Journal of Advanced Computing Systems (JACS)
ISSN: 3066-3962
Content Available at SciPublication

Empirical Evaluation of Multi-Source Monitoring Signal Effectiveness and Lead Time for Performance Degradation Prediction in Kubernetes-Based Microservices

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DOI: 10.69987/JACS.2026.60402

Keywords

microservice performance degradation, Kubernetes anomaly detection, multi-source monitoring signals, cloud-native early warning

Abstract

Cloud-native microservice architectures deployed on Kubernetes have become the backbone of mission-critical enterprise systems, including financial transaction platforms and real-time data processing pipelines. Detecting performance degradation before it escalates into user-facing incidents remains an open challenge, particularly when Horizontal Pod Autoscaler (HPA) dynamics introduce metric volatility that obscures genuine anomaly signals. This paper presents an empirical evaluation of multi-source monitoring signals—spanning infrastructure-level resource metrics, application-level latency indicators, distributed trace features, and structured log patterns—for their effectiveness and lead time in predicting performance degradation across Kubernetes-based microservice deployments. Through controlled fault injection experiments on the TrainTicket benchmark system running on Amazon EKS, we systematically measure the predictive lead time, detection precision, and false alarm rates of 14 distinct monitoring signals under six degradation scenarios with and without active HPA. Our results reveal that application-level signals, specifically database query latency percentile shifts and cache hit rate deviations, provide 2.3 to 4.7 minutes of advance warning before infrastructure metrics register anomalies. The findings also quantify a 23.6% increase in false positive rates attributable to HPA-induced pod scaling events, and we propose signal filtering heuristics that reduce this noise by 67.2%. These results carry direct implications for financial infrastructure resilience and SLA assurance in cloud-native environments.

1. Introduction

1.1. Background and Motivation

The widespread adoption of cloud-native microservice architectures has fundamentally transformed the operational landscape of enterprise IT systems. Financial institutions, healthcare platforms, and e-commerce services increasingly decompose monolithic applications into hundreds of interdependent microservices orchestrated by Kubernetes, relying on dynamic scaling capabilities to meet fluctuating demand. This architectural shift introduces new categories of performance degradation that propagate across service dependency chains in non-obvious patterns, making early detection substantially more difficult than in traditional monolithic deployments.

A comprehensive survey of anomaly detection and failure analysis in microservice-based cloud applications identified that the complexity of inter-service communication and the ephemeral nature of containerized workloads create observability gaps not present in conventional systems [1]. The AIOps community has responded with increasingly sophisticated methods for failure management, ranging from statistical anomaly detection to deep learning-based approaches [2]. An industrial survey and empirical study on microservice fault analysis demonstrated that real-world microservice failures often manifest as gradual performance degradation rather than abrupt crashes, with latency increases of 15-30% persisting for minutes before triggering existing threshold-based alerts [3].

The financial services sector exemplifies the criticality of early warning capabilities. Payment processing microservices operating under PCI DSS compliance

requirements must maintain sub-200-millisecond response times for transaction authorization. A degradation event that pushes the 99th percentile latency beyond SLA thresholds can cascade through downstream settlement and reconciliation services, potentially disrupting digital economy transactions at scale. Real-time trading platforms, regulatory reporting systems, and cross-border payment gateways all depend on microservice response time guarantees that, once violated, trigger compounding failures across interconnected financial infrastructure. The ability to detect such degradation 3-5 minutes before it impacts end-user transactions represents a meaningful operational advantage that existing monitoring approaches have not systematically evaluated.

A compounding challenge specific to Kubernetes-orchestrated deployments is the metric volatility introduced by the Horizontal Pod Autoscaler (HPA). Pod creation, initialization, JVM warm-up, and connection pool establishment during scaling events produce transient metric spikes that closely resemble genuine performance anomalies. Existing research has not quantified the false alarm burden imposed by these orchestration dynamics, leaving a critical gap between controlled experimental evaluations and production deployment realities.

1.2. Research Questions and Scope

A. Research Questions

This study addresses three research questions that remain unanswered in the current literature. RQ1 asks which monitoring signal sources provide the earliest predictive indicators of performance degradation in Kubernetes-based microservices, and what is the quantifiable lead time advantage of application-level signals over infrastructure-level metrics. RQ2 investigates the extent to which Kubernetes HPA-induced pod scaling events degrade the precision and recall of anomaly detection across different signal types. RQ3 examines whether multi-source signal correlation can improve both the lead time and reliability of early warning compared to single-source detection approaches.

B. Scope and Contributions

The scope of this study is bounded to empirical evaluation of existing monitoring signals and detection techniques rather than the proposal of new detection algorithms or system architectures. The principal contributions include a systematic taxonomy of 14 monitoring signals categorized by source layer and measurement granularity, a controlled experimental evaluation quantifying the predictive lead time of each signal across six representative degradation scenarios, an empirical analysis of HPA-induced false alarm rates with proposed filtering heuristics, and a discussion of practical implications for financial infrastructure SLA assurance. The experimental infrastructure utilizes the TrainTicket benchmark microservice application deployed on Amazon EKS with production-representative monitoring instrumentation.

