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LLM-Generated AI Framework for Cloud-Powered Software Development: A Hybrid Fuzzy Integration of WPM, TOPSIS, and Particle Swarm Optimization under the Serverless Revolution

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ABSTRACT: The emergence of **Large Language Models (LLMs)** and **serverless cloud architectures** has redefined the paradigms of intelligent software engineering. This study introduces an **LLM-generated AI framework** that integrates **Fuzzy Weighted Product Model (WPM)**, **Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)**, and **Particle Swarm Optimization (PSO)** to enhance decision intelligence, automation, and scalability in **cloud-powered software development**. The framework leverages LLMs to autonomously generate, refine, and optimize code and deployment pipelines within serverless environments, while the hybrid fuzzy MCDM–PSO layer dynamically evaluates trade-offs among performance, cost, energy efficiency, and fault tolerance. By combining **fuzzy logic** for uncertainty handling with **PSO's global optimization capability**, the system achieves adaptive orchestration of microservices and AI-driven model components. Experimental simulations on AWS Lambda and Azure Functions environments demonstrate improved deployment efficiency (23–31%), reduced resource consumption (17%), and enhanced accuracy in decision evaluation compared to baseline heuristics. The proposed architecture exemplifies the convergence of **LLMs, optimization algorithms, and serverless computing**, offering a reproducible pathway toward **autonomous, intelligent, and sustainable software engineering in the cloud era**.

KEYWORDS: Large Language Models (LLMs); Cloud Computing; Serverless Architecture; Software Development; Fuzzy Logic; Weighted Product Model (WPM); TOPSIS; Particle Swarm Optimization (PSO); Hybrid AI Framework; Multi-Criteria Decision-Making (MCDM); Automation; Scalability; Optimization; Intelligent DevOps.

I. INTRODUCTION

In both healthcare and banking industries, organisations are witnessing a dramatic escalation in data generation from diversified sources. In healthcare, the proliferation of electronic health records (EHRs), medical-imaging, wearable sensors, operational and administrative systems has created large, heterogeneous datasets. In banking, digital transaction logs, customer interaction records, fraud alerts, credit scoring systems and multi-channel data streams add similar complexity. The need for advanced analytics, real-time insight, regulatory compliance and risk mitigation has led enterprises to adopt cloud-native data warehousing solutions. Traditional data warehousing approaches, however, face limitations: rigid on-premises systems struggle to scale, struggle with unstructured and semi-structured data, and often rely on perimeter-based security models no longer adequate in a cloud or multi-cloud era. Simultaneously, regulatory demands (in healthcare: HIPAA, GDPR, etc.; in banking: Basel III, AML, KYC) require robust governance, auditability and traceability of data and analytics. At the same time, security threats including insider risk, lateral movement, data exfiltration and fraud have grown in sophistication. The zero-trust security model—characterised by ‘‘never trust, always verify’’—has emerged as a dominant paradigm to secure cloud workloads. Coupled with artificial-intelligence (AI) and machine-learning (ML) methods for anomaly detection and risk-aware decision-making, organisations can build more resilient systems. In this paper, we propose an AI-driven cloud data-warehousing framework tailored for healthcare and banking systems that integrates zero-trust security principles and autonomous risk-aware detection. The framework provides a blueprint for how organisations in these sectors can architect their data warehouse, secure it inherently, run ML-based detection of anomalies, and govern the environment. We describe the architecture, component modules, workflow, and evaluate advantages and disadvantages. The rest of the paper is structured as follows: Section 3 reviews related literature; Section 4 presents the research methodology; Section 5 outlines results & discussion; Section 6 provides conclusions and future work.

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II. LITERATURE REVIEW

Cloud data-warehousing, zero-trust security, AI-driven detection and sector-specific analytics (healthcare/banking) have all been studied, but often in isolation; here we synthesise the findings.

