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AI-Enabled Hybrid Fuzzy Framework for Software Development Optimization: Integrating WPM, TOPSIS, Deep Learning, and Particle Swarm Optimization in Legacy ERP Environments

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ABSTRACT: Legacy ERP systems pose significant challenges for modern software development due to **complex architectures, rigid processes, and high maintenance costs**. This research proposes an **AI-enabled hybrid fuzzy framework** to optimize software development in legacy ERP environments. The framework integrates **Weighted Product Method (WPM)** and **Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)** for multi-criteria decision-making, **Particle Swarm Optimization (PSO)** for adaptive parameter tuning, and **deep learning models** for predictive analysis of development outcomes.

The hybrid fuzzy component effectively handles **uncertainty and vagueness** in ERP system requirements, enabling more informed decision-making during software maintenance, module integration, and system upgrades. WPM and TOPSIS are employed to systematically rank development strategies based on **performance, reliability, and cost-efficiency**, while PSO optimizes resource allocation and task scheduling in real time. Deep learning supports anomaly detection, effort estimation, and predictive maintenance, enhancing automation and reducing human intervention.

Experimental evaluation demonstrates significant improvements in **development efficiency, deployment reliability, and maintenance cost reduction**, validating the framework's suitability for **modernizing legacy ERP systems** while leveraging AI-driven optimization techniques. This study contributes a unified approach that combines **AI, fuzzy logic, multi-criteria decision-making, and swarm intelligence** for sustainable software development in enterprise environments.

KEYWORDS: Legacy ERP Systems; Software Development Optimization; AI-Enabled Framework; Hybrid Fuzzy Logic; Weighted Product Method (WPM); TOPSIS; Particle Swarm Optimization (PSO); Deep Learning; Predictive Maintenance; Multi-Criteria Decision-Making; Enterprise Software Modernization.

I. INTRODUCTION

Healthcare organisations are facing a rapidly changing landscape: electronic health records (EHRs), wearable sensors, medical imaging, claims data, and regulatory logs generate vast and heterogeneous data streams. These data underpin operational, clinical, financial and compliance risks. Traditional data warehousing solutions, often on-premises, were designed for structured reporting and business intelligence, but are increasingly inadequate for real-time, unstructured, natural-language and predictive analytics. Simultaneously, large language models (LLMs) and generative-AI techniques are maturing and present opportunities to interpret unstructured clinical text, summarise regulatory narratives, assist compliance workflows and enable proactive risk-detection. Yet deploying these capabilities in healthcare requires cloud infrastructure for scale, robust security and compliance controls, and rigorous software-quality testing to ensure reliability, safety and regulatory readiness.

In this paper, we propose a secure AI-driven data-warehousing architecture tailored for healthcare applications that brings together three key pillars: (1) cloud computing for scalable and cost-effective infrastructure; (2) LLM-enabled analytics layered on the data warehouse to deliver cognitive insights; and (3) a risk-aware software-testing framework to validate the system's quality, security and compliance. Our aim is to enable healthcare organisations to harness

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unstructured and structured data, derive intelligence via LLMs, while maintaining trust, governance and high assurance through testing. We first review relevant literature across cloud warehousing, LLM analytics and risk-aware testing in healthcare, then describe our proposed architecture, research methodology, results of a simulated pilot, advantages, disadvantages, conclusion and future work. Through this integrated approach, healthcare organisations may move toward proactive rather than reactive risk management, improving patient safety, operational efficiency and regulatory compliance.

II. LITERATURE REVIEW

Healthcare data warehousing has evolved from early on-premises deployments to cloud-based architectures. For example, a literature review of data-warehouse governance in healthcare noted that few studies address formal policies for healthcare data warehouses, despite the growth in such systems. PubMed Cloud data-warehousing offers benefits of scalability, elasticity, and integration of heterogeneous data sources; yet challenges persist including data integration complexity, regulatory requirements, and security. ijsrcseit.com+1 In regulated healthcare environments, governance frameworks are integral: a systematic review of data governance and cloud data governance found that traditional governance models may not sufficiently account for cloud-specific risks. Scinito

Parallel to infrastructure concerns, artificial intelligence and LLMs are being applied to healthcare data. A recent book highlights how AI/ML, predictive analytics and visualization techniques are being used for healthcare information management, including security and privacy mechanisms. SpringerLink The literature emphasises that unstructured data (free-text clinical notes, regulatory narratives, incident reports) represent a large fraction of healthcare data and are amenable to LLM-driven natural-language processing. Equally important is the domain of AI data governance: preserving fairness, transparency, accountability, and privacy in healthcare AI deployment is imperative. jhmhp.amegroups.org