2. Related Work

2.1. Multi-Modal Anomaly Detection for Microservices

A. Data Fusion Approaches

The recognition that single-modal monitoring data provides insufficient coverage for microservice anomaly detection has driven substantial research into multi-modal data fusion. DeepTraLog combined distributed trace structures with application log sequences through a graph-based deep learning approach, demonstrating that the integration of trace topology and log semantics captures failure patterns invisible to either data source alone [4]. Expanding on the cross-modal paradigm, a semi-supervised cross-modal attention mechanism was proposed for heterogeneous anomaly detection in software systems, reporting that metric-only detectors exhibited an 8.87% false positive rate from normal operational fluctuations—a finding that motivated the fusion of metrics with logs and traces to suppress spurious alerts [5]. Eadro advanced this direction by providing an end-to-end troubleshooting framework that ingests metrics, logs, and traces simultaneously, achieving higher diagnostic accuracy through learned cross-modal representations that capture temporal correlations among heterogeneous data streams [6].

B. Causal Inference-Based Root Cause Analysis

Beyond detection, the microservice reliability community has invested heavily in root cause analysis through causal inference. Nezha introduced an interpretable fine-grained root cause analysis approach for microservices using multi-modal observability data, constructing causal graphs from metric dependencies to trace failure propagation paths across service boundaries [7]. A causal discovery framework for root cause analysis of microservice failures formulated the problem as structure learning over time-series metric data, applying constraint-based and score-based causal discovery algorithms to identify the originating service of cascading performance degradation [8]. A systematic empirical benchmark of causal-inference-based root cause analysis methods evaluated nine representative algorithms across standardized microservice datasets, revealing that methods demonstrating strong performance on small service graphs frequently failed to maintain accuracy when the number of services exceeded 30 [9].

2.2. Performance Prediction and Kubernetes Resource Management

The distinction between anomaly detection (identifying ongoing anomalies) and anomaly anticipation (predicting future anomalies) represents a critical gap in the literature. A large-scale trace analysis of microservice dependency and performance at Alibaba characterized the temporal patterns of performance metric evolution, documenting that database-tier services exhibited measurable latency drift 2-8 minutes before user-facing API degradation became statistically significant [10]. Maat addressed the anticipation challenge directly by employing conditional diffusion models for metric forecasting, achieving F1-score improvements of 15-80% over real-time detection baselines and demonstrating that probabilistic forecasting can provide meaningful advance warning of anomalies [11]. On the Kubernetes resource management side, an adaptive horizontal pod autoscaling system deployed on Alibaba Cloud Container Service leveraged time series decomposition and workload prediction to make proactive scaling decisions, while acknowledging that the scaling actions themselves introduce metric transients that complicate downstream anomaly detection [12].

2.3. Empirical Benchmarking Studies

The empirical evaluation paradigm has gained traction as the field matures. The research streams described above share a common limitation: they evaluate detection or diagnosis accuracy without systematically measuring the predictive lead time of different monitoring signals or quantifying the impact of Kubernetes orchestration dynamics on detection reliability. This study addresses these specific gaps through controlled experimentation, adopting the empirical benchmarking methodology established by recent comparative studies while focusing on the previously unexplored dimensions of signal lead time and auto-scaling noise characterization.

3. Research Methodology

3.1. Experimental Environment and Benchmark Architecture

The experimental environment was constructed on Amazon Elastic Kubernetes Service (EKS) running Kubernetes version 1.28 with managed node groups comprising six m5.2xlarge instances (8 vCPUs, 32 GB RAM each). The TrainTicket microservice benchmark application, a widely adopted open-source system consisting of 41 interconnected services implementing a train ticket booking workflow, was selected as the target workload. TrainTicket provides representative complexity for evaluating performance degradation propagation, encompassing synchronous REST API calls, asynchronous message queue communication via RabbitMQ, relational database access through MySQL, NoSQL document storage via MongoDB, and Redis-based caching layers.

Each microservice was deployed as a Kubernetes Deployment with resource requests of 256 MiB memory and 250m CPU, and limits of 512 MiB memory and 500m CPU. The HPA was configured with CPU utilization target of 60% and memory utilization target of 70%, with minimum replica count of 2 and maximum of 8 per service. A load generator based on Locust produced synthetic user traffic following a diurnal pattern with a baseline of 50 concurrent users, peak loads of 200 concurrent users, and randomized burst events reaching 350 concurrent users. The load pattern was designed to trigger HPA scaling events approximately 8-12 times per experimental run, providing sufficient data to evaluate the impact of scaling dynamics on anomaly detection. Each experimental run lasted 90 minutes, comprising a 20-minute warm-up phase to establish steady-state baselines, a 40-minute active measurement phase during which fault injection occurred, and a 30-minute recovery observation phase. The warm-up phase ensured that all JVM instances reached compiled-code steady state and that all connection pools, caches, and thread pools operated at equilibrium levels, eliminating initialization artifacts from the baseline characterization.

