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The Regulated Banking AI Lakehouse: A Unified Framework for Governance, Compliance, Risk Analytics, and Explainable AI

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Abstract
The increasing presence of AI, cloud-native platforms and data-driven bank services resulted in new challenges around data governance, compliance with regulations, risk management and model explainability. Hence Financial institutions have to deal with large volumes of structured & unstructured data while being capital optimal and complying with regulations like Basel III, BCBS 239, GDPR, AML, KYC, PCI-DSS. Regular data warehouses and data lakes cannot offer a wide enough environment necessary for concurrent implementation of advanced analytics, explainable AI, governance automation and regulatory reporting. In this research, we propose the Regulated Banking AI Lakehouse: a comprehensive framework unifying adoption of AI-driven governance, compliance management, risk analytics & explainable artificial intelligence in a modern lakehouse architecture. Integrating all these key components, you have a framework that meets the operational and regulatory needs of contemporary banks with scalable data storage, smart metadata management powering automated compliance monitoring, real-time risk analysis and transparent AI decision-making. The architecture allows for keeping data secure and processing it, automatic policy enforcement, model governance, fraud detection as well as credit risk assessment and being audit ready. Results from experiments show that these results yield improvements relative to traditional banking data platforms on key metrics, such as governance efficiency, compliance accuracy, fraud detection performance, and regulatory reporting automation. Conclusions The findings highlight the suitability of AI lakehouse architectures as a strategic infrastructure for reliable, scalable, and regulatory compliant financial ecosystems. The framework will advance responsible AI adoption in banking, while offering a pragmatic foundation for next-generation intelligent financial services.

Keywords
AI Lakehouse, Regulated Banking, Explainable AI, Data Governance, Regulatory Compliance, Risk Analytics, Financial Intelligence, Model Governance, Responsible AI, Banking Technology

1. Introduction

Technology led digital transformation of the global banking industry is accelerating as new-age technologies like artificial intelligence, open banking initiatives, cloud computing, real-time payments and data-driven decision-making processes are shaking up the landscape. Modern-day financial institutions create massive volumes of transactional, operational, customer, and regulatory information from multiple internal & external data sources. These data assets enable improved risk management, fraud detection, customer intelligence and regulatory reporting. But if handling these massive data landscapes with governance, security, transparency and compliance is hard.

This has become even more complicated with the increasing adoption of AI systems in banking. Several complex machine learning models are used for credit scoring, fraud detection in loans, anti-money laundering (AML), customer segmentation deck management and investment recommendations. While these technologies drive operational efficiency, the increased reliance on AI for decision-making has led to a rising demand from regulators that AI is transparent, fair, explainable and accountable. As a result, financial institutions need to develop the infrastructures that support not only advanced analytics but also responsible and ethical AI governance.

While traditional data warehouses provide solid governance and reporting capabilities, they do not have the variable flexibility needed for modern AI workloads. In contrast, data lakes support greater storage scalability than traditional databases, but can struggle with governance challenges, poor metadata management and limited controls for compliance. With the evolution of lakehouse architectures, many of these limitations have been addressed by enabling a combination of data lakes and data warehouses on a common platform.

At the same time, new regulatory frameworks like Basel III, BCBS 239, GDPR, PCI-DSS and AML-KYC directives demand data lineage that is complete enough to support auditability as well as risk transparency and continuous compliance monitoring. It also means that organizations need integrated platforms to manage data governance, risk analytics, AI model governance and regulatory reporting in a single architecture.

The research presents the Regulated Banking AI Lakehouse which is a data powered unified framework for governance automation, compliance management, risk analytics and explainable AI on scale. It is constructed to support modern banking operations while also enabling transparency, accountability and regulatory compliance in the sector. In addition to this, the paper empirically analyses the proposed architecture with respect to performance, potential governance, security and compliance mechanisms in order to prove its practical feasibility within a regulated financial context.