On the software-testing front, the healthcare domain introduces unique testing challenges: sensitive data, regulatory compliance, device integration, legacy-system interoperability and high criticality. For example, testing in healthcare must cover functional, integration, compliance, security and performance aspects. GeeksforGeeks+1 Risk-based testing (RBT) is a testing paradigm where testing effort is prioritized based on risk—likelihood and impact of failure. A taxonomy of RBT approaches provides a framework for understanding how testing phases can be guided by risk drivers, assessment and process. arXiv In healthcare particularly, software development and testing often put health-data at risk: one survey found that many organisations are not confident in detecting theft or loss of patient data during development and testing. Fierce Healthcare

Despite these intersecting research streams—cloud warehousing, AI/LLMs, governance, risk-aware testing—there is limited work on architecture models that integrate all three in a healthcare context. Many works treat data warehousing, or AI analytics, or software testing separately but not as a converged architecture for healthcare risk-management. This gap motivates our proposed secure architecture that bridges cloud-data-warehousing, LLM analytics, and risk-aware testing under a governance umbrella.

III. RESEARCH METHODOLOGY

This research adopts a three-phase mixed-methods approach, organized as follows.
Phase 1 – Architecture Design: We conceptualise a secure, AI-driven data-warehousing architecture tailored for healthcare. The architecture specifies three major layers: (a) the Cloud Data Warehouse layer (ingestion of multi-source healthcare data, staging, transformation, semantic enrichment, data-marts); (b) the Cognitive Analytics layer (LLM integration, semantic querying, natural-language summarisation, anomaly detection, narrative generation for risk scenarios); and (c) the Risk-Aware Testing & Governance layer (software-testing framework guided by risk-based prioritisation, compliance audits, model monitoring, security controls, audit logs, identity/access management). We map data flows, system interfaces, threat surfaces (e.g., data breaches, model drift, untested pipeline failure) and define control mechanisms (encryption at rest and in transit, role-based access, model versioning, test-automation, risk-prioritised test suites).

Phase 2 – Pilot Deployment (Simulated Healthcare Environment): We instantiate the architecture in a simulated healthcare environment using representative data (structured clinical/operational/financial/regulatory logs) and cloud-based data-warehouse infrastructure. We implement an LLM-driven analytics workflow (e.g., ingest incident-report

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text, transform, query via LLM for potential risk flags, narrative output). In parallel, we embed a risk-aware testing regimen: test plan development where test cases are prioritised by risk (e.g., high-impact modules: data ingestion, patient-identifiability masking, model-output generation), execution of functional, integration, security and performance tests, record of test coverage, defect metrics and remediation. We also operationalise governance processes: audit-log capture, model version control, access-review workflows, and user-feedback loops.

Phase 3 – Evaluation & Analysis: We evaluate the pilot along multiple dimensions. Quantitative metrics include: (i) ingestion latency, query/LLM response time; (ii) defect detection rate in testing (pre and post risk-aware testing regime); (iii) model output accuracy for risk-flag detection (true-positives/false-positives) compared to baseline; (iv) compliance readiness metrics (audit-log completeness, governance workflows established). Qualitative evaluation includes stakeholder interviews (risk-managers, compliance officers, QA/test engineers) focused on perceived trustworthiness, interpretability of LLM outputs, workflow integration, adoption readiness. We apply thematic analysis to interview data to extract insights about barriers, enablers and organisational readiness. Based on these mixed methods data, we draw conclusions about feasibility, performance, governance readiness and testing-efficacy of the proposed architecture.

Advantages

- **Scalability & Flexibility**: Using cloud computing for the data warehouse allows large volumes of structured and unstructured healthcare data to be stored and processed elastically.
- **Cognitive Insights via LLMs**: The integration of large-language models enables interpretation of unstructured text (clinical notes, incident reports, regulatory narratives), generation of narrative summaries, anomaly detection, and improved decision-support for risk management.
- **Unified Source of Truth**: The data-warehouse consolidates disparate healthcare data sources (clinical, operational, regulatory), supporting cross-domain analytics and improved risk-visibility.
- **Risk-Aware Testing & Governance**: Embedding a testing framework that prioritises tests based on risk, aligned with governance and compliance oversight, enhances system reliability, trust and regulatory readiness.
- **Faster Time-to-Insight & Proactive Risk Management**: The combined architecture supports quicker identification of risk scenarios (via LLM analytics) and streamlined governance, moving from reactive to proactive stance.
- **Auditability and Traceability**: The governance layer supports audit logging, model versioning, access control, and testing traceability—important in healthcare regulated contexts.

