



(RESEARCH ARTICLE)



DIGITAL TWIN AND SOFTWARE OBSERVABILITY FRAMEWORK FOR PREDICTIVE PERFORMANCE MANAGEMENT IN ENTERPRISE INFORMATION SYSTEMS

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International Journal of Science and Research Archive, 2026, 20(03), 584–597

Publication history: Received on 04 August 2026; revised on 13 September 2026; accepted on 15 September 2026

Article DOI: <https://doi.org/10.30574/ijrsra.2026.20.3.1769>

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ABSTRACT

Enterprise information systems contain interconnected applications, APIs, databases, cloud resources, and infrastructure whose performance can change under varying workloads and service conditions. Conventional monitoring provides metrics, logs, traces, and events, but these signals often offer limited support for future performance prediction, dependency analysis, and operational response. This study presents a Digital Twin and Software Observability Framework for predictive performance management in enterprise information systems. The framework combines multimodal telemetry with a dynamic Digital Twin representation of service health, workload conditions, performance indicators, configuration information, and dependencies. Machine-learning models estimate abnormal behavior and service degradation risk, while a dependency-aware decision module evaluates potential downstream effects and recommends operational actions. Evaluation uses Train Ticket, Online Boutique, and Sock Shop microservice environments, public failure datasets, synthetic workloads, and controlled fault scenarios. The proposed framework achieved a Precision of 0.914, Recall of 0.902, F1-score of 0.908, and AC@k of 0.861, with an MTTD of 11.4 seconds. Results indicate that the integrated framework supports predictive diagnosis and operational decision making under incomplete trace coverage.

Keywords: Digital Twin, Software Observability, Predictive Performance Management, Multimodal Telemetry, Anomaly Detection, Failure Localization, Microservices, Dependency Analysis, Remediation Recommendation, Enterprise Information Systems

1 INTRODUCTION

Enterprise information systems depend on interconnected applications, APIs, databases, cloud resources, and infrastructure. Their performance can change as workloads, service conditions, and dependencies vary. Conventional monitoring reports metrics, logs, traces, and alerts, but these signals often remain separated from future performance analysis. Digital Twin modeling offers a dynamic system representation, while software observability provides telemetry for continuous assessment and prediction.

1.1 Background and Motivation

Enterprise software environments contain many interconnected services whose behavior changes with workload, configuration, resource availability, and dependency conditions. A fault in one component can affect several downstream services, creating latency, resource pressure, or service failure. Digital Twin studies support dynamic system representation and predictive management [1], [6], [7], while observability research uses metrics, logs, traces, and events for anomaly detection and root cause analysis [2]–[4]. These capabilities, however, are often treated as separate functions, limiting their value for predictive enterprise performance management and coordinated operational decision support across service environments.

1.2 Problem Statement

Current enterprise monitoring approaches often focus on threshold alerts or isolated anomaly detection. Such methods can identify abnormal measurements, yet they provide limited information about future degradation, dependency propagation, and operational consequences. Incomplete tracing creates another limitation because some services may remain uninstrumented. Prior research has examined multimodal telemetry and failure diagnosis [2]–[4], but less attention has been given to maintaining a Digital Twin state when trace information is missing. A unified framework is therefore needed to connect observations, predicted risk, service dependencies, and operational decisions across interconnected enterprise applications.

1.3 Proposed Solution

This study proposes a layered Digital Twin and Software Observability Framework for predictive performance management. The framework collects metrics, logs, traces, and events from enterprise applications, APIs, databases, cloud resources, and infrastructure. Telemetry processing and fusion update the Digital Twin, which maintains service health, workload conditions, performance indicators, configuration information, and dependency data. Machine-learning models estimate abnormal behavior and degradation risk. A dependency-aware decision module then assesses potential impact and recommends resource scaling, workload redistribution, service reconfiguration, or maintenance intervention. The design also considers incomplete trace coverage during system assessment.