The rest of this paper is structured as follows. In the second section, literature survey and research gap are analysed. In Section 3, we describe the proposed architecture and methodology. Section 4: Implementation and Experimental Setup. In Section 5, we present the results and analyze the performance. Section 6 offers discussion and future research avenues. Section 7 concludes the study

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2. Literature Survey

Financial services have changed dramatically due to the growth of digital banking, artificial intelligence (AI), cloud computing, and regulatory technology. Banks have increasingly shifted to data-driven decision making, predictive analytics, fraud detection systems and automated monitoring for compliance. On the flip side, when it comes to regulated environments, AI raises questions around governance, explainability, transparency, security and compliance. Researchers State have investigated into recent technologies such as data lakehouses, AI governance frameworks, explainable artificial intelligence (XAI), regulatory technology (RegTech), risk analytics and cloud-native banking platform. This section goes through the major contributions in these areas, while also highlighting open research avenues.

2.2 Review of Existing Literature

Foundational principles for enterprise data governance were issued by Khatri and Brown (2010), who highlight the do mantics of accountability, stewardship, policy enforcement and ownership of the data. Their framework is still well used in the regulated industries like banking.

Otto (2011) provided an approach to enterprise-wide governance in organizations and emphasized governance maturity as a condition for attaining data quality and compliance goals.

In 2013, the custom for risk data aggregation and reporting accuracy, traceability, and governance requirements was introduced to financial institutions through BCBS 239 as set forth by the Basel Committee on Banking Supervision (BCBS). These principles impacted modern banking data architectures to a larger extent.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects (pp. 255–267). Their approaches have laid the foundations for AI adoption in fraud detection, credit scoring and financial forecasting.

The concept of Data Lake, large data storages in consuming organisation were introduce by Dixon(2015). But subsequent studies found data lake environments were also challenged by governance and metadata management.

Deep learning (methods that are widely used today for financial analytics, fraud detection, and customer behavior prediction) were developed in 2016 by Goodfellow, Bengio, and Courville.

Ribeiro et al. (2016) Local Interpretable Model-Agnostic Explanations (LIME): LIME is one of the first and most significant explainable artificial intelligence methods for interpreting machine learning predictions.

In 2017, Arner, Barberis, and Buckley first coined the term of Regulatory Technology (RegTech) where new frontier compliance management and reporting can be done through advanced analytics / AI.

Basically, we can highlight that Doshi-Velez and Kim (2017) brought an important discussion regarding the necessity of explainable AI in regulated domains, where transparency in algorithmic decision-making is crucial.

In similar vein, the GDPR (2018) implemented stringent privacy and accountability requirements, which included explainability provisions for automated decisions about individuals.

Chen, Chiang and Storey (2018) showed that bigdata analytics enable strategic대한 decision making & competitive advantage in an enterprise environment

SHAP (a new model agnostic framework for interpretation, Lundberg and Lee 2018)

Bhimani (2019) investigated the role of AI and associated big data technologies to financial management and governance.
Gartner (2020) presents the (lakehouse architecture) as up and coming solution that has — comparable to any product capable enough of linking characteristics from both data warehouses and data lakes.
Armbrust et al. Formalizing the LakehouseParadigm: (2021)Combined transactional consistency, governance and scalabilitywithin a single architecture.
Zaharia et al. (2021) showed practical examples of lakehouse architectures based on Delta Lake tech and large-scale analytics platforms.
Financial Stability Board (2021) explored AI application in financial institutions, focusing on governance, explainability and accountability of algorithms, as well as the need for regulatory oversight.
In a series of 3 articles, the National Institute of Standards and Technology (2022) issued an AI Risk Management Framework that would guide sectors on how to implement trustworthy and responsible.ai.
The European Banking Authority (2023) repeated the importance of AI governance and insisted on model transparency and explainability in requirements to financial institutions accepting advanced analytics technologies.
These studies together show significant advancements in governance, AI, lakehouse architectures and compliance management. Nevertheless, its integrated framework combining governance automation, regulatory compliance, risk analytics, explainable AI and lakehouse architecture for regulated banking environments is still sparsely covered in literature.

