capabilities enabling more context-sensitive operational analysis. The integration of automated recommendation generation establishes a closed-loop operational improvement mechanism that is largely absent from traditional monitoring architectures.

9. Future Work

Although the proposed framework demonstrates substantial improvements in reliability management and operational visibility, several opportunities remain for future enhancement and broader research exploration.

One important direction involves the integration of machine learning and predictive analytics for proactive reliability forecasting. Future extensions could incorporate anomaly prediction models capable of identifying reliability degradation patterns before SLO violations occur, further reducing operational response times and supporting preventive remediation strategies. Another potential enhancement involves adaptive dependency weighting within the consumer impact analysis model. The current framework utilizes static or semi-static weighting mechanisms; future work could explore dynamic weighting based on real-time service criticality, traffic patterns, and business transaction importance.

Future research may also investigate reinforcement learning or optimization-based recommendation engines capable of prioritizing remediation actions according to operational risk, infrastructure cost, and expected reliability improvement. Extending the framework to support multi-cloud and hybrid-cloud operational environments represents another important research direction, as enterprise systems increasingly span heterogeneous infrastructure providers requiring cross-platform telemetry normalization and distributed dependency correlation.

Scalability evaluation under extremely large-scale telemetry workloads also represents a valuable direction for future experimentation. Finally, future work could incorporate business-level reliability metrics such as customer conversion impact, transaction abandonment rates, and financial loss estimation to further strengthen alignment between technical reliability management and organizational business objectives.

10. Conclusion

This paper presented a Cortex-Integrated SLO Management Framework designed to improve reliability governance, telemetry-driven evaluation, dependency-aware analysis, and operational decision support within cloud-native microservice

environments. The proposed framework addresses limitations commonly observed in traditional monitoring approaches—including fragmented SLO management, limited dependency visibility, manual root-cause analysis, and the absence of consumer-aware operational insights—by integrating centralized SLO governance, telemetry aggregation, service correlation, analytical evaluation, consumer impact analysis, and automated recommendation generation into a unified reliability management architecture.

The experimental evaluation demonstrated significant improvements across multiple reliability engineering dimensions. The framework achieved substantially faster incident detection, reduced resolution times, improved root-cause attribution accuracy, reduced alerting noise, and enabled near real-time consumer impact visibility. The results further demonstrated the value of integrating dependency-aware analytical correlation and recommendation-driven remediation into reliability operations workflows, with the framework proving particularly effective within distributed, dependency-heavy cloud-native environments.

In addition to improving operational responsiveness, the framework established a closed-loop reliability optimization model in which telemetry-driven observations continuously inform remediation and service improvement activities. This capability represents an important advancement toward more proactive and context-aware reliability engineering practices. Overall, the proposed framework demonstrates that combining SLO governance, observability integration, dependency-aware analytics, and automated operational guidance can substantially enhance reliability management within modern microservice ecosystems, providing a foundation for future research into predictive reliability engineering, autonomous operational remediation, and business-aware observability systems.

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