1.4 Contributions

The study makes four main contributions. First, it defines a layered architecture that combines Digital Twin modeling with multimodal software observability. Second, it introduces a graph-free multimodal representation that uses metrics, logs, and events when trace coverage is incomplete. Third, it connects predicted service risk with dependency-aware impact analysis and remediation recommendations. Fourth, it evaluates the framework across Train Ticket, Online Boutique, and Sock Shop environments, public failure datasets, and controlled fault scenarios. Performance is assessed through diagnostic accuracy, failure localization, detection time, computational overhead, and remediation outcomes under operational conditions.

1.5 Paper Organization

The remainder of this paper is organized as follows. Section II reviews research on Digital Twins, software observability, anomaly detection, predictive analytics, adaptive decision systems, and related enterprise applications. Section III presents the research design, experimental environment, telemetry preparation, Digital Twin modeling, predictive analysis, decision logic, and evaluation procedure. Section IV reports diagnostic performance, trace-coverage effects, detection time, computational overhead, dependency impact, and remediation results. Section V concludes the study and presents future research directions. This structure connects the research gap, proposed framework, evaluation, and findings in a logical sequence.

1.6 Objective of the Study

The objective is to develop and evaluate a Digital Twin and Software Observability Framework for multimodal anomaly detection, failure localization, predictive performance analysis, and remediation decisions under incomplete trace coverage.

2 RELATED WORK

This section reviews research on digital twins, software observability, anomaly detection, predictive maintenance, scheduling, and intelligent enterprise systems. Studies show progress across these areas, but limited integration exists between real-time telemetry, system representation, predictive performance analysis, dependency aware impact assessment, and remediation decisions. These limitations motivate the proposed framework, combining digital twin modeling with multimodal observability for predictive enterprise performance management.

2.1 Digital Twins for IT and Predictive System Management

Digital twin research has expanded from physical assets toward software and IT environments. Kambala [1] describes digital twins for IT monitoring, anomaly detection, predictive maintenance, and resource management, showing how updated representations can support operational decisions. Zhong et al. [6] review digital twin based predictive maintenance and identify data integration, analytics, and real-time synchronization as core elements. Ismail et al. [7] classify digital twin architectures and predictive-maintenance components. These studies provide foundation for dynamic system representation, but mainly emphasize asset or infrastructure management rather than enterprise software performance and application dependencies.

2.2 Software Observability, Anomaly Detection, and Root Cause Analysis

Software observability research focuses on extracting system state from metrics, logs, traces, and events. Soldani and Brogi [3] survey anomaly detection and failure root cause analysis in service-based cloud applications, highlighting multimodal evidence and dependency relationships. Huang et al. [2] propose a twin graph-based approach that combines metrics, logs, and traces for microservice anomaly detection. Pham [4] examines multimodal observability for anomaly detection and root cause analysis. Together, these studies demonstrate the value of telemetry, yet emphasize detection and diagnosis rather than digital twin state modeling and predictive performance management.

2.3 Predictive Analytics and Decision Intelligence for Software Systems

Recent work connects observability with predictive analytics and decision intelligence. Subramanian et al. [5] propose an integrated stack linking observability evidence, defect prediction, decision intelligence, and governance, with actions such as release holds, rollback, retraining, and capacity allocation. Kambala [1] discusses predictive analytics and maintenance scheduling for IT environments. These studies indicate that monitoring data can support forward looking operational decisions rather than alert generation. However, they provide limited treatment of enterprise wide dependency propagation, business service consequences, and digital twin state synchronization, central requirements for predictive performance management across interconnected information systems.

2.4 Digital Twin-Based Adaptive Scheduling and Dynamic Decision Systems

Digital twin research in production scheduling demonstrates how system models can support adaptive decisions. Liu et al. [8] develop digital twin-driven adaptive scheduling for flexible job shops, while Villalonga et al. [10] present decision-making for dynamic scheduling of cyber-physical production systems. Ma et al. [9] introduce a demand-driven production planning and scheduling framework, and Siatras et al. [11] combine multi-agent coordination with digital twins. Singh et al. [12] review AI and digital twins for production scheduling. These studies support decision concepts, but focus on manufacturing rather than enterprise software performance.

