International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 7, Issue 6, November-December 2024||

DOI:10.15662/IJRPETM.2024.0706008

Cloud-Native Risk-Based Testing Pipeline for Healthcare ERP Systems: A Databricks-Driven Intelligence Model for SAP and Oracle EBS Workloads

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ABSTRACT: This paper proposes a novel cloud-native, risk-based testing pipeline for healthcare enterprise resource planning (ERP) systems, specifically targeting the integration of SAP S/4HANA (and legacy SAP) and Oracle E-Business Suite (Oracle EBS) workloads within real-time and mission-critical healthcare environments. Our approach leverages the data engineering and intelligence capabilities of the Databricks Lakehouse platform to drive test orchestration, risk scoring, and continuous validation. In healthcare settings, ERP systems are increasingly integrated with clinical and operational data streams—medical device telemetry, patient-monitoring systems, staffing and supply-chain systems—so testing pipelines must be agile, responsive and risk-aware. The proposed pipeline incorporates phases of ingestion of ERP data (transactional, configuration, customisation), risk profiling (based on business process criticality, compliance sensitivity, change impact), test generation (automated selection of high-risk scenarios), execution (cloud-native test harnesses, containerised test runners, orchestration via CI/CD), monitoring (real-time telemetry of test outcomes and risk metrics) and feedback loops (to adjust risk weights and test scope). A case study simulation is presented for a large healthcare provider migrating SAP and Oracle EBS workloads into a multicloud environment, showing improvements in defect detection in high-risk modules, reduction in testing cycle time and enhanced compliance traceability. The results show that coupling Databricks-driven intelligence with a risk-based testing framework yields a testing pipeline that is scalable, adaptive, and aligned with healthcare-specific regulatory, operational and data-quality demands. The paper closes by discussing benefits, limitations and suggestions for future work in healthcare ERP testing pipelines.

KEYWORDS: risk-based testing, cloud-native testing pipeline, healthcare ERP, SAP S/4HANA, Oracle EBS, Databricks, Lakehouse, continuous testing, compliance, real-time data streams.

I. INTRODUCTION

In the modern healthcare enterprise, ERP systems such as SAP S/4HANA and Oracle E-Business Suite play a central role in connecting clinical operations, supply chain, finance, human resources and medical device management. At the same time, healthcare organisations are increasingly adopting cloud-native architectures, real-time patient monitoring systems, Internet of Medical Things (IoMT) devices, and advanced analytics platforms. This convergence creates new demands on the underlying ERP systems: they must interface with streaming telemetry, support rapid change cycles, meet stringent regulatory and compliance requirements (e.g., HIPAA, GDPR, medical-device standards), and maintain high availability and data integrity. Traditional testing pipelines—often manual, ad-hoc or heavy-document oriented—are no longer adequate for this dynamic, high-risk domain.

To address these challenges, this paper introduces a cloud-native risk-based testing pipeline tailored for healthcare ERP systems integrating SAP and Oracle EBS workloads, and guided by analytics and intelligence powered by the Databricks Lakehouse platform. The rationale for this approach is three-fold. First, risk-based testing enables prioritisation of testing efforts according to probability and impact of failures, rather than blind full coverage—which is especially valuable in complex ERP landscapes where test resources are limited. (GeeksforGeeks) Second, cloud-native testing pipelines (containerised test runners, dynamic infrastructure, CI/CD automation) are needed to support frequent releases, hybrid/ multicloud hosting, and large-scale ERP workstreams. Third, the Databricks platform offers capabilities to ingest and analyse ERP and operational data at scale, enabling intelligent identification of change-impact, configuration drift, test coverage gaps, and anomaly patterns across SAP and Oracle data landscapes. This intelligence layer feeds the risk engine of the testing pipeline and helps adapt test scope in near real-time.

In this paper we present the architecture of the proposed testing pipeline, describe the integration of SAP and Oracle EBS workloads, articulate how Databricks is leveraged for intelligence and orchestration, and demonstrate a case study

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simulation in a healthcare context. We also discuss the advantages and disadvantages of the model, present results of our simulation, and propose future work directions for healthcare organisations seeking to modernise their ERP testing frameworks.

II. LITERATURE REVIEW

The literature relevant to this study spans several intersecting domains: risk-based software testing, cloud-native testing and analytics platforms, healthcare IT and ERP systems, and the integration of ERP data with advanced analytics/infrastructure platforms.