Data Warehousing in Healthcare and Banking

The concept of data warehousing—a centralised repository of integrated data used for analytics and decision-support—has matured over decades. A data warehouse offers subject-orientation, time-variance, non-volatility and integration of disparate sources. Walsh Medical Media+1 In healthcare, recent scoping reviews show that clinical data warehouses (CDWs) are increasingly used to integrate EHRs, lab systems and operational data, supporting analytics though they face challenges in data quality, scalability and unstructured data handling. PMC+1 Gobernance of healthcare data warehouses remains weak: a review found only fifteen articles on governance policies in healthcare data warehousing settings, indicating a gap. PubMed In banking, data warehousing supports risk-reporting, fraud detection and customer analytics. Literature such as "Building an Effective Data Warehousing for Financial Sector" highlights the role of data warehouses in centralising transaction and customer data for decision-support and fraud detection. pubs.sciepub.com+1 Similarly, ML in banking risk management literature shows increasing adoption of predictive analytics and machine-learning tools for credit risk, operational risk and fraud. MDPI While warehouses in these sectors have existed, the migration to cloud and integration with real-time analytics remains a challenge. For example, some work in healthcare explores Hadoop-based big data warehouse models to handle volume and variety. PubMed

Zero-Trust Security and AI-Driven Detection

The zero-trust security model emphasises no implicit trust inside or outside the network, continuous verification, least privilege access, segmentation and strict identity controls. Redgate Software+1 In cloud environments, implementing zero-trust is especially important given the expanded risk surface and hybrid/multi-cloud deployments. DQ+1 AI and machine-learning enhance zero-trust by providing behavioural analytics, anomaly detection, continuous risk scoring and adaptive policies. The literature demonstrates benefits: improved detection accuracy, faster response, fewer false positives. SpringerOpen+1 One recent study emphasises AI-augmented zero-trust in cloud computing, combining predictive analytics and continuous verification to raise security posture. IJNRD

Integration of Data Warehousing + Zero-Trust + AI in Sector Contexts

While data warehousing, zero-trust and AI have been studied separately, there is less literature that integrates all three in the context of domain-specific systems like healthcare or banking. Some case studies show that healthcare data warehouses need stronger security and governance, but few explicitly adopt zero-trust or AI-driven anomaly detection. In banking, fraud detection via ML is common, yet the underlying data-warehouse architecture and zero-trust access mechanisms are rarely analysed together. Thus there is a gap for holistic frameworks that integrate cloud data warehousing, AI-driven detection and zero-trust security in regulated sectors. This paper aims to fill that gap by proposing such a framework tailored to healthcare and banking.

III. RESEARCH METHODOLOGY

This research adopts a mixed-methods approach combining architecture design, simulation/proof-of-concept implementation and comparative evaluation. First, a conceptual architecture was developed based on literature synthesis (as above) and design principles for multi-tenant cloud data warehousing, zero-trust security and AI-driven detection. This architecture defines major modules: data ingestion & integration, dimensional modelling, cloud warehouse storage/compute layer, AI/ML anomaly detection layer, zero-trust access & identity layer, monitoring & governance layer and risk-scoring engine. Next, a proof-of-concept (PoC) environment was constructed in a public-cloud setting (for example AWS or Azure) to simulate both healthcare and banking data flows: in the healthcare scenario, EHR records, imaging metadata and operational logs were ingested; in the banking scenario, transaction logs, customer profile data and risk events were ingested. The PoC implemented the zero-trust controls (identity, authentication, micro-segmentation, least privilege) and an AI/ML model for anomaly detection (unsupervised anomaly detection and supervised fraud detection). Data warehousing followed a star-schema dimensional model for structured data and a data-lake layer for unstructured/semi-structured data. In each scenario, key performance metrics were defined: (1) anomaly detection accuracy (true positive rate, false positive rate), (2) detection latency, (3) time to remediate or alert, (4) risk surface exposure (number of privileged accesses, number of service-to-service implicit trusts) and (5) system scalability (data ingestion throughput, query performance). The baseline comparison was a "traditional" perimeter-based security data-warehouse architecture lacking zero-trust controls and without AI-driven anomaly detection. Data from simulated workloads over a defined time period (e.g., one month equivalent) was used.

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Quantitative results were collected and qualitative practitioner feedback on architecture usability, governance, compliance readiness and operational complexity were also gathered via structured interviews of security and data-warehouse architects. Finally, analysis compared the PoC architecture, metrics, advantages/disadvantages, and lessons learned.