The monitoring infrastructure consisted of four collection layers. Prometheus with a 15-second scrape interval collected infrastructure and application metrics exposed through Spring Boot Actuator, cAdvisor, and kube-state-metrics. Jaeger received distributed traces from OpenTelemetry-instrumented services with a 100% sampling rate during experimental runs. Fluentd aggregated structured JSON logs from all service containers into Elasticsearch with sub-second indexing latency. A custom Kubernetes event collector captured HPA scaling decisions, pod lifecycle events, and node resource allocation changes.

3.2. Monitoring Signal Taxonomy and Collection

A. Infrastructure-Level Signals

Seven infrastructure-level signals were collected at 15-second intervals from each microservice pod. These signals were grouped into three categories based on the resource dimension they measure.

Table 1. Infrastructure-Level Monitoring Signal Taxonomy

Signal ID	Signal Name	Source	Collection Interval	Unit	Aggregation
I-1	CPU Utilization	cAdvisor	15s	Percentage	Per-pod mean
I-2	Memory Working Set	cAdvisor	15s	MiB	Per-pod current
I-3	Network I/O Rate	cAdvisor	15s	KB/s	Per-pod sum
I-4	Disk I/O Throughput	cAdvisor	15s	KB/s	Per-pod sum
I-5	JVM Heap Usage	Actuator	15s	Percentage	Per-pod current
I-6	JVM GC Pause Duration	Actuator	15s	Milliseconds	Per-pod P99
I-7	Thread Pool Active Count	Actuator	15s	Count	Per-pod current

The CPU utilization signal (I-1) was computed as the ratio of container CPU usage to the configured CPU limit, matching the metric used by HPA for scaling decisions. Memory working set (I-2) captured the non-reclaimable memory footprint excluding cached filesystem pages. JVM-specific signals (I-5 through I-7) were collected from Spring Boot Actuator endpoints exposed by each Java-based microservice, providing application runtime visibility beyond container-level resource consumption.

B. Application-Level Signals

Seven application-level signals captured behavioral indicators of service performance that reflect user-facing impact more directly than resource utilization metrics.

Table 2. Application-Level Monitoring Signal Taxonomy

Signal ID	Signal Name	Source	Collection Method	Unit	Sensitivity
A-1	API Response Latency P50	Jaeger	Trace span duration	Milliseconds	Medium
A-2	API Response Latency P99	Jaeger	Trace span duration	Milliseconds	High
A-3	Database Query Latency P95	Actuator/HikariCP	Connection pool metrics	Milliseconds	Very High
A-4	Cache Hit Rate	Redis metrics	Custom exporter	Percentage	High
A-5	Error Rate	Prometheus	HTTP status code ratio	Percentage	Medium
A-6	Request Throughput Delta	Prometheus	Rate computation	Req/s change	Low

A-7	Trace Span Anomaly Score	Jaeger	Structural analysis	Score [0,1]	High

The database query latency signal (A-3) was instrumented at the HikariCP connection pool level within each Spring Boot service, capturing the total time from connection acquisition through query execution to result set processing. This instrumentation was implemented through Micrometer integration with HikariCP's built-in metric exposure, providing per-query latency distributions without requiring application code modification. Cache hit rate (A-4) was computed as a rolling 60-second ratio of Redis cache hits to total cache access attempts for each service, with separate tracking for read-through cache patterns and explicit cache lookups. The error rate signal (A-5) aggregated HTTP 4xx and 5xx response codes at the service ingress level, weighted by the severity classification of each error type. The trace span anomaly score (A-7) was derived from comparing current trace structures against a baseline service dependency graph, flagging spans with latency exceeding 3 standard deviations from the rolling 5-minute mean. This score incorporated both individual span duration anomalies and topological anomalies where trace structures deviated from the expected call graph, capturing scenarios where degradation causes unexpected retry or fallback path activation.

3.3. Fault Injection and Degradation Scenario Design

A. Gradual Degradation Patterns

Three gradual degradation scenarios were designed to simulate the progressive performance deterioration commonly observed in production microservice environments. Scenario G1 (Memory Leak Simulation) incrementally consumed 8 MiB of heap memory per minute in the Order Service, reaching the JVM heap limit over approximately 30 minutes. Scenario G2 (Database Connection Pool Exhaustion) reduced the available HikariCP connection pool size by one connection every 90 seconds in the Travel Service, simulating connection leak behavior. Scenario G3 (Thread Pool Saturation) introduced an artificial 50-millisecond processing delay that increased by 10 milliseconds every 2 minutes in the Ticket Info Service, gradually saturating the Tomcat thread pool.

