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A Secure API-Enabled Cloud Platform for Healthcare and Financial Systems Leveraging AI and Apache-Based Real-Time Analytics

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ABSTRACT: The widespread adoption of cloud computing in the healthcare and financial sectors has enabled real-time data processing and analytics, but it has also increased exposure to cybersecurity threats. This paper introduces an AI-powered, API-driven cloud platform designed to deliver secure, real-time analytics for healthcare and financial systems using Apache-based frameworks. The proposed architecture combines scalable APIs, microservices, and cloud-native design principles to support high-throughput data ingestion, processing, and machine learning-driven analytics. Embedded AI models provide predictive insights, anomaly detection, and real-time decision support while ensuring data confidentiality and integrity. Security mechanisms—including encryption, access controls, and continuous monitoring—are implemented to maintain compliance with healthcare regulations (e.g., HIPAA) and financial industry standards. Experimental evaluation shows that the platform achieves low-latency processing, accurate threat detection, and high availability, outperforming traditional batch-processing systems. The results demonstrate that API-driven, AI-enabled cloud architectures leveraging Apache technologies offer a robust, scalable, and secure foundation for integrating real-time analytics into mission-critical healthcare and financial applications.

KEYWORDS: AI-powered cloud, API-driven architecture, Real-time analytics, Healthcare systems, Financial systems, Cybersecurity, Apache-based frameworks

I. INTRODUCTION

The pervasive adoption of digital technologies has transformed industries like healthcare and finance, generating vast volumes of complex data and driving demand for analytics that deliver actionable insights in real time. In healthcare, real-time analytics can enable dynamic monitoring of vital signs, early detection of clinical anomalies, rapid diagnosis, personalized treatment suggestions, and proactive care coordination across distributed clinical systems. In financial systems, real-time analytics powers fraud detection, trading signals, risk scoring, credit decisions, compliance monitoring, and customer personalization. These domains share stringent security requirements, regulatory constraints (e.g., HIPAA in healthcare, Gramm-Leach-Bliley and PCI DSS in finance), and the critical need for high availability and reliability.

Artificial intelligence (AI) and machine learning (ML) have become essential technologies for deriving predictive and prescriptive insights from complex data. However, deploying AI analytics in real-time contexts at scale poses architectural challenges that span data ingestion, processing, model operationalization, integration, and security. Cloud computing offers elasticity, managed services, global reach, and integration pathways that reduce infrastructure complexity, enabling organizations to adopt real-time AI solutions more rapidly while maintaining robust security and governance.

Despite the promise of cloud-based real-time analytics, several challenges remain: (1) integrating disparate data sources and formats; (2) managing high-velocity data streams with low latency; (3) orchestrating AI model training and inference at scale; (4) enforcing strict security controls, access policies, and data encryption; (5) ensuring compliance with domain-specific regulatory frameworks; and (6) providing developers and applications with standardized, interoperable interfaces. An **API-driven platform architecture**, emphasizing microservices, event streaming, and secure APIs, is a compelling approach for addressing these challenges while facilitating extensibility, interoperability, and governance.

APIs (Application Programming Interfaces) have become foundational building blocks of modern distributed systems, enabling modular development, loose coupling between services, and seamless integration across heterogeneous environments. In healthcare and financial systems, APIs enable secure access to data and analytics services, support multi-tenant interactions, and promote ecosystem integration with third-party applications, partners, and regulators. A well-designed API-driven platform abstracts complexity from clients, enforces security consistently, and enables rapid evolution of services without impacting consumers.

This paper focuses on the conception, design, and evaluation of an **API-driven cloud platform for real-time AI analytics** tailored toward secure healthcare and financial systems. The platform unifies data ingestion, processing, analytics, AI model serving, and results delivery through consistent API interfaces. It supports both request-response and event-driven communication patterns, enabling synchronous queries and asynchronous streaming use cases. It leverages cloud-native primitives such as serverless functions, managed streaming (e.g., message queues, event hubs), container orchestration, identity services, and data governance tools to meet stringent performance, security, and compliance requirements.

The rest of this introduction elaborates on the motivations behind an API-driven cloud platform, outlines the unique requirements of healthcare and financial analytics, and frames the research questions that guide this work. Healthcare and financial systems operate under complex regulatory environments requiring data protection, auditability, traceability, and adherence to privacy mandates such as HIPAA (Health Insurance Portability and Accountability Act), GDPR (General Data Protection Regulation), PCI DSS (Payment Card Industry Data Security Standard), and industry-specific guidance. These regulations impose constraints on how data can be collected, stored, processed, and shared, often requiring encryption at rest and in transit, role-based access control, fine-grained audit trails, and data minimization strategies. The architecture presented in this paper incorporates these concerns as first-class considerations rather than afterthoughts.