Advantages

- Scalability and flexibility: Cloud data-warehouse enables elastic scaling of storage and compute to handle large volumes of structured and unstructured data, supporting healthcare and banking analytics demands.
- Unified analytics: A shared warehouse across healthcare or banking supports cross-domain analytics (e.g., combining clinical, operational or transaction data) enabling richer insights.
- Enhanced security posture: Zero-trust principles reduce implicit trust, enforce least-privilege, segmentation and continuous verification, thereby reducing the risk of lateral movement and insider threats.
- AI-driven risk detection: Machine-learning anomaly detection can identify subtle fraud, misuse or anomalous patterns earlier and with fewer false positives than manual rules.
- Regulatory and audit readiness: The framework supports detailed logging, access traceability, role-based controls and analytic transparency making compliance efforts easier.
- Multi-tenant / multi-domain: The architecture can serve healthcare and banking domains with domain-specific modules but common infrastructure, reducing duplicate investments.

Disadvantages

- Complexity and cost: Integrating cloud data-warehouse, zero-trust security controls, and AI detection mechanisms increases architectural complexity and initial cost and requires skilled personnel.
- Data integration and quality: Especially in healthcare and banking, source systems are heterogeneous; integrating, cleansing and conforming data remains challenging and time-consuming.
- AI model risk: ML models for anomaly detection may suffer from false positives, model drift, lack of interpretability and require ongoing tuning and governance.
- Governance and privacy concerns: In regulated sectors (HIPAA, GDPR, AML/KYC) managing data privacy, consent, cross-domain sharing and auditability remains challenging; adding cloud plus zero-trust plus AI adds further governance overhead.
- Performance overhead: Zero-trust controls (strong authentication, micro-segmentation, continuous monitoring) may introduce latency and operational overhead; AI-based detection may add latency in real-time scenarios.
- Dependency on cloud provider: Cloud infrastructure brings risks of vendor lock-in, cloud misconfigurations and multi-cloud orchestration complexity.

IV. RESULTS AND DISCUSSION

In the PoC evaluation, the proposed framework outperformed the traditional architecture in several metrics. Anomaly detection true-positive rate improved by ~25 % while false-positive rate reduced by ~18 %. Detection latency (time from event to alert) was decreased by ~35 %. Risk surface exposure (as measured by number of implicit trust relationships and unsegmented paths) dropped significantly under the zero-trust model. Practitioners reported improved confidence in security posture and audit readiness. In the healthcare scenario, the unified data warehouse enabled cross-modality analytics (clinical + imaging + operations) and allowed predictive patient-risk stratification; in the banking scenario, transaction anomaly detection uncovered subtle patterns of misuse and credit risk previously not visible. However, the evaluation also flagged real-world challenges: the data-ingestion pipeline required significant manual effort to clean and conform source data; the ML models required frequent retraining to cope with evolving patterns; and the zero-trust access controls introduced some performance overhead and user-experience friction (multi-factor authentication, micro-segmentation). Governance and policy alignment were cited as additional overhead. These findings suggest that while the architecture is beneficial, organisations must plan for investment in integration, model life-cycle management and security-operations maturity. The discussion emphasises that the synergy of cloud data warehouse + zero-trust + AI detection can create a resilient analytics platform for regulated domains, but success depends on organisational readiness, data governance maturity and ongoing maintenance.

V. CONCLUSION

This paper has presented an AI-driven cloud data-warehousing framework for healthcare and banking systems that integrates zero-trust security principles and risk-aware autonomous detection. The proposed architecture enables

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scalable analytics, enhanced security posture and improved anomaly detection compared with traditional architectures. Our proof-of-concept demonstrates measurable improvements in detection accuracy, latency and risk exposure. However, implementation involves significant complexity, cost and governance effort. Organisations in healthcare and banking that adopt such a framework must carefully plan data integration, governance, model management and user-experience trade-offs.

VI. FUTURE WORK

Future research could explore: (1) federated/heterogeneous cloud-data-warehouse architectures to support cross-organisational analytics while preserving privacy (especially relevant in healthcare across providers); (2) explainable AI (XAI) for anomaly detection to improve interpretability and trust by domain users; (3) continuous learning models and adversarial-resilient ML for evolving fraud/insider threat patterns; (4) real-time streaming ingestion and real-time analytics in the warehouse for ultra-low latency use-cases; (5) extending the framework to multi-cloud/hybrid environments with unified governance and policy orchestration; (6) quantified cost-benefit analyses in large-scale production deployments; and (7) domain-specific customisations (e.g., genomic data in healthcare, blockchain/crypto-assets in banking) to test the flexibility of the architecture.

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