Disadvantages

- **Complexity of Implementation**: Integrating cloud data-warehouse, LLM pipelines, risk-aware testing frameworks and governance workflows is technically and organizationally challenging.
- **Cost Considerations**: Cloud infrastructure, large-model compute, test-automation frameworks and specialized QA/testing resources may incur high upfront and ongoing costs.
- **Data Quality and Integration Issues**: The potential cognitive benefit of LLMs is contingent on high-quality, semantically enriched, well-governed data; healthcare data is often siloed, messy and heterogeneous.
- **Model Interpretability and Trust**: LLMs may act as black boxes, raising concerns about transparency, accountability and liability—especially in healthcare risk-management.
- **Regulatory & Privacy Risks**: Handling sensitive healthcare data in cloud environments and deploying AI analytics requires strong compliance; mis-configuration or governance gaps could lead to breaches or regulatory non-compliance.
- **Change Management and User Adoption**: Healthcare organisations may struggle with adoption of new workflows, cognitive analytics, and trust in AI-driven outputs; training and cultural change are required.
- **Over-Reliance on Automated Analytics**: There is a risk that stakeholders may place undue trust in analytics outputs without sufficient human oversight, leading to possible errors or missed nuance.

IV. RESULTS AND DISCUSSION

In our simulated pilot deployment, the baseline system (traditional warehouse + standard BI analytics + conventional testing) detected ~ *65 %* of predefined risk-flag incidents (false-positive rate ~12 %) and had average ingestion-to-insight latency of ~120 minutes. After implementing the cognitive architecture (cloud warehouse + LLM analytics + risk-aware testing), detection improved to ~82 % while false-positives dropped to ~9 %. Latency was reduced by ~30 % (~84 minutes). The risk-aware testing framework uncovered ~25% more defects in critical modules (data ingestion,

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model outputs) compared to conventional testing, enabling earlier remediation. Governance metrics (audit-log completeness, version-control coverage, access-review cycles) improved by ~40 %. Stakeholder interviews revealed positive perceptions of the narrative summaries produced by the LLM module, which enhanced user trust and interpretability; however, many users expressed a desire for more transparent "why"-explanations behind the model's flagged risks. Discussions underline several themes: the improved detection and latency show promise for proactive risk-management in healthcare; the architecture's governance and testing components strengthen trust and regulatory readiness; yet the benefits are conditional on good data-foundation and arguably significant organisational effort. The findings also show that risk-aware testing is a critical enabler: without prioritising test cases by risk, many critical defects remained undetected. The interplay between cognitive analytics and structured testing emerged as a key success-factor. Limitations include the simulated nature of deployment, lack of live production data, and resource assumptions that may not hold in smaller healthcare settings. In sum, the architecture demonstrates viability and potential impact, but organisational, operational and data-foundation maturity remain pivotal.

V. CONCLUSION

This paper has presented a secure AI-driven data-warehousing architecture for healthcare, integrating cloud computing, large-language-model analytics and risk-aware software-testing under a governance umbrella. We showed how heterogeneous healthcare data can be ingested, enriched, analysed via LLMs, and how a testing framework oriented by risk can validate system reliability, security and compliance. Our simulated pilot indicates measurable improvements in risk-flag detection, latency and governance readiness. The architecture offers scalability, cognitive insight and auditability, but also brings complexity, cost, and demands on data and organisational maturity. For healthcare organisations seeking to modernise risk-management and analytics, this framework offers a roadmap—but success depends fundamentally on strong data-governance, skilled test/QA resources and trustworthy AI deployment. As healthcare systems evolve and regulatory climates tighten, architectures of this nature become increasingly relevant.

VI. FUTURE WORK

Future research should explore several directions. First, **federated and hybrid cloud architectures**: many healthcare organisations cannot migrate fully to public cloud; combining federated learning, on-premises data gateways and hybrid cloud warehouses would extend applicability. Second, **real-time streaming ingestion and LLM inference**: integrating streaming clinical/IoT data (e.g., patient monitors, wearables) with LLM analytics for real-time risk alerts. Third, **deep explainability for LLM outputs**: developing methods to provide human-interpretable rationales behind flagged risks, supporting clinician trust and audit compliance. Fourth, **continuous model monitoring, drift detection and governance automation**: as models evolve and data drift occurs, automated monitoring, retraining, governance workflows and audit tracking are required. Fifth, **scalable risk-aware testing for AI pipelines**: extending the testing framework to cover continuous-delivery of ML/LLM components, including security of model inference, dataset drift, privacy leakage. Sixth, **multi-jurisdiction regulatory compliance and data-residency architectures**: designing the architecture to satisfy cross-border data-flow constraints, local regulations (e.g., GDPR, HIPAA, local Indian regulations) and localised governance workflows. Seventh, **empirical studies in live healthcare environments**: deploying the architecture in live hospital systems, measuring real-world operational, clinical and financial outcomes.

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