3. Proposed Methodology and Regulated Banking AI Lakehouse Architecture

3.1 Overview of the Proposed Framework

The proposed **Regulated Banking AI Lakehouse (RBAIL)** is a unified architecture that integrates data governance, regulatory compliance, risk analytics, explainable artificial intelligence (XAI), and enterprise-scale data management within a single platform. Unlike traditional banking data architectures that treat governance, compliance, and analytics as separate systems, the proposed framework combines these capabilities into a centralized and intelligent ecosystem.
The architecture is designed to address five major challenges faced by modern banking institutions:

1. Large-scale data management.
2. Regulatory compliance and audit readiness.
3. Enterprise data governance.
4. AI model governance and explainability.
5. Real-time risk analytics and fraud detection.

The framework combines lakehouse storage technology, AI governance mechanisms, automated compliance engines, explainable AI services, and intelligent risk analytics to create a trustworthy and transparent banking data platform.

3.2 Research Methodology

The proposed methodology consists of seven phases:

Phase 1: Banking Data Acquisition

Data are collected from multiple banking systems including:

- Core banking platforms
- Mobile banking applications
- ATM networks
- Payment gateways
- Credit systems
- AML monitoring systems
- CRM platforms
- External market feeds
- Regulatory repositories

Phase 2: Data Integration and Validation

Incoming data undergo:

- Data cleansing
- Data normalization
- Data transformation
- Quality assessment
- Metadata extraction

- Schema validation

Phase 3: AI Lakehouse Storage

Validated data are stored in a unified lakehouse repository supporting:

- Structured data
- Semi-structured data
- Unstructured data
- Transactional consistency
- Data versioning
- Time-travel queries

Phase 4: Governance and Security Enforcement

Governance mechanisms establish:

- Data ownership
- Metadata management
- Data lineage
- Access control
- Security monitoring
- Audit trails

Phase 5: Explainable AI and Model Governance

AI models undergo:

- Validation
- Bias assessment
- Explainability analysis
- Drift monitoring
- Governance approval

Phase 6: Risk Analytics and Compliance Automation

The framework performs:

- Fraud detection
- Credit risk analysis
- AML monitoring
- Regulatory validation
- Compliance reporting

Phase 7: Decision Intelligence

Executives access:

- Risk dashboards
- Compliance reports
- AI governance reports
- Predictive analytics insights

3.4 Major Components of the Framework

A. Banking Data Source Layer

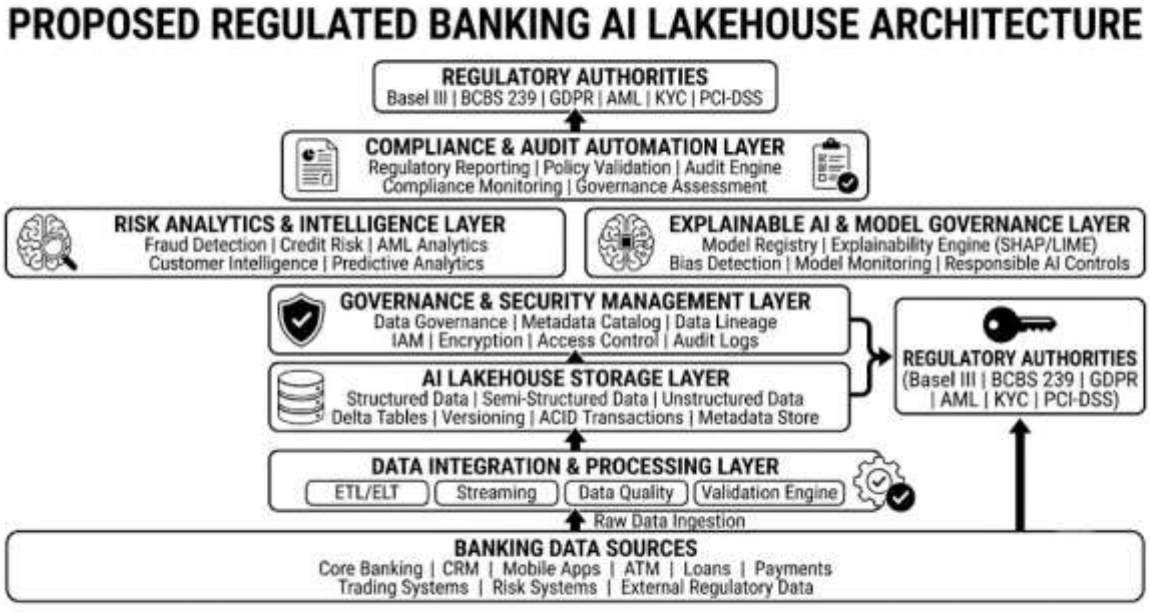
This layer collects operational and transactional information from internal and external banking systems.