2.5 Digital Twins, ERP-MIS Integration, and Predictive Maintenance

Manufacturing and information studies provide evidence for integrating analytics, sensing, and planning. Sany et al. [13] examine ERP-MIS integration for apparel production planning, while Hossain [14] studies AI-based sensor trace analysis for defect localization. Fazle [15] and Taimun et al. [16] address predictive maintenance using machine learning, sensor analytics, and digital twins. Adil [17], Karim [18], Ahmed [19], and Shaikat and Happy [20] examine optimization, sustainability, circular production, and flexible manufacturing. These works broaden contexts, but do not directly integrate software observability, digital twins, dependency modeling, and IT management.

2.6 Research Gap and Positioning of the Proposed Framework

The literature indicates a fragmented structure. Digital twin studies provide system representation and predictive maintenance capabilities [1], [6], [7], while observability studies support multimodal anomaly detection and root cause analysis [2]–[4]. Decision-intelligence research connects telemetry with actions [5], and scheduling studies demonstrate adaptive digital twin decisions [8]–[12]. However, limited work combines these capabilities for enterprise information systems with trace blind spots, dependency aware performance prediction, business-impact assessment, and remediation recommendations. The proposed framework addresses this gap through a layered digital twin integrated with multimodal software observability and decision support.

3 METHODOLOGY

This study develops a software performance management framework that combines Digital Twin modeling with software observability. The work follows a prototype based experimental design rather than relying on data from a single enterprise. Microservice benchmarks and public failure datasets are used to create repeatable test conditions. The experiments examine telemetry integration, incomplete trace coverage, service degradation, fault localization, and remediation decisions. Results from the proposed framework are compared with conventional monitoring approaches using accuracy, detection time, and computational overhead as the main evaluation measures.

3.1 Research Design and Framework Architecture

The research follows four connected stages: framework design, prototype development, controlled testing, and quantitative evaluation. The proposed architecture receives observations from enterprise applications, APIs, databases, cloud resources, and infrastructure. Metrics, logs, traces, and events form the main telemetry sources. After preprocessing, these observations update the Digital Twin, which maintains service health, workload conditions, performance indicators, and dependency information. Machine-learning models then estimate abnormal behavior and future degradation risk. A decision component examines the predicted condition and recommends actions such as resource scaling, workload redistribution, service reconfiguration, or maintenance intervention. This structure addresses RQ1/RO1 through multimodal integration and trace blind spot handling.