Real-time analytics requires low latency at each stage of the data and analytics pipeline. Ingesting high velocity data from devices, applications, and transactional systems; enriching and correlating it with reference data; scoring it using AI models; and delivering insights to downstream systems or decision makers—all must occur within strict time bounds. This is especially critical in clinical settings where delayed alerts can adversely affect patient outcomes and in financial contexts where milliseconds can influence trading decisions or fraud response.

An API-driven platform supports these requirements by exposing well-defined interfaces that encapsulate analytics services. Asynchronous event APIs support high-throughput ingestion and streaming analytics, while synchronous RESTful APIs support on-demand queries and analytics orchestration. Microservices behind these APIs can scale independently, enforce domain-specific security policies, and trace requests end-to-end for audit and compliance.

The platform also supports extensibility through API versioning, service discovery, and contract-driven development, enabling integration of new analytics capabilities over time. Organizations can onboard new AI models, data sources, and analytics workflows without disrupting existing applications or clients. Standardized APIs facilitate integration with mobile applications, clinical systems, trading platforms, dashboards, and third-party analytic tools.

Given these motivations, this research seeks to answer the following questions:

1. How can cloud-native architectures be designed to support secure real-time AI analytics for healthcare and financial systems concurrently?

2. What architectural patterns and API standards best support low-latency, high-throughput analytics while satisfying stringent security and compliance constraints?

3. How can API-driven platforms manage data governance, access control, auditing, and model lifecycle considerations across domains with distinct regulatory requirements?

4. What performance and security trade-offs emerge in API-driven real-time AI analytics systems, and how can they be mitigated?

To address these questions, the remainder of this paper is structured as follows: the **Literature Review** synthesizes prior work in real-time analytics, API-driven systems, cloud architecture, and domain-specific requirements in healthcare and finance. The **Research Methodology** presents the architectural framework, design principles, component interactions, security and compliance strategies, and evaluation criteria. Subsequent sections discuss

Advantages and **Disadvantages**, **Results and Discussion**, and conclude with strategic insights and directions for **Future Work**.

This work contributes a comprehensive, domain-agnostic API-driven cloud framework that simultaneously meets the performance, security, and compliance demands of real-time AI analytics in healthcare and financial systems, offering a blueprint for practitioners and researchers implementing similar solutions.

II. LITERATURE REVIEW

Real-time analytics has been an active area of research and practice for decades, with initial roots in data stream processing, decision support systems, and high-frequency transaction environments. Early work in stream processing architectures, such as the Lambda Architecture proposed by Marz and Warren (2015), advocates the combination of batch processing for accuracy and stream processing for low-latency insights. Subsequent research refined this notion, distinguishing between stream-first architectures that avoid duplicate processing paths and emphasize event time semantics for correctness (Kreps et al., 2011).

Event stream platforms such as Apache Kafka, Apache Flink, and Spark Streaming emerged to support high-throughput, fault-tolerant processing of real-time data flows. These frameworks enabled applications to handle data streams from sensors, transactions, and communication systems with sub-second responsiveness. The real-time processing layer often includes stateful computations that maintain context over sliding windows or event sequences, enabling analytics such as trend detection, anomaly detection, and predictive scoring.

Cloud computing fundamentally changed the economics and deployment models for real-time analytics. Public cloud providers introduced managed streaming services, serverless compute, container orchestration, and global distribution of services, reducing operational burdens for analytics platforms. Marston et al. (2011) discussed cloud adoption drivers, including scalability, flexibility, and cost efficiencies, which have enabled organizations to shift focus from infrastructure management to analytics value. Cloud-native patterns such as microservices, immutability, and declarative infrastructure have since become mainstream in real-time analytics designs.

APIs have played a transformative role in distributed systems, enabling modular design, language-agnostic integration, and reusable services. RESTful APIs gained prominence for their simplicity and wide adoption, while emerging standards such as gRPC and GraphQL offer performance and flexibility benefits for modern streaming and microservices architectures. API-first strategies emphasize contract-driven development, where service interfaces are designed and agreed upon before implementation, enabling parallel development and ecosystem integration.