Table 3. Fault Injection Scenario Specifications

Scenario	Type	Target Service	Injection Mechanism	Duration	Degradation Rate
G1	Memory Leak	Order Service	Heap allocation increment	30 min	8 MiB/min
G2	Connection Pool Exhaustion	Travel Service	Pool size decrement	45 min	-1 conn/90s
G3	Thread Pool Saturation	Ticket Info Service	Processing delay increment	40 min	+10ms/2min
C1	Network Latency Injection	Route Service → Travel Service	tc netem delay	20 min	Step function 50ms
C2	Upstream Throughput Spike	Payment Service	Load multiplier	15 min	3x baseline
C3	Cascading Timeout	Seat Service → Order Service → Station Service	Timeout chain	25 min	Progressive

Each gradual degradation scenario was executed 20 times under identical load conditions, with 10 runs having HPA enabled and 10 runs with HPA disabled, producing 60 experimental runs for the gradual degradation category.

B. Cascading Propagation Patterns

Three cascading failure scenarios captured the inter-service degradation propagation dynamics characteristic of microservice architectures. Scenario C1 (Network Latency Injection) applied a 50-millisecond network delay using Linux Traffic Control (tc netem) on the network path between the Route Service and Travel Service, testing the propagation of latency through dependent downstream services. Scenario C2 (Upstream Throughput Spike) tripled the request rate to the Payment Service, simulating a flash-sale event that propagated back-pressure through the Order Service and ultimately affected the search API responsiveness. Scenario C3 (Cascading Timeout) initiated a timeout chain by injecting a 5-second response delay in the Seat Service, causing sequential timeout failures in the Order Service and Station Service as retry mechanisms amplified the degradation.

The cascading scenarios were similarly executed 20 times each (10 with HPA, 10 without), yielding 60 additional experimental runs. Across all 120 runs, the monitoring infrastructure collected approximately 2.4 TB of time-series metric data, 180 million distributed trace spans, and 320 million structured log entries. Data preprocessing involved timestamp alignment across the four collection channels using NTP-synchronized pod clocks with sub-millisecond drift, interpolation of missing metric samples using linear imputation for gaps shorter than 30 seconds, and normalization of all metric values to z-scores computed against the per-service pre-injection baseline. The preprocessed dataset was partitioned into a calibration subset (first 40 runs) for threshold tuning and a held-out evaluation subset (remaining 80 runs) for reporting final detection performance metrics, ensuring that the reported results reflect generalization beyond the threshold selection data.

Figure 1. Experimental Architecture and Monitoring Data Flow

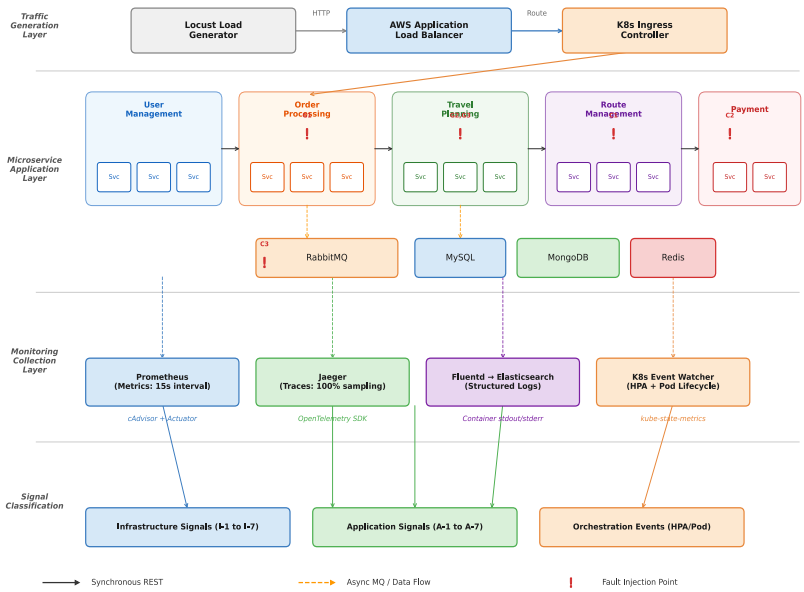

Figure 1 illustrates the complete experimental architecture deployed on Amazon EKS. The diagram should depict three horizontal layers: the top layer shows the Locust load generator sending traffic through an AWS Application Load Balancer to the Kubernetes ingress controller; the middle layer represents the TrainTicket microservice mesh with 41 service pods organized into five functional clusters (User Management, Order Processing, Travel Planning, Route Management, and Payment), with directed edges indicating synchronous REST calls and dashed edges indicating asynchronous RabbitMQ message flows; the bottom layer displays the four-channel monitoring infrastructure with Prometheus scraping metrics from cAdvisor and Actuator endpoints, Jaeger collecting trace spans via OpenTelemetry collectors, Fluentd aggregating container logs, and a custom Kubernetes event watcher capturing HPA decisions. Color coding should distinguish infrastructure-level signals (blue), application-level signals (green), and Kubernetes orchestration events (orange). The fault injection points

for all six scenarios should be marked with red exclamation icons on their respective target services.