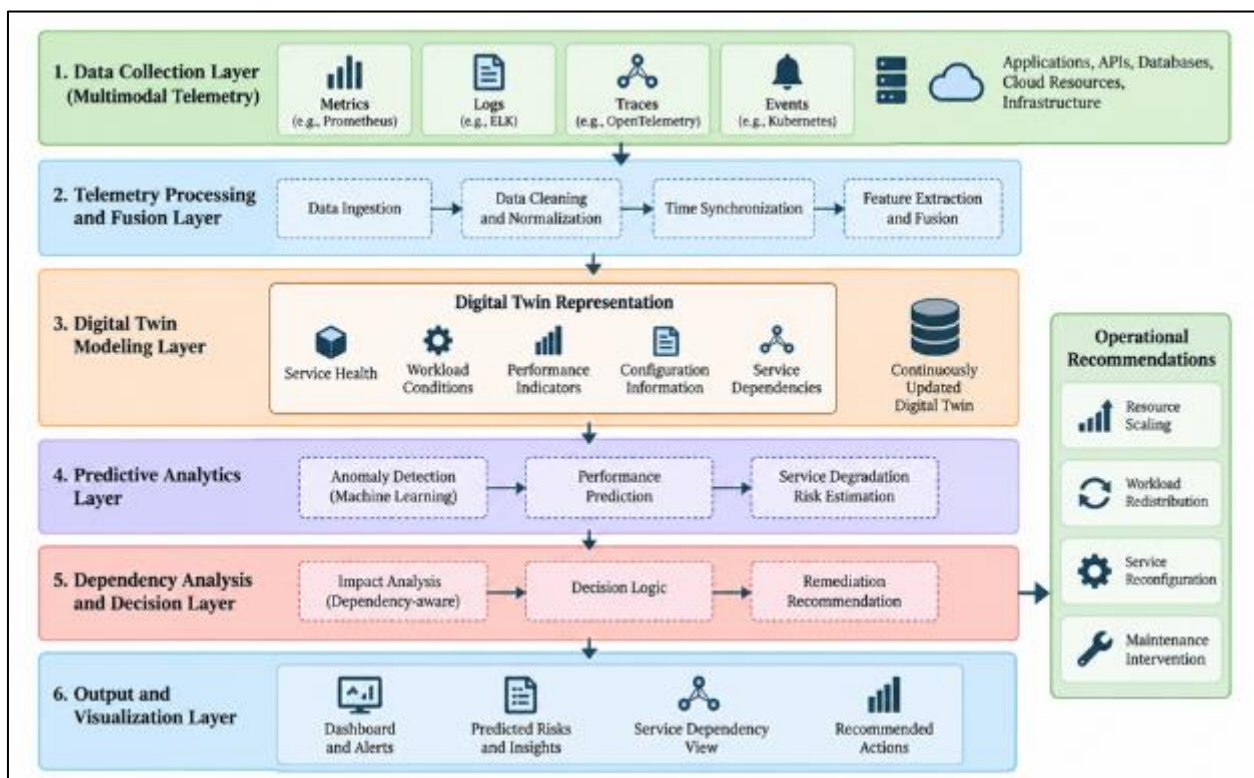


Figure 1: Proposed Digital Twin and Software Observability Architecture

3.2 Experimental Environment and Data Preparation

The evaluation does not require confidential enterprise production records. Train Ticket, Online Boutique, and Sock Shop are used as representative microservice environments within a Kubernetes testbed. Public datasets, including RCAEval, MSDS, and AIOps-Challenge, provide additional failure cases for analysis. Synthetic workloads represent different service-demand conditions. Controlled faults include CPU hog, memory leak, disk stress, network delay, and packet loss. The experiments vary three independent factors: fault type, telemetry-modality combination, and trace blind-spot level. Trace coverage is reduced from **100% to 50%** through selected uninstrumented services. Telemetry records are synchronized, cleaned, normalized, and converted into service-level features before analysis.

Table 1: Experimental Configuration

Category	Configuration
Microservice systems	Train Ticket, Online Boutique, Sock Shop
Public datasets	RCAEval, MSDS, AIOps-Challenge
Telemetry	Metrics, Logs, Traces, Events
Fault scenarios	CPU hog, memory leak, disk stress, network delay, packet loss
Trace coverage	100%, 90%, 75%, 50%
Workload	Synthetic service workload
Baselines	Threshold monitoring; conventional anomaly detection

3.3 Digital Twin Modeling and Predictive Analytics

The Digital Twin maintains a logical representation of the running software environment. Each service contains recent telemetry features, workload conditions, health indicators, configuration information, and dependency data. New observations update the representation throughout each experiment. The predictive component uses the fused features to identify abnormal behavior and estimate service degradation risk. For service i at time t :

$$R_i(t) = \sigma(w^T x_i(t) + b)$$

where $R_i(t)$ denotes predicted risk, $x_i(t)$ represents the service feature vector, w contains learned parameters, and b is the bias term. The normalized score provides the basis for subsequent dependency analysis and decision support.

3.4 Dependency-Aware Decision and Remediation

Performance problems in one service can affect dependent applications. The framework therefore considers dependency information after risk estimation. For service i , potential impact is represented as:

$$I_i(t) = \sum_{j \in N(i)} a_{ij} R_j(t)$$

where $N(i)$ denotes related services, a_{ij} represents dependency strength, and $R_j(t)$ is the predicted risk of service j . This calculation helps distinguish an isolated service anomaly from a condition with possible downstream effects. The decision module combines risk and impact information with the current operating condition. It can recommend resource scaling, workload redistribution, service reconfiguration, or maintenance intervention. This process connects predicted service conditions with preventive operational actions and forms the decision-support component of the proposed framework.