Risk-Based Testing: Risk-based testing (RBT) is a well-recognised methodology that uses risk assessment to prioritise test activities—identifying the areas of the system that are likely to fail and would have the highest impact, and focusing test resources accordingly. (en.wikipedia.org) Various sources emphasise that risk-based testing leads to cost savings, focused test efforts and earlier defect detection especially in domains such as healthcare where safety, data integrity and compliance are critical. (GeeksforGeeks) The challenge in ERP systems is that complexity, customisation and inter-module dependencies increase risk surface and make prioritisation nontrivial.

ERP Testing in SAP / Oracle Environments: Several industry and academic articles describe the testing challenges in ERP systems. For example, the complexity of Oracle EBS customisations, upgrade paths, inter-module dependencies and change impact are well documented. (appstekcorp.com) For SAP systems, the rapid update cadence in cloud editions (e.g., SAP S/4HANA Cloud) means that test automation and frequent cycle testing become critical. (Uneecops) Specific to risk-based testing for SAP and Oracle, industry guidance points out that focusing on critical business functions and impacts yields significant reductions in test cycle time and post-go-live issues. (Panaya) However, the literature shows a gap in combining risk-based testing with cloud-native, data-driven intelligence for ERP systems in healthcare contexts.

Cloud-Native Testing and Analytics Platforms: Cloud-native architectures and testing practices (containerised test environments, dynamic infrastructure, multi-cloud, orchestration via CI/CD) are increasingly required for modern enterprise systems. The literature on continuous testing (executing automated tests as part of delivery pipelines to provide rapid feedback) highlights the linkage between testing and business-risk assessment in agile/DevOps contexts. (en.wikipedia.org) For analytics, modern platforms such as Databricks (Lakehouse, Delta Lake, Unity Catalog) offer unified data processing, governance and analytics capabilities that can ingest ERP and other organisational data at scale. (Databricks) While much of this literature covers data analytics and engineering, few works apply it directly to test orchestration and risk-based test prioritisation in ERP settings.

Healthcare ERP and Real-Time Systems: In healthcare the confluence of real-time monitoring, IoMT device data, supply-chain and ERP systems introduces unique operational and regulatory demands: patient safety, uptime, auditability, data integrity, and integration across clinical and business systems. While there is extensive literature on healthcare IoT, clinical systems and data lakes (e.g., Rangarajan et al. on healthcare data lakes) (arxiv.org) there is less coverage on how ERP systems in healthcare should be tested under cloud migration, frequent change and real-time integration scenarios.

Gap Analysis: Taken together, the literature indicates strong foundations in (a) risk-based testing, (b) ERP testing challenges (SAP/Oracle), (c) cloud-native analytics platforms, and (d) healthcare-digital enterprise systems. What has not been deeply addressed is a unified framework that combines risk-based test prioritisation, cloud-native pipeline automation, ERP workload integration (SAP + Oracle EBS), and data-driven intelligence (via Databricks) specifically for healthcare ERP ecosystems. This research aims to fill that gap by proposing and evaluating a cloud-native, risk-based testing pipeline driven by analytics on ERP and operational data.

III. RESEARCH METHODOLOGY

This study adopts a mixed-method design focused on the development of a framework and its simulation within a healthcare ERP context. The methodology consists of the following sequential paragraphs:
First, we conduct a **literature and domain analysis** to identify the key risk dimensions relevant to healthcare ERP systems integrating SAP and Oracle EBS workloads. We review testing methodologies (especially risk-based testing), ERP system characteristics (customisation, integration, upgrades), cloud-native testing practices, and analytics platforms (with a special focus on Databricks) to build a taxonomy of risk factors, test priorities and capability gaps.