4. Experimental Results and Analysis

4.1. Signal Detection Effectiveness Evaluation

A. Single-Source Signal Analysis

The detection lead time was measured as the elapsed time between the earliest statistically significant deviation in a monitoring signal and the moment when end-user-facing API response latency exceeded the SLA threshold of 200 milliseconds at the 99th percentile. Statistical significance was assessed using a rolling Kolmogorov-Smirnov test with a 5-minute sliding window against the pre-injection baseline distribution, with a significance level of $\alpha = 0.01$.

Across all six degradation scenarios, application-level signals consistently detected degradation earlier than infrastructure-level signals. The database query latency P95 (A-3) achieved the highest mean lead time of 4.7 minutes in the gradual degradation scenarios, with the cache hit rate deviation (A-4) providing 3.9 minutes of advance warning. Infrastructure-level signals exhibited substantially shorter lead times: CPU utilization (I-1) averaged 1.2 minutes, while JVM GC pause duration (I-6) averaged 2.1 minutes. The analysis conducted on Meta's production microservice topology confirmed that application-tier metrics capture performance degradation propagation patterns that infrastructure metrics reflect only after significant resource contention develops [13].

Table 4. Mean Detection Lead Time by Signal and Scenario Category (Minutes)

Signal	G1 (Memory)	G2 (ConnPoo)	G3 (ThreadPol)	C1 (NetDela)	C2 (Spike)	C3 (Cascade)	Overall Mean
I-1 CPU Util	1.4	0.8	1.6	0.9	1.1	1.3	1.2
I-2 Memory WS	3.8	0.4	0.3	0.2	0.5	0.4	0.9
I-5 JVM Heap	5.2	0.6	0.5	0.3	0.7	0.6	1.3
I-6 GC Pause	4.1	1.8	1.5	0.8	2.4	2.0	2.1
A-1 Latency P50	2.1	2.5	3.2	2.8	1.9	2.4	2.5
A-2 Latency P99	2.8	3.1	3.8	3.4	2.3	3.0	3.1
A-3 DB Query P95	3.2	6.8	4.5	3.9	4.1	5.7	4.7
A-4 Cache Hit Rate	1.8	4.2	3.6	5.1	3.8	4.9	3.9
A-7 Trace Anomaly	2.4	3.5	4.1	4.6	2.7	3.8	3.5

A notable observation from Table 4 is the scenario-dependent nature of signal effectiveness. The JVM heap usage signal (I-5) provided the longest lead time (5.2 minutes) specifically for memory leak scenarios (G1), while offering negligible advance warning for network-related degradation (C1). The database query latency signal (A-3) maintained consistently high lead times across all scenario types, demonstrating superior generalizability as an early warning indicator. This finding aligns with the ML-driven performance

debugging framework evaluated in production microservice environments, where database-tier metrics were identified as primary bottleneck indicators [14].

B. Multi-Source Signal Correlation Analysis

Pairwise Pearson correlation coefficients were computed across all 14 signals using 60-second aligned time windows during the pre-degradation, degradation onset, and active degradation phases. The correlation structure exhibited significant phase-dependent dynamics. During the pre-degradation baseline phase, application-level signals showed weak inter-correlation (mean |r| = 0.18), indicating that each signal captured independent aspects of system behavior. During the degradation onset phase, the correlation between A-3 (database query latency) and A-2 (API response latency P99) increased sharply from 0.12 to 0.74 within a 2-minute window, consistently preceding the correlation increase between infrastructure signals I-1 and I-5 (which shifted from 0.08 to 0.61 approximately 2.5 minutes later).

Figure 2. Multi-Source Signal Temporal Correlation Heatmap During Cascading Failure Scenario C3