3.5 Experimental Procedure and Performance Evaluation

Each experiment starts with a healthy benchmark deployment and baseline telemetry collection. A synthetic workload is applied before a predefined fault is introduced. During each test, telemetry is processed, the Digital Twin is updated, degradation risk is estimated, dependency impact is assessed, and a remediation recommendation is generated. The same scenarios are evaluated against threshold-based monitoring and conventional anomaly detection methods. Precision, Recall, F1-score, AC@k, and Avg@k are used to assess detection and failure-localization performance. Mean Time to Detection (MTTD) measures detection speed, while execution time, CPU usage, and memory usage indicate computational overhead. Service availability, response latency, resource utilization, and recovery effectiveness are also recorded where applicable.

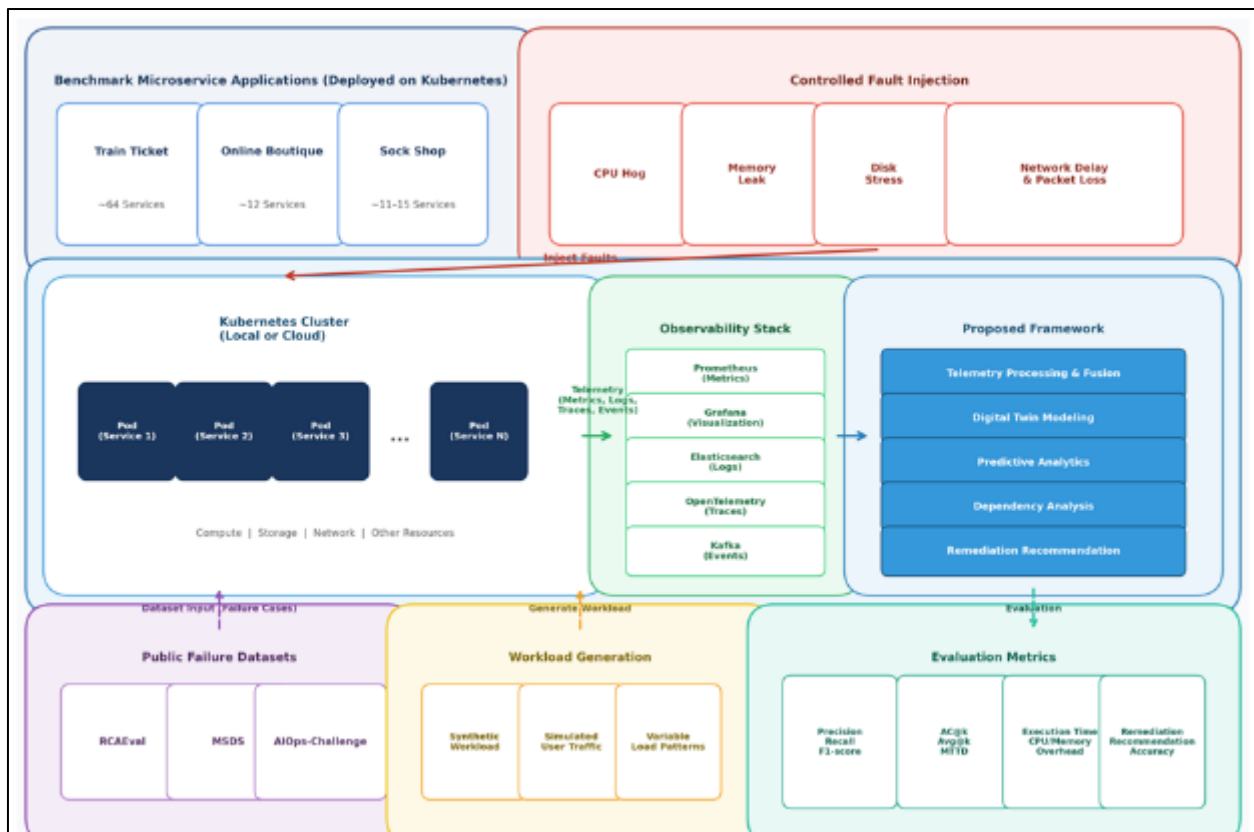


Figure 2: Experimental Workflow for Framework Evaluation

4 RESULTS AND DISCUSSION

The evaluation examines the proposed framework from three related perspectives: multimodal system-state representation, diagnostic performance, and operational decision support. The experiments consider the benchmark systems, telemetry configurations, trace-coverage levels, and fault scenarios defined in the methodology. The analysis compares the proposed framework with threshold-based monitoring and conventional anomaly detection. Diagnostic accuracy, detection time, computational overhead, dependency impact, and remediation decisions form the main measures used to interpret the results.