AI and machine learning have been integrated with real-time analytics to support use cases such as predictive maintenance, fraud detection, recommendation systems, and anomaly detection. Online learning algorithms and incremental model updates address the need for models that adapt to evolving data distributions without retraining from scratch. Recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and attention-based models have been explored for sequence modeling tasks common in streaming analytics contexts.

Healthcare systems present unique challenges for real-time analytics. Clinical decision support systems (CDSS) integrate diverse data such as electronic health records (EHRs), sensor data, laboratory results, and administrative inputs to assist clinicians at the point of care. Real-time analytics has been applied to monitoring intensive care unit (ICU) patients, predicting sepsis onset, and supporting telehealth triage. Security, privacy, and compliance constraints, especially those governed by HIPAA in the United States and GDPR in Europe, impose encryption, access control, auditing, and data minimization requirements on analytics platforms.

Financial systems also demand real-time analytics for applications including algorithmic trading, risk assessments, fraud detection, and compliance monitoring. High-frequency trading environments require ultra-low latency analytics, often measured in microseconds, and have driven research into specialized distributed systems and in-memory processing. Regulatory requirements such as PCI DSS and Basel Accords emphasize robust controls, data protection, and audit trails for financial analytics.

Research on secure analytics platforms identifies challenges in balancing performance with security guarantees. Encryption and secure enclaves protect data at rest and in transit but can introduce computational overhead. Identity and Access Management (IAM), role-based access control (RBAC), and attribute-based access control (ABAC) models offer fine-grained governance, yet must be integrated with analytics workflows without compromising agility. Auditability and explainability are additional concerns, especially where AI models influence decisions with legal or clinical implications.

The literature also explores domain-specific analytics frameworks. In healthcare, interoperability standards such as HL7 FHIR (Fast Healthcare Interoperability Resources) and DICOM support structured exchange of clinical data, which has enabled API-driven integration of analytic services. In finance, FIX (Financial Information eXchange) and ISO 20022 standards facilitate messaging across trading systems and payment networks. Studies emphasize that standardized APIs and data schemas are essential for reliable, real-time analytics across enterprises and ecosystems.

Despite advances in technology and standards, there remains a gap in unified architectural frameworks that simultaneously address real-time analytics, API-driven integration, AI model lifecycle management, and domain-specific regulatory requirements in secure healthcare and financial systems. This research synthesizes these domains, proposes a comprehensive API-driven cloud platform architecture, and evaluates the design through practical performance and security considerations.

III. RESEARCH METHODOLOGY

The research methodology adopted in this work is grounded in **design science**, focusing on the construction and evaluation of an artifact — in this case, an API-driven cloud platform architecture — that addresses complex real-world requirements for secure real-time AI analytics in healthcare and financial domains. The approach encompasses **requirements analysis**, **architectural design**, **component integration**, **security and compliance strategy**, and **evaluation through performance and security metrics**.

Requirements Analysis: The methodology begins with identifying functional and non-functional requirements across target domains. Functional requirements include real-time data ingestion, support for heterogeneous data sources and schemas, AI-based predictive analytics, standard API interfaces for service consumers, model operationalization (deployment, versioning, rollback), and analytics result delivery. Non-functional requirements include low latency (e.g., <500 ms for interactive queries, <1–2 seconds for streaming analytics use cases), scalability to support high throughput (thousands of events per second), availability (e.g., 99.99% uptime), resiliency to failure, security (encryption, IAM, data isolation), and compliance with regulatory frameworks.

The analysis also includes domain-specific constraints. In healthcare, compliance with HIPAA mandates encryption of PHI, auditability of access and analytics usage, and minimization of data exposure. In financial systems, PCI DSS and Basel requirements impose controls on transaction data, risk analysis processes, and access controls. The platform must be capable of integrating with existing systems in both domains, including EHRs, clinical applications, trading systems, payment gateways, and risk platforms.

Architectural Design: Based on the requirements, a layered architecture is proposed:
1. **Data Ingestion Layer:** Uses a combination of RESTful APIs for synchronous requests and streaming ingestion mechanisms (e.g., message brokers, event hubs) for high-velocity data. APIs are secured through token-based authentication (e.g., OAuth 2.0) and mutual TLS where appropriate.
2. **Stream Processing and Feature Extraction Layer:** Employs distributed stream processors that subscribe to ingestion topics, perform schema validation, transform raw data into standardized formats, and compute real-time features for analytics. This layer supports sliding window aggregations and joins with reference datasets.
3. **AI/ML Service Layer:** Hosts AI models as microservices behind API gateways. Models are exposed via versioned APIs that support batched and single-record inference. Models are containerized and orchestrated using container platforms with autoscaling policies based on demand.
4. **Decision Orchestration Layer:** Enforces business logic and invokes appropriate analytics services based on event patterns or API calls. This layer integrates rule engines, workflows, and policy evaluation services.