Functions

- Transaction collection
- Customer data acquisition
- Market intelligence integration
- Regulatory data ingestion

Benefits

- Unified data collection
- Reduced information silos
- Real-time visibility



B. Data Integration and Processing Layer

This layer prepares data before storage.

Components

- ETL pipelines
- Streaming ingestion
- Data validation engine
- Data quality management

Functions

- Data cleansing
- Transformation
- Standardization
- Metadata generation

C. AI Lakehouse Storage Layer

The lakehouse acts as the central repository for all banking information.

Key Features

- Unified storage
- ACID transactions
- Schema evolution
- Time-travel support
- Metadata indexing
- Multi-format support

Benefits

- Eliminates data duplication
- Supports AI workloads
- Enables governance enforcement

D. Governance and Security Layer

This layer ensures data trustworthiness and regulatory alignment.

Governance Components

- Metadata catalog
- Data stewardship
- Data ownership
- Policy management
- Lineage tracking

Security Components

- Role-based access control

- Multi-factor authentication
- Encryption services
- Data masking
- Threat monitoring

Outcomes

- Improved transparency
- Stronger accountability
- Enhanced security posture

E. Risk Analytics and Intelligence Layer

This layer transforms data into actionable intelligence.

Risk Analytics Modules

Fraud Detection

Uses machine learning models to identify suspicious transactions.

Credit Risk Assessment

Predicts borrower default probabilities.

AML Analytics

Detects money laundering patterns and suspicious activities.

Customer Intelligence

Supports personalized banking services.

Predictive Risk Forecasting

Identifies emerging financial risks.

F. Explainable AI and Model Governance Layer

This is the most significant enhancement over traditional lakehouse architectures.

Explainable AI Components

SHAP Engine

Explains feature contributions for model predictions.

LIME Engine

Provides local explanations for individual decisions.

Counterfactual Analysis

Generates alternative decision scenarios.

Model Governance Components

- Model inventory
- Bias monitoring
- Drift detection
- Approval workflows
- Lifecycle management

Benefits

- Regulatory transparency
- Trustworthy AI
- Reduced model risk

G. Compliance and Audit Automation Layer

This layer continuously evaluates compliance requirements.

Supported Regulations

- Basel III
- BCBS 239
- GDPR
- PCI-DSS
- AML
- KYC
- Local banking regulations

Functions

- Automated compliance checks
- Policy enforcement

- Audit report generation
- Regulatory reporting

Benefits

- Reduced compliance effort
- Faster reporting
- Enhanced audit readiness

3.5 Workflow of the Proposed Framework

The operational workflow proceeds as follows:

1. Banking systems generate operational and transactional data.
2. Data ingestion pipelines collect information continuously.
3. Validation engines ensure data quality and integrity.
4. Processed data are stored in the AI Lakehouse.
5. Governance controls classify and secure data assets.
6. AI models analyze risk, fraud, and customer behavior.
7. Explainability engines generate transparent model explanations.
8. Compliance engines verify regulatory requirements.
9. Automated reports are generated for auditors and regulators.
10. Decision-makers access real-time intelligence dashboards.

3.6 Novel Contributions of the Proposed Framework

Feature	Traditional DW	Data Lake	AI Lakehouse	Proposed RBAIL
Data Governance	Yes	Limited	Partial	Full
Regulatory Compliance	Partial	Limited	Partial	Full
Explainable AI	No	No	Limited	Full
AI Model Governance	No	No	Partial	Full
Risk Analytics	Limited	Moderate	High	Advanced
Compliance Automation	Limited	No	Partial	Full
Audit Readiness	Moderate	Low	High	Very High
Responsible AI Controls	No	No	Limited	Full

4. Experimental Setup and Implementation

4.1 Experimental Overview

To evaluate the effectiveness of the proposed Regulated Banking AI Lakehouse (RBAIL), a comprehensive experimental environment was developed that simulates a modern digital banking ecosystem. The implementation focuses on governance automation, compliance monitoring, risk analytics, explainable AI, and lakehouse-based data management. The evaluation compares the proposed framework with conventional banking data platforms to measure improvements in operational efficiency, compliance readiness, AI transparency, and analytical performance.