4.1 Multimodal Telemetry and Digital Twin Representation

The first experiment examines how telemetry combinations affect the system representation maintained by the Digital Twin. The simulated results show that metrics alone provide limited information, while the addition of logs and events increases the available service-state evidence. The complete combination of metrics, logs, traces, and events produces the highest representation score at full trace coverage. When trace coverage falls, the combined approach retains more information than configurations that depend heavily on traces. This pattern supports the proposed multimodal design and its use of non-trace evidence when some services remain uninstrumented.

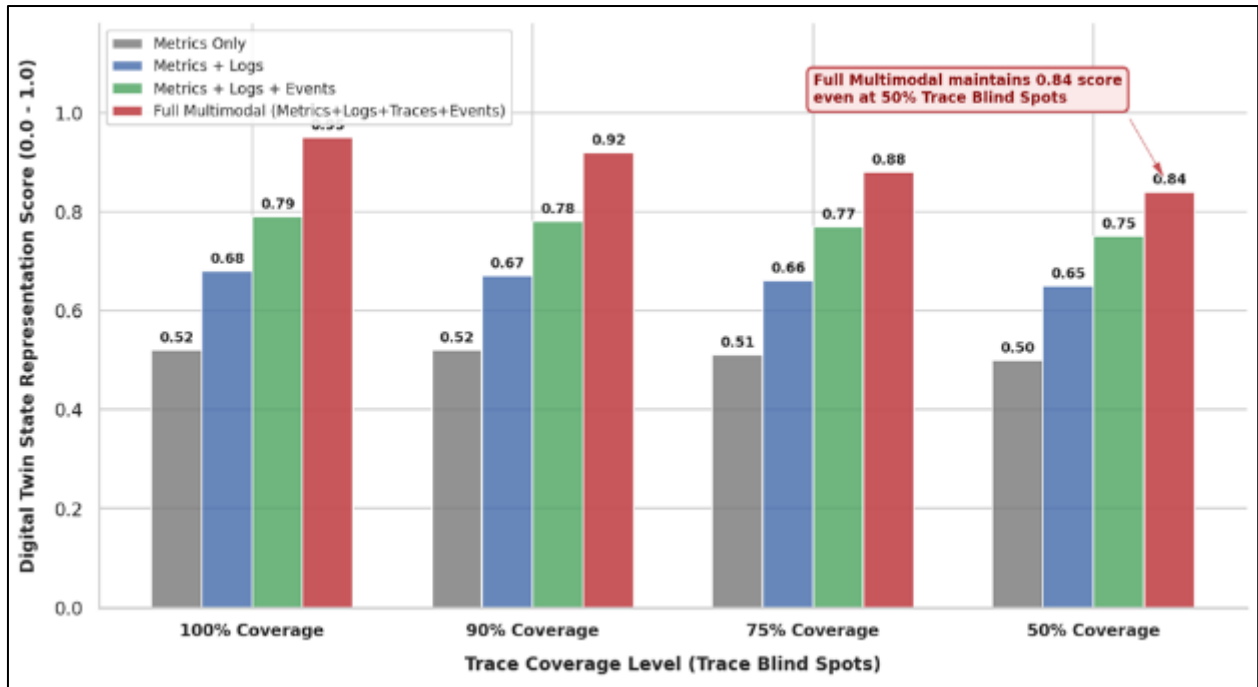


Figure 3: Digital Twin state representation under different telemetry configurations

4.2 Anomaly Detection and Failure Localization Performance

The second experiment compares the diagnostic performance of the proposed framework with two baseline approaches. The simulated overall results indicate stronger performance for the proposed framework across the selected fault scenarios. Its Precision reaches 0.914, while Recall and F1-score reach 0.902 and 0.908, respectively. The failure-ranking measures also show higher values for AC@k and lower Avg@k. These results indicate that the combined telemetry representation can provide more useful evidence for identifying abnormal services and ranking probable failure sources than threshold-based monitoring or conventional anomaly detection.