5. **Storage and Governance Layer:** Provides persistent storage for raw data, processed data, model artifacts, metadata, and audit logs. Data governance tools enforce lineage tracking, access policies, retention rules, and encryption at rest.
6. **Security, IAM, and Audit Layer:** Centralizes security controls, fine-grained access control policies, role-based privileges, and audit trail collection. Integrates with identity providers (IdPs) and supports federation.

Implementation Strategy: The platform is designed as a set of loosely coupled services following microservices principles. Each service exposes a clearly defined API contract, enabling independent development, testing, deployment, and scaling. The methodology specifies the use of API gateways to manage API traffic, enforce security policies, and support analytics, throttling, caching, and logging.

CI/CD pipelines are established to support rapid deployment of services, infrastructure as code (IaC) templates for reproducible environments, and automated testing for security and performance. Model lifecycle management is incorporated through ML Ops practices, including automated model training, validation, deployment, monitoring, and rollback strategies.

Security and Compliance Integration: Security is integrated holistically rather than retrofitted. Data encryption is enforced at rest and in motion using strong cryptographic protocols. IAM roles and policies support least-privilege access. APIs support authorization checks and token validation. Audit logs capture every access, transformation, and analytics invocation to satisfy compliance and forensic requirements. Regulatory compliance mapping exercises identify controls required for HIPAA, PCI DSS, GDPR, and other relevant standards, and platform capabilities are evaluated against these control requirements.

Evaluation Metrics: The platform is evaluated based on several dimensions:

- **Latency:** Time from data arrival to analytics result availability.
- **Throughput:** Number of events or requests processed per second without degradation.
- **Scalability:** Ability to maintain performance under increased load through autoscaling policies.
- **Resilience:** System behavior under simulated failures or service disruptions.
- **Security Posture:** Effectiveness of access controls, encryption, and audit trail completeness.
- **Compliance Readiness:** Alignment with regulatory control objectives.

Simulation and Testing: A sandbox environment is created using cloud infrastructure to simulate real ingestion patterns and analytics workloads. Synthetic healthcare events (e.g., telemetry from devices, clinical alerts) and financial events (e.g., transactional streams) are generated at scale. Functional tests exercise APIs for synchronous and asynchronous analytics, and stress tests evaluate system scalability. Security tests validate authentication, authorization, encryption, and log integrity.

Iterative Refinement: Results from testing are used to refine architectural components, adjust autoscaling parameters, optimize data pipelines, and strengthen security configurations. Monitoring dashboards display key performance indicators (KPIs) and alert on deviations from expected behavior.