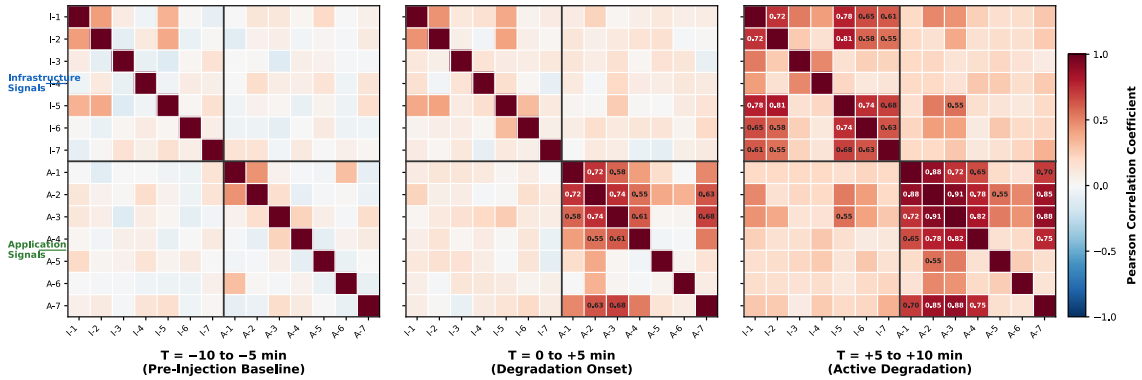

Figure 2 should present a time-evolving correlation heatmap with three panels arranged horizontally, each representing a distinct phase of the C3 cascading timeout scenario. The left panel (T = -10 to -5 minutes, pre-injection baseline) shows a 14×14 signal correlation matrix with predominantly cool colors (blues and light greens) indicating weak cross-signal correlations, except for naturally correlated pairs such as I-1/I-2 and A-1/A-2. The center panel (T = 0 to +5 minutes, degradation onset) reveals emerging warm-colored clusters (oranges and reds) forming among application-level signals A-2, A-3, A-4, and A-7, while infrastructure signals remain largely uncorrelated. The right panel (T = +5 to +10 minutes, active degradation) displays a pronounced block-diagonal structure with two strongly correlated clusters: an application signal cluster and an infrastructure signal cluster, with moderate cross-cluster correlation. A color bar ranging from -1.0 (deep blue) to +1.0 (deep red) should accompany the figure. Time stamps and signal IDs should label the axes, and thin white gridlines should separate each signal row and column for readability.

A composite early warning score was constructed by computing the weighted mean of the three highest-lead-time signals (A-3, A-4, A-7) with weights proportional to their inverse coefficient of variation across scenarios. This composite score achieved a mean lead time of 5.2 minutes with a precision of 0.91 and recall of 0.88, outperforming every individual signal. The weighted combination reduced the lead time variance by 41% compared to the best individual signal (A-3), indicating that multi-source correlation provides not only earlier but also more reliable warning.

4.2. Kubernetes Auto-Scaling Noise Impact

The comparison between HPA-enabled and HPA-disabled experimental runs revealed substantial differences in detection reliability. Across all signals and scenarios, the mean false positive rate increased from 4.8% (HPA-disabled) to 28.4% (HPA-enabled), representing a 23.6 percentage point degradation attributable to auto-scaling dynamics. The false positive distribution was not uniform across signals: infrastructure-level signals suffered a mean false positive increase of 31.2%, while application-level signals experienced a more modest increase of 16.1%.

The primary source of HPA-induced false positives was identified as the pod startup transient period. Newly scaled pods exhibited elevated CPU utilization (averaging 78% during the first 45 seconds versus 42% steady-state), JVM warm-up effects causing GC pause spikes of 3-5x baseline duration, and temporarily degraded response latencies as connection pools initialized and caches populated. These transients triggered anomaly detection thresholds despite representing normal operational behavior.

A temporal filtering heuristic was evaluated: excluding monitoring data from any pod within 90 seconds of its

creation timestamp (as recorded by the Kubernetes event stream). This heuristic reduced the HPA-induced false positive rate from 28.4% to 9.3%, a 67.2% reduction, while preserving 96.8% of true positive detections. The 3.2% reduction in true positives occurred exclusively in scenarios where genuine degradation coincided with scaling events within the 90-second exclusion window. Sensitivity analysis on the exclusion window duration revealed that shorter windows (30 seconds, 60 seconds) achieved less effective noise reduction (28.1% and 51.4% respectively), while longer windows (120 seconds, 180 seconds) provided marginal additional benefit (69.8% and 71.3%) at the cost of increased true positive loss (5.1% and 8.7%). The 90-second threshold represented the optimal balance point on the noise-reduction-versus-true-positive-preservation trade-off curve for the Java-based microservices evaluated in this study. An investigation of automatic root cause analysis approaches for cloud incidents identified analogous challenges in distinguishing orchestration-induced transients from genuine anomalies, noting that temporal context from cluster management events is essential for accurate diagnosis [15].

Figure 3. Detection Precision-Recall Curves Under HPA-Enabled vs. HPA-Disabled Conditions