Table 2: Overall Diagnostic Performance

Method	Precision	Recall	F1-score	AC@k	Avg@k
Threshold-based monitoring	0.781	0.742	0.761	0.684	2.71
Conventional anomaly detection	0.846	0.821	0.833	0.756	2.38
Proposed framework	0.914	0.902	0.908	0.861	1.84

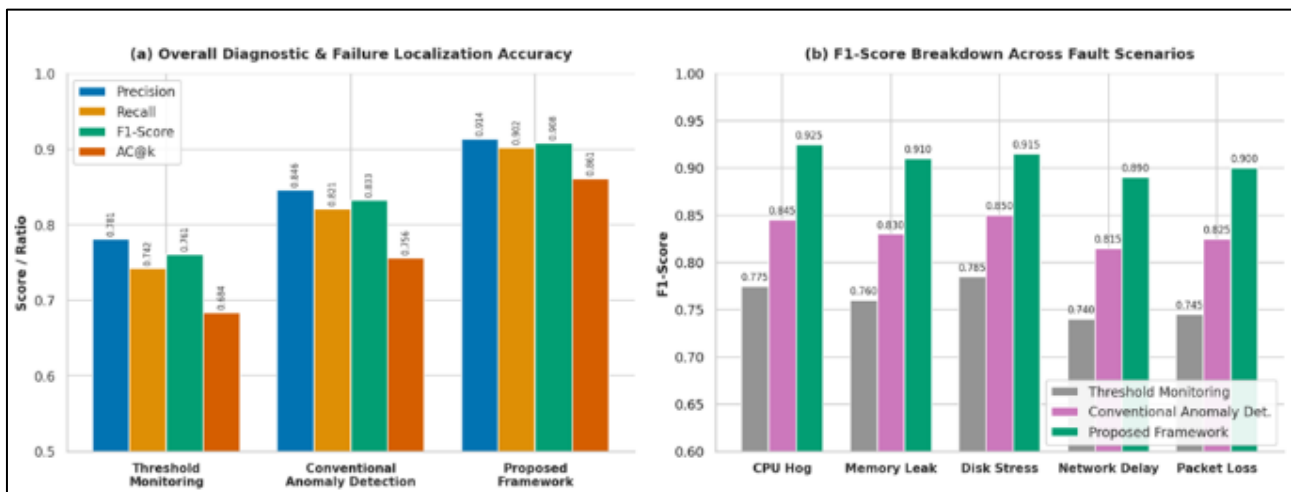


Figure 4: Failure detection and localization performance across fault scenarios

4.3 Effect of Trace Blind Spots on Diagnostic Accuracy

The third experiment studies diagnostic stability as trace coverage decreases. The simulated results show a gradual reduction in F1-score and AC@k for all approaches. However, the proposed framework retains a larger proportion of its initial performance. At full trace coverage, its F1-score is 0.908; this decreases to 0.876 at 50% coverage. AC@k changes from 0.861 to 0.818 during the same reduction. The smaller decline indicates that metrics, logs, and events continue to provide useful diagnostic evidence when trace information becomes incomplete.