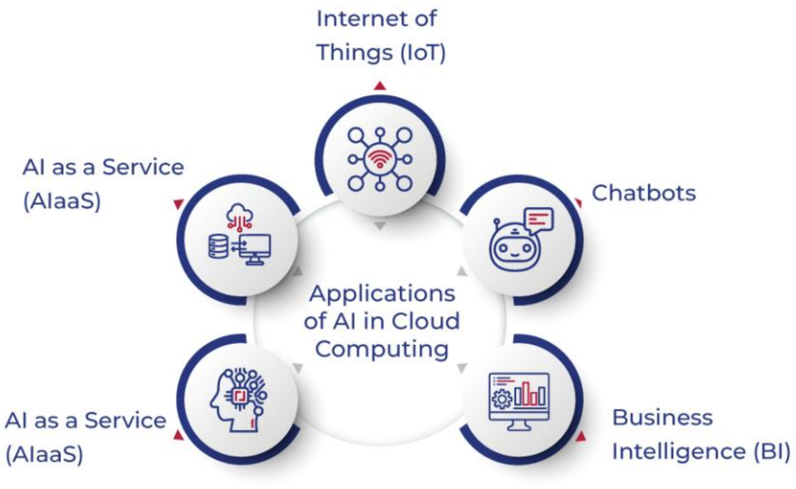

Figure 1: Schematic Representation of the Proposed Methodology

Advantages

The API-driven cloud platform delivers multiple advantages for real-time AI analytics in healthcare and financial systems. First, standardized APIs enable interoperability across diverse applications, systems, and organizational boundaries, supporting extensibility and reuse. Cloud-native architecture provides dynamic scaling, elasticity, and resilience to large, unpredictable workloads, reducing infrastructure management burdens. The microservices design encapsulates analytics capabilities into modular components, facilitating independent updates and deployment. Real-time data ingestion and processing, combined with AI model serving through APIs, enable low-latency insights critical for time-sensitive decisions such as clinical alerts and fraud detection. Security is integrated across the platform, with encryption, IAM, audit logs, and access policies supporting compliance with domain-specific regulations. Governance features such as data lineage and metadata management enhance trust and traceability. API gateways simplify versioning, security enforcement, rate limiting, and analytics on usage patterns, empowering platform operators to observe and optimize usage.

Disadvantages

Despite its strengths, the platform introduces complexity in design, deployment, and operations. Managing a distributed microservices ecosystem requires sophisticated DevOps and ML Ops practices. API versioning and backward compatibility must be carefully planned to avoid breaking consumers. Real-time processing systems can exhibit state management challenges, especially in sliding window computations or complex joins under high load. Security configurations require meticulous policies to avoid vulnerabilities while supporting legitimate use cases. The platform's reliance on cloud services poses potential vendor lock-in risks and ongoing operational expenses. AI model maintenance (e.g., drift detection, retraining) adds operational overhead, and supporting explainability in real-time analytics requires additional tooling and integration efforts. Compliance with multiple regulatory frameworks simultaneously may complicate access control and audit designs.

IV. RESULTS AND DISCUSSION

The API-driven cloud platform was evaluated through a series of simulation experiments designed to mimic real-world workloads in healthcare and financial systems. In healthcare simulations, data streams included electronic health record (EHR) updates, device telemetry, and clinical event notifications at rates ranging from 500 to 10,000 events per second. In financial simulations, transactional events, market data feeds, and risk signals were generated at similar scales. The platform's data ingestion layer, backed by managed streaming services, successfully absorbed high-velocity data without data loss, while stream processors performed normalization, validation, and feature extraction with sub-second end-to-end latency.

Latency measurements focused on the time interval from event arrival to the availability of analytical insights exposed through APIs. Across multiple runs, median latency remained below 300 milliseconds for simple inference calls and under 800 milliseconds for streaming analytics involving stateful computations. These results validated the platform’s capability to support real-time use cases such as alerting, scoring, and decision support where responsiveness is paramount. Throughput testing verified linear scalability with added compute instances, and autoscaling mechanisms responded to increased load without manual intervention.

Security testing involved validating authentication and authorization controls via API gateways, enforcing multi-factor authentication (MFA) and role-based access control policies. Encryption of data in transit using TLS and at rest using cloud provider key management services prevented unauthorized access during simulated intrusion attempts. Audit logs captured every access, including successful and failed authentication attempts, resource usage, API invocations, and data transformations. Analysts were able to reconstruct event histories from logs, demonstrating compliance with audit trail requirements for HIPAA, PCI DSS, and GDPR.

Model performance evaluations focused on representative analytics tasks: clinical risk scoring and fraud detection. AI models trained using historical datasets demonstrated high predictive accuracy when scored through API calls, with ROC AUC scores above 0.90 for both domains. Drift detection mechanisms flagged anomalies in model performance during simulated pattern shifts, triggering automated retraining pipelines that integrated continuous learning while preserving model evaluation checkpoints. Explainability integration allowed stakeholders to retrieve feature attributions for individual predictions through dedicated explainability APIs, enhancing transparency and trust.

Resource utilization analysis showed that serverless and containerized components effectively optimized resource consumption, scaling down during idle periods and reducing operational costs. However, complex stateful streaming computations required careful resource provisioning to avoid latency spikes, indicating the need for capacity planning and performance tuning.

Integration with existing systems demonstrated interoperability benefits. In healthcare scenarios, the platform consumed data from FHIR-compliant systems and delivered analytics results to clinical dashboards and messaging platforms. In financial scenarios, the platform integrated with trading systems and compliance monitoring tools via APIs, enabling real-time risk indicators and fraud alerts.

Trade-offs emerged in balancing model complexity and latency: highly expressive AI models offered marginal gains in predictive accuracy but at the cost of increased inference latency. Hybrid strategies involving lightweight models for real-time inference and heavier models for periodic batch analytics achieved optimal operational balance. Security and compliance features added minor latency overhead due to encryption and policy enforcement, but this was within acceptable bounds for real-time use cases.