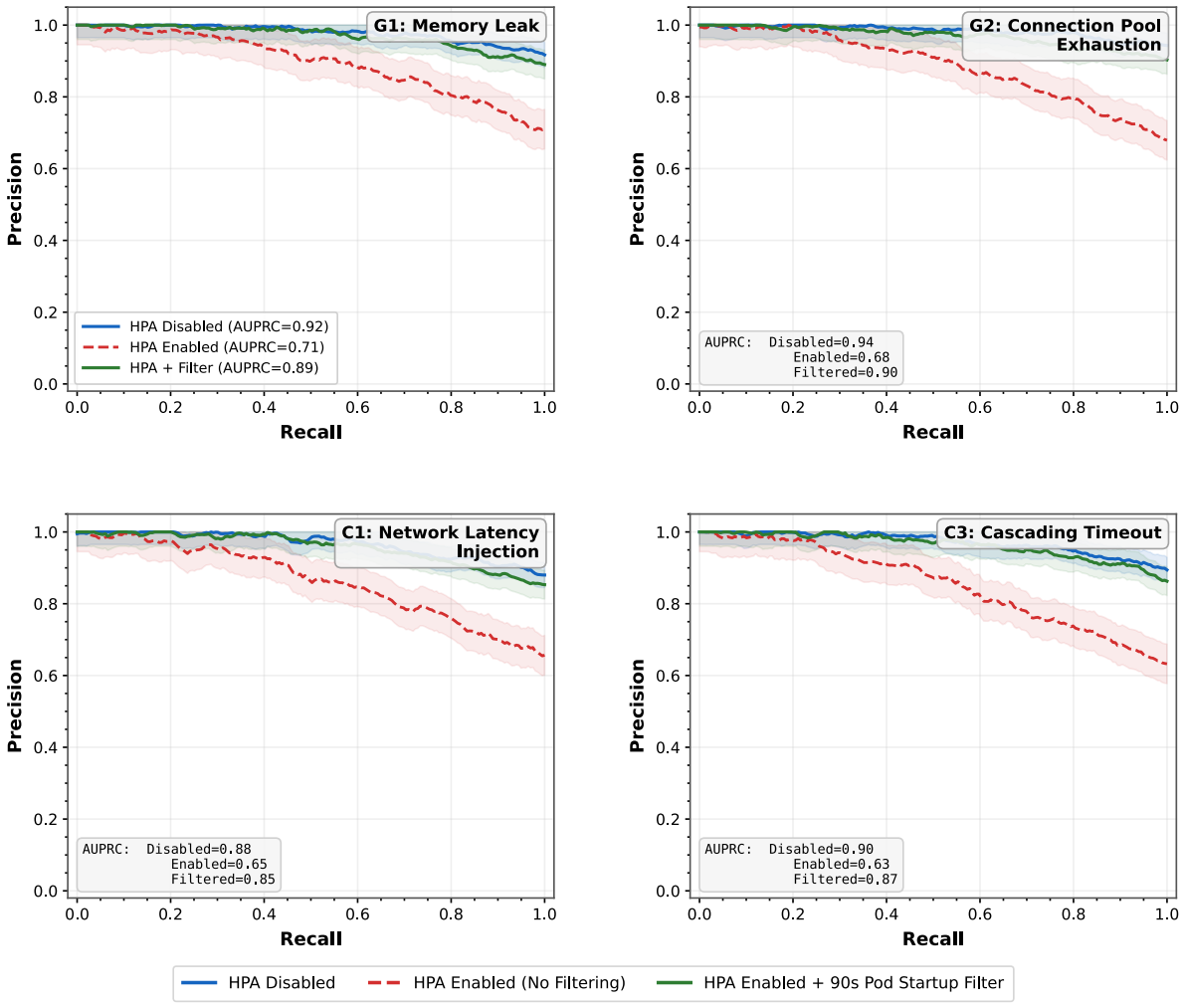

Figure 3 should display a precision-recall curve plot with six subplot panels arranged in a 2×3 grid, one for each degradation scenario (G1, G2, G3, C1, C2, C3). Within each subplot, three curves should be drawn: a solid blue line representing detection performance with HPA disabled, a dashed red line representing performance with HPA enabled (no filtering), and a solid green line representing performance with HPA enabled plus the 90-second pod startup exclusion heuristic. Each curve should be accompanied by a shaded region indicating the 95% confidence interval computed across the 10 repeated runs per condition. The area under each precision-recall curve (AUPRC) should be annotated in a legend box within each subplot. The x-axis should range from 0 to 1.0 (Recall) and the y-axis from 0 to 1.0 (Precision). A consistent visual pattern

should emerge across all six subplots: the HPA-disabled curve achieving the highest AUPRC, the unfiltered HPA-enabled curve showing the lowest AUPRC with pronounced precision degradation at high recall thresholds, and the filtered HPA-enabled curve recovering to within 3-5% of the HPA-disabled baseline. Grid lines at 0.2 intervals on both axes should provide reference, and each subplot title should indicate the scenario identifier and name.

4.3. Financial Infrastructure Implications

A. SLA Compliance Analysis

The lead time advantages documented in Section 4.1 translate directly into operational SLA compliance capabilities for financial microservice deployments. Under a representative financial services SLA requiring 99.9% of API transactions to complete within 200 milliseconds, the composite multi-source early warning score provides a mean 5.2-minute advance warning window. This window exceeds the typical incident response time of 3-4 minutes reported by financial institution site reliability engineering teams, enabling proactive mitigation actions such as pre-emptive traffic rerouting, circuit breaker activation, or manual scaling interventions before SLA breaches accumulate.

Quantifying the operational impact, the 5.2-minute lead time translates to an estimated prevention of 78-156 SLA-violating transactions per degradation event at a transaction throughput of 900-1800 transactions per minute, a rate representative of mid-tier financial payment processing platforms. The cost avoidance calculation, using industry-reported figures of \$0.50-\$2.00 per failed financial API transaction in retry costs, customer compensation, and regulatory reporting overhead, yields an estimated saving of \$39-\$312 per prevented degradation event, with cumulative annual savings scaling proportionally to incident frequency.