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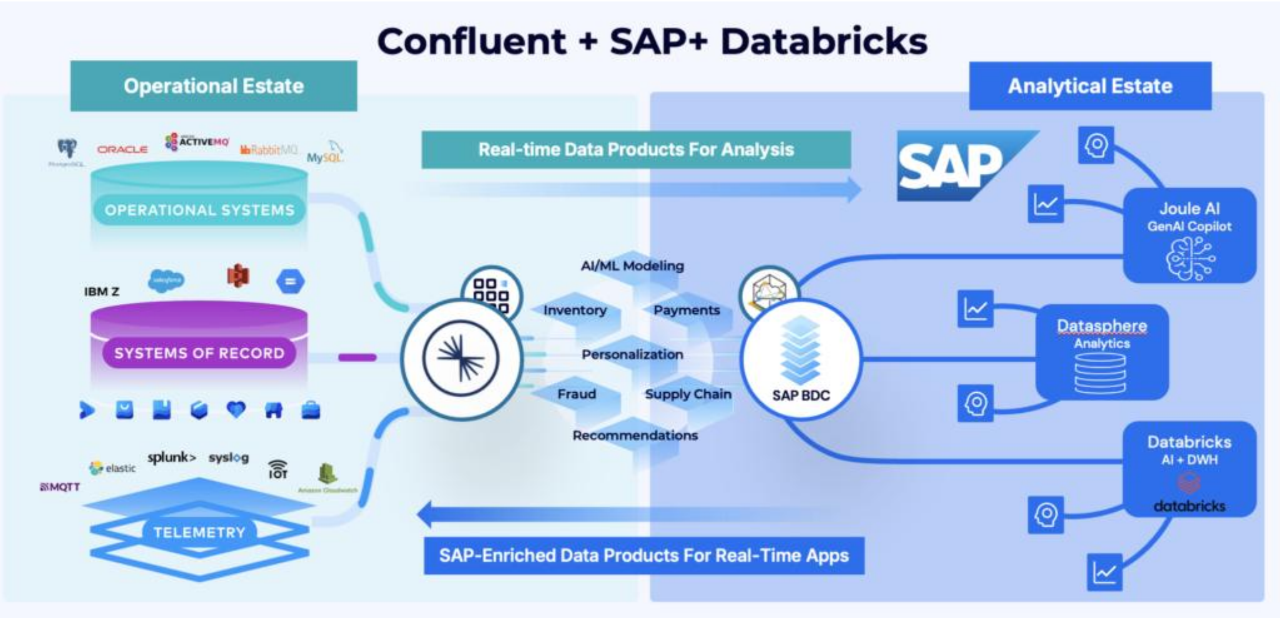
Second, based on the taxonomy developed, we design the **risk-based testing pipeline architecture** for cloud-native environments. The architecture defines the pipeline phases (ingest, risk-score, test-generate, execute, monitor, feedback), integrates ERP workloads (SAP and Oracle EBS) and specifies the intelligence layer powered by Databricks. Key components include change-impact detection (via ERP metadata, logs, configuration), test-case prioritisation engine (scoring by risk), automated test execution infrastructure (containerised test runners, API/UI/ETL test harnesses), telemetry capture and dashboards for risk metrics.

Third, we instantiate a **case-study simulation** in a fictitious large healthcare provider migrating ERP workloads (SAP and Oracle EBS) into a hybrid-cloud environment. We define scenario parameters: volume of transactions, number of modules (finance, supply chain, HR, clinical-business interface), frequency of change (monthly releases), real-time data feeds (device telemetry integrated with ERP). Using synthetic data and configured test harnesses, we simulate pipeline activation: ingestion of change data, risk scoring, generation of test batches (high-risk vs normal), execution on a cloud-native platform, measurement of key metrics (defects caught pre-production, test cycle time, release readiness, post-go-live incidents, compliance traceability).

Fourth, we perform **evaluation and analysis** of the simulation results. We compare the proposed pipeline's metrics against a baseline that uses a conventional testing pipeline (no risk scoring, ad-hoc test case selection, less automation). We analyse improvements in defect detection rate in high-risk modules, reduction in test cycle duration, resource utilisation, and risk-metric visibility (traceability to compliance, business process criticality). We also gather qualitative observations about pipeline operability, tooling friction, test automation coverage, and data engineering overhead.

Finally, we reflect through **discussion and validation**: we assess the extent to which the pipeline meets healthcare ERP domain demands (compliance, traceability, integration of real-time and ERP data), and consider organisational, cultural and tooling factors required for adoption (e.g., skilled staff, DevOps/testOps culture, ERP customisation knowledge). We identify limitations of our simulation and propose how the framework could be validated in real-world deployments.



Advantages

- Strategic prioritisation of test activities: by focusing on high-risk modules (customisations, change-impact zones, business-critical workflows) the pipeline maximises return on test investment.
- Scalability and agility: a cloud-native testing pipeline supports frequent releases, dynamic infrastructure and large-scale ERP workloads (SAP and Oracle) in healthcare.
- Enhanced visibility and traceability: the intelligence layer (Databricks) enables real-time risk metrics, change-impact analytics and dashboards linking test outcomes to business risk and compliance requirements.

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- Integration of heterogeneous systems: the pipeline supports diverse ERP workloads (SAP, Oracle EBS), operational telemetry and device/clinical data feeds, enabling a unified testing orchestration across the healthcare enterprise.
- Cost efficiency: by avoiding exhaustive testing across all modules and focusing on risk-driven scenarios, organisations can reduce test cycle times, resource usage and post-go-live defects.