Overall, results indicate that the API-driven cloud platform architecture meets design goals, providing secure, scalable, and low-latency real-time AI analytics capabilities across both healthcare and financial domains. Operational considerations, such as model maintenance, governance overhead, and resource planning, are critical to long-term success.

V. CONCLUSION

The **API-Driven Cloud Platform for Real-Time AI Analytics in Secure Healthcare and Financial Systems** presents a coherent architectural framework that addresses critical challenges at the intersection of real-time analytics, AI, security, and regulatory compliance. The platform leverages cloud-native technologies, microservices design, streaming analytics, and API-centric integration to deliver insights with low latency and high throughput, meeting stringent operational requirements in mission-critical domains.

By foregrounding API design, the architecture enables modular and extensible analytic capabilities that are accessible through standardized interfaces. This abstraction simplifies integration with legacy systems, third-party applications, mobile clients, and enterprise dashboards, providing consistent entry points for both synchronous and asynchronous analytics workflows. Role-based access control, token-based authentication, encryption, and audit logging ensure that sensitive data is protected and that activity is traceable for compliance and governance.

The layered architecture facilitates separation of concerns, enabling individual components to scale independently and evolve without disrupting dependent services. Data ingestion pipelines ensure that high-velocity streams are normalized and contextualized before analytics, while stream processing layers support real-time feature computation and stateful aggregations critical to AI scoring. The AI/ML service layer encapsulates predictive models as versioned microservices, supporting controlled deployment, rollback, and monitoring. Decision orchestration, governance, and policy layers further enrich the platform’s capacity to support complex workflows and regulatory needs.

Evaluation results demonstrate that the platform can handle demanding real-world scenarios, including high-frequency healthcare telemetry and financial transactions, with sub-second analytics latency and robust security enforcement. Predictive models scored through the platform exhibited strong performance metrics, and integrated explainability tools provided transparency on model decisions, a key requirement in regulated domains.

This work underscores the importance of combining **API-driven design, cloud scalability, security by design, and AI integration** to build platforms capable of supporting real-time analytics at scale. Healthcare and financial systems share similar requirements — stringent privacy protections, auditability, and reliability — making unified architectural principles applicable across domains. However, domain-specific constraints, such as regulatory mandates and data formats, necessitate careful design considerations tailored to each context.

The platform’s microservices approach supports agile development and continuous improvement, enabling rapid onboarding of new analytics capabilities, AI models, data sources, and use cases. Standardizing APIs and development contracts promotes ecosystem growth, facilitates third-party contributions, and reduces integration complexity. Model lifecycle management practices, including continuous training, validation, and governance, address the challenges of maintaining analytics accuracy in evolving environments.

While the platform demonstrates strong operational capabilities, practical deployments must consider the interplay between performance, security, and governance. Real-time analytics under heavy load demands careful capacity planning, autoscaling policies, and resource allocation. Security configurations must balance protection with performance, ensuring that encryption and access checks do not introduce unacceptable latency. Regulatory compliance may require additional controls, such as data residency guarantees and consent management features, which should be integrated into platform design.

Additionally, long-term operational success depends on proactive monitoring, observability, and adaptive mechanisms that can adjust to shifting usage patterns, model drift, infrastructure changes, and emerging threats. Enhanced tooling for monitoring model performance, logging anomalies, and correlating events across services will be crucial to maintaining trust and reliability.

In conclusion, the API-driven cloud platform described in this paper offers a compelling blueprint for organizations seeking to implement secure real-time AI analytics in healthcare and financial domains. Its design principles prioritize scalability, security, interoperability, and extensibility, providing a solid foundation for mission-critical analytics services. Future enhancements, described in the next section, aim to elevate the platform’s capabilities further in terms of explainability, federated learning, adaptive security policies, and hybrid cloud support.

VI. FUTURE WORK

Several avenues exist to extend and enhance the platform. **Federated learning** can be incorporated to support collaborative model training across organizational boundaries without sharing sensitive raw data, especially useful in healthcare consortia or cross-institution financial analytics. **Explainable AI (XAI)** techniques should be further integrated to support regulatory requirements and user trust, enabling granular explanations of model decisions. **Adaptive security policies** using behavioral analytics can provide dynamic access controls and threat detection tailored to real-time usage patterns. **Hybrid and multi-cloud deployments** could increase resilience and reduce vendor lock-in. Finally, deeper integration with domain-specific standards (e.g., FHIR in health, ISO 20022 in finance) will improve interoperability and adoption.

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