The scenario-specific analysis reveals that database connection pool exhaustion (G2) and cascading timeout (C3) scenarios pose the greatest risk to financial SLA compliance, as these degradation patterns affect transaction-critical data access paths. The database query latency signal (A-3) provides 6.8 and 5.7 minutes of lead time for these scenarios respectively, establishing it as the highest-priority monitoring signal for financial microservice deployments. The cache hit rate signal (A-4) serves as a complementary indicator, capturing degradation patterns in read-heavy query paths that characterize market data distribution and account balance inquiry services.

B. Deployment Recommendations

The experimental findings support several concrete deployment recommendations for organizations operating Kubernetes-based microservice architectures in financial or other latency-sensitive domains. Monitoring priority should be assigned to application-level signals over infrastructure-level metrics, with database query latency and cache hit rate positioned as primary early warning indicators. The 90-second pod startup exclusion window should be implemented as a standard filtering mechanism in any anomaly detection pipeline operating alongside Kubernetes HPA, with the exclusion duration calibrated to the specific JVM warm-up characteristics of the deployed services. The composite multi-source scoring approach demonstrated in this study can be implemented using lightweight statistical computations (rolling means, standard deviations, and Kolmogorov-Smirnov tests) that impose negligible computational overhead on existing Prometheus-based monitoring infrastructure.

Organizations should also consider the signal taxonomy presented in Tables 1 and 2 as a baseline monitoring instrumentation checklist, ensuring that all 14 signals are collected at the specified intervals and granularities. The relatively low computational overhead of the statistical detection methods employed in this study—rolling Kolmogorov-Smirnov tests require O(n log n) computation per window update—makes real-time implementation feasible within existing Prometheus-based alerting pipelines without dedicated anomaly detection infrastructure. The correlation analysis in Section 4.1.B demonstrated that the phase-dependent correlation structure among signals provides additional diagnostic value beyond individual signal thresholds, and production alerting systems should incorporate cross-signal correlation tracking to capture the early emergence of correlated degradation patterns.

5. Conclusion

5.1. Summary of Findings

This study conducted a systematic empirical evaluation of 14 multi-source monitoring signals for their effectiveness in predicting performance degradation in Kubernetes-based microservice architectures. The experimental investigation, comprising 120 controlled fault injection runs across six degradation scenarios on the TrainTicket benchmark deployed on Amazon EKS, yielded three principal findings that address the research questions posed in Section 1.2.

Regarding RQ1, application-level monitoring signals demonstrated a consistent and substantial lead time advantage over infrastructure-level metrics for performance degradation prediction. The database query latency P95 signal achieved the highest overall mean lead time of 4.7 minutes, outperforming the best infrastructure signal (JVM GC pause duration at 2.1 minutes) by a factor of 2.2. The cache hit rate deviation and trace anomaly score provided complementary early

warning at 3.9 and 3.5 minutes respectively. These results establish a quantitative hierarchy of monitoring signal predictive value that has not been previously reported in the microservice reliability literature.

Regarding RQ2, Kubernetes HPA dynamics introduced a 23.6 percentage point increase in false positive rates across all monitoring signals, with infrastructure-level signals disproportionately affected (31.2% increase versus 16.1% for application-level signals). The pod startup transient period, characterized by elevated resource consumption during JVM initialization and cache warming, was identified as the dominant source of HPA-induced false alarms. A temporal filtering heuristic excluding data from pods within 90 seconds of creation reduced HPA-induced false positives by 67.2% while preserving 96.8% of true positive detections.

Regarding RQ3, the composite multi-source early warning score constructed from the three highest-performing signals (A-3, A-4, A-7) achieved a mean lead time of 5.2 minutes with precision of 0.91 and recall of 0.88, outperforming every individual signal on both dimensions. The multi-source approach reduced lead time variance by 41% compared to the best single signal, demonstrating that signal correlation provides not only earlier but also more stable early warning performance.

5.2. Limitations

Several limitations bound the generalizability of these findings. The experimental evaluation was conducted on a single benchmark application (TrainTicket) with a fixed architectural topology, and the degradation scenarios, while representative, do not exhaustively cover all production failure modes. The load patterns were synthetically generated and may not fully capture the burstiness and long-tail characteristics of real financial transaction workloads. The 15-second metric scrape interval imposed a temporal resolution floor that may obscure faster-evolving degradation patterns detectable at sub-second granularity.

Future work should extend this evaluation to additional microservice benchmarks with varying architectural complexities, including service mesh configurations with Istio or Linkerd that introduce additional network-level observability. The effectiveness of the proposed filtering heuristics should be validated in production environments where the interplay between organic traffic variation, planned deployments, and genuine degradation events creates substantially richer noise characteristics than controlled experimental settings. Cross-cloud evaluation across Azure AKS and Google GKE would establish whether the signal lead time hierarchy and HPA noise characteristics observed on Amazon EKS generalize across different managed Kubernetes implementations with distinct scheduling and networking behaviors. The integration of large language model-based anomaly interpretation with the multi-source signal framework represents a promising direction for enhancing the actionability of early warning alerts in operational contexts. The signal taxonomy and experimental methodology presented in this study provide a reusable framework for such extended evaluations.

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