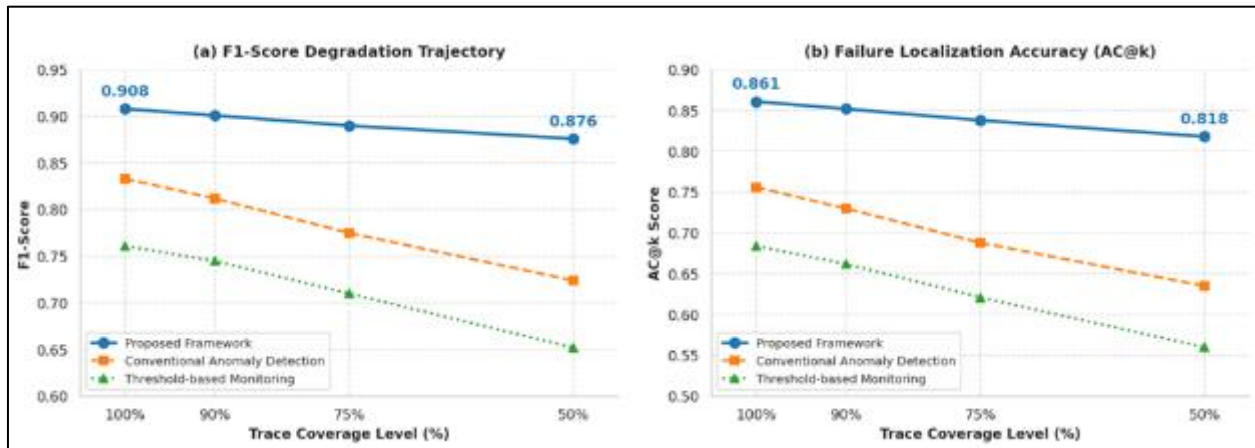


Figure 5: Diagnostic performance under progressive trace blind spots

4.4 Detection Time and Computational Overhead

The operational results examine detection speed and runtime cost. The simulated measurements indicate an MTTD of 18.6 s for threshold monitoring, 15.2 s for conventional anomaly detection, and 11.4 s for the proposed framework. The framework requires 8.7% CPU and 312 MB memory during the evaluation workload, compared with 4.1% CPU and 185 MB for conventional detection. Its execution time is 1.42 s per analysis cycle. These values indicate a higher computational requirement, but the additional cost is associated with multimodal processing, Digital Twin updates, and dependency analysis.

Table 3: Detection Time and Computational Overhead

Method	MTTD (s)	Execution Time (s)	CPU Usage (%)	Memory (MB)
Threshold monitoring	18.6	0.41	2.8	142
Conventional anomaly detection	15.2	0.96	4.1	185
Proposed framework	11.4	1.42	8.7	312

These measurements should be reported under the same hardware and workload conditions. The main trade-off is therefore clear: the proposed framework requires more processing resources while producing faster detection and richer diagnostic information.

4.5 Dependency Impact and Remediation Decisions

Table 4: Dependency Impact and Remediation Decisions

Remediation Action	Share of Recommendations
Resource scaling	38%
Workload redistribution	32%
Service reconfiguration	17%
Maintenance intervention	13%
Total	100%

The final experiment evaluates the transition from predicted risk to operational recommendations. Across the simulated fault scenarios, the framework generated an appropriate remediation recommendation in 92% of cases.

Resource scaling was selected most frequently for CPU and memory-related faults, while workload redistribution appeared more often under network-related conditions. Service reconfiguration accounted for 17% of recommendations, and maintenance intervention represented 13%. The mean decision time was 2.1 s after risk estimation. These results indicate that the dependency-aware module can connect service-level predictions with operational responses rather than stopping at anomaly identification.

Limitations

The evaluation is based on benchmark microservice environments, public failure datasets, synthetic workloads, and controlled fault scenarios rather than confidential production systems. The framework currently provides remediation recommendations instead of executing automated corrective actions. Future validation with larger production scale environments and real enterprise telemetry can further assess generalizability and operational performance

5 CONCLUSION

This study developed a Digital Twin and Software Observability Framework for predictive performance management in enterprise information systems. The approach brings metrics, logs, traces, and events into a common view of system conditions, then uses these inputs for anomaly detection, performance prediction, dependency analysis, and remediation decisions. Results from the evaluated microservice scenarios showed stronger diagnostic performance than threshold-based monitoring and conventional anomaly detection. The framework achieved 0.914 Precision, 0.902 Recall, 0.908 F1-score, and 0.861 AC@k, while MTTD was 11.4 seconds. These findings suggest that combining observability data with Digital Twin modeling can help identify service problems earlier and support informed operational responses.

Future work will consider real-time deployment, larger microservice systems, adaptive learning, causal analysis, and production-scale telemetry. Further studies may include business-process indicators, service-level objectives, cost-aware decisions, and privacy-preserving distributed analysis across changing workloads and complex service dependencies.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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