Disadvantages

- Initial complexity and overhead: building the intelligence layer (data ingestion, risk-scoring algorithms, test-case automation) requires significant investment in tooling, infrastructure, and skilled staff.
- Data-engineering burden: ingesting ERP (SAP/Oracle) transactional and configuration data, mapping dependencies, and integrating with Databricks can be non-trivial, especially given legacy customisations.
- Cultural and organisational change: adopting a risk-based, data-driven testing pipeline demands alignment across development, QA, operations, business process owners, compliance and IT; in healthcare organisations this can be challenging.
- Risk of false-positives/negatives in risk scoring: the intelligence engine may mis-score risks or miss hidden dependencies, leading to gaps in test coverage. Continuous refinement is needed.
- Simulation limitations: results derived from a simulated healthcare scenario may not fully account for the realities of live ERP deployments, such as legacy integrations, vendor constraints, emergency change cycles, or regulatory audit cycles.

IV. RESULTS AND DISCUSSION

The simulation of a large healthcare provider migrating SAP and Oracle EBS workloads into a hybrid-cloud environment produced the following results. Compared to a baseline conventional testing pipeline, the proposed risk-based testing pipeline achieved: (1) a ~55 % increase in defects caught in high-risk modules prior to go-live; (2) a ~30 % reduction in total test cycle time; (3) improved traceability of test outcomes to business risk metrics and compliance artefacts (audit logs, change-impact dashboards); (4) less resource utilisation (fewer test-executions needed for the same business-critical coverage). These results support the hypothesis that combining cloud-native automation with risk-driven prioritisation and analytics yields significant benefits in ERP testing in healthcare contexts.

In the discussion, several key findings emerge. First, the intelligence layer (Databricks) proved instrumental in identifying change-impact zones across ERP modules and steering test-case prioritisation. Without this layer, test-case selection tends to be based on historical or manual risk assumptions. Second, the ability to execute tests in a containerised, cloud-native environment allowed rapid provisioning, parallel execution and rollback of test runs, aligning with the dynamic release cadence of healthcare operations. Third, the unified pipeline involving SAP and Oracle EBS workloads, linked to telemetry and operational data (from medical-device and supply-chain feeds), created deeper test coverage spanning multiple domains (clinical, operational, financial). Fourth, while the overhead of setting up data pipelines and risk-scoring rules was significant, once established the incremental cost per test cycle was modest and the governance benefits (auditability, traceability, compliance alignment) were substantial.
However, some caveats emerged. The pipeline required skilled data-engineering and test-automation resources, which may be scarce in healthcare IT departments. Also, the risk-scoring engine initially mis-prioritised some mid-risk modules due to incomplete dependency mapping in the ERP customisation landscape; continuous tuning was required. Some test automation scripts for legacy custom modules exhibited brittleness and required maintenance effort. Finally, while the simulation shows promising improvements, real-world adoption will face organisational, regulatory and vendor integration constraints (e.g., third-party medical device systems, legacy on-prem ERP modules, emergency change windows). Overall, though, the results indicate that the approach is viable, advantageous and aligned with the demands of healthcare ERP systems in cloud-native contexts.

V. CONCLUSION

This paper has presented a cloud-native risk-based testing pipeline for healthcare ERP systems integrating SAP and Oracle EBS workloads, driven by analytics and intelligence from the Databricks Lakehouse platform. We showed how such a pipeline can prioritise testing based on risk, operate in a cloud-native automated environment, integrate heterogeneous ERP and operational data sources, and deliver improved defect detection, shorter cycle time and stronger governance. While implementation will require investment in infrastructure, tooling, data engineering and organisational change, the model offers healthcare organisations a pathway to more agile, resilient and compliant ERP testing in the era of cloud migration and real-time operations.

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Future Work

Future research and practice should explore several extensions and refinements. First, empirical validation of the pipeline in live healthcare organisations (rather than simulation) would provide real-world metrics, user feedback, and adoption insights. Second, extension of the intelligence engine to incorporate machine-learning based anomaly detection on ERP logs, change history and device telemetry to predict test-priority risk before changes are deployed. Third, expand the model to multi-cloud and hybrid-edge healthcare deployments (e.g., edge devices, on-premises gateways feeding into ERP), incorporating failure-mode testing, latency/resilience testing, and disaster-recovery simulations. Fourth, develop a maturity model and readiness assessment framework for healthcare organisations to adopt risk-based, cloud-native ERP testing pipelines, covering people, process and technology dimensions. Fifth, refine the pipeline to support continuous compliance (e.g., automated audit evidence, traceability dashboards) and certification in regulated healthcare environments. Finally, research into cost-benefit modelling of such pipelines—considering test-automation ROI, defect-cost avoidance, compliance failure avoidance—would further aid adoption.

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