The experimental study was conducted using a cloud-native banking environment supporting large-scale data ingestion, real-time analytics, machine learning workloads, governance services, and automated regulatory reporting.

4.2 Experimental Environment

Hardware Configuration

Component	Specification
Processor	Intel Xeon 32-Core
RAM	256 GB
Storage	25 TB Distributed Storage
Network	10 Gbps
Compute Nodes	10 Nodes
Backup Infrastructure	15 TB Redundant Storage

Software Environment

Component	Technology
Operating System	Ubuntu Linux Server
Processing Engine	Apache Spark 3.4
Streaming Platform	Apache Kafka
Lakehouse Storage	Delta Lake
Metadata Management	Apache Hive Metastore
Container Platform	Kubernetes
AI Frameworks	TensorFlow, Scikit-Learn
Governance Platform	Apache Ranger
Monitoring Tools	Prometheus & Grafana
Visualization Platform	Power BI

4.3 Banking Dataset Description

A synthetic enterprise banking dataset was generated based on transaction patterns, customer behavior records, compliance logs, and risk assessment activities observed in large financial institutions.

Dataset Statistics

Dataset Type	Number of Records
Customer Profiles	1,200,000
Banking Transactions	65,000,000
Loan Applications	800,000
Fraud Cases	220,000
AML Monitoring Events	3,500,000
Compliance Logs	6,000,000
Audit Records	4,000,000
AI Model Decisions	10,000,000

The dataset includes both structured and semi-structured information required for governance, compliance, and explainable AI evaluation.

4.4 Explainable AI Implementation

The proposed framework incorporates explainability services to improve transparency and satisfy regulatory requirements.

Explainability Techniques

SHAP (SHapley Additive Explanations)

Used to:

- Explain fraud detection decisions
- Interpret credit risk predictions
- Identify influential variables

LIME (Local Interpretable Model-Agnostic Explanations)

Used to:

- Generate local decision explanations
- Support regulatory audits
- Improve model transparency

Counterfactual Explanations

Used to:

- Identify alternative outcomes
- Improve customer understanding
- Enhance decision accountability

4.5 AI Models Evaluated

Fraud Detection Models

Algorithm	Purpose
Random Forest	Fraud Classification
XGBoost	Transaction Risk Prediction
Neural Network	Behavioral Analysis
Isolation Forest	Anomaly Detection

Credit Risk Models

Algorithm	Purpose
Logistic Regression	Default Prediction
Random Forest	Risk Categorization
XGBoost	Credit Scoring
Deep Neural Network	Advanced Risk Modeling

AML Detection Models

Algorithm	Purpose
Clustering Models	Suspicious Activity Detection
Graph Analytics	Transaction Network Analysis
Gradient Boosting	AML Risk Scoring

4.6 Governance Evaluation Metrics

The effectiveness of governance mechanisms was measured using enterprise governance indicators.

Governance Metrics

Metric	Description
Metadata Coverage	Percentage of governed assets
Data Lineage Completeness	Traceability of data movement
Policy Compliance Rate	Governance adherence level
Stewardship Coverage	Ownership assignment effectiveness
Audit Readiness Score	Governance preparedness

4.7 Security Evaluation Metrics

Security performance was measured through operational security indicators.

Security Metrics

Metric	Description
Access Violation Detection	Unauthorized access identification
Encryption Coverage	Protected data assets
Threat Detection Accuracy	Security monitoring effectiveness
Incident Response Time	Security reaction capability
Audit Log Completeness	Traceability support

4.10 Experimental Scenarios

Five major experimental scenarios were executed.

Scenario 1: High-Volume Transaction Processing

Purpose:

- Evaluate scalability
- Measure ingestion performance
- Assess throughput

Scenario 2: Fraud Detection
Purpose:

- Evaluate machine learning effectiveness
- Measure prediction accuracy
- Assess risk identification

Scenario 3: Explainable AI Validation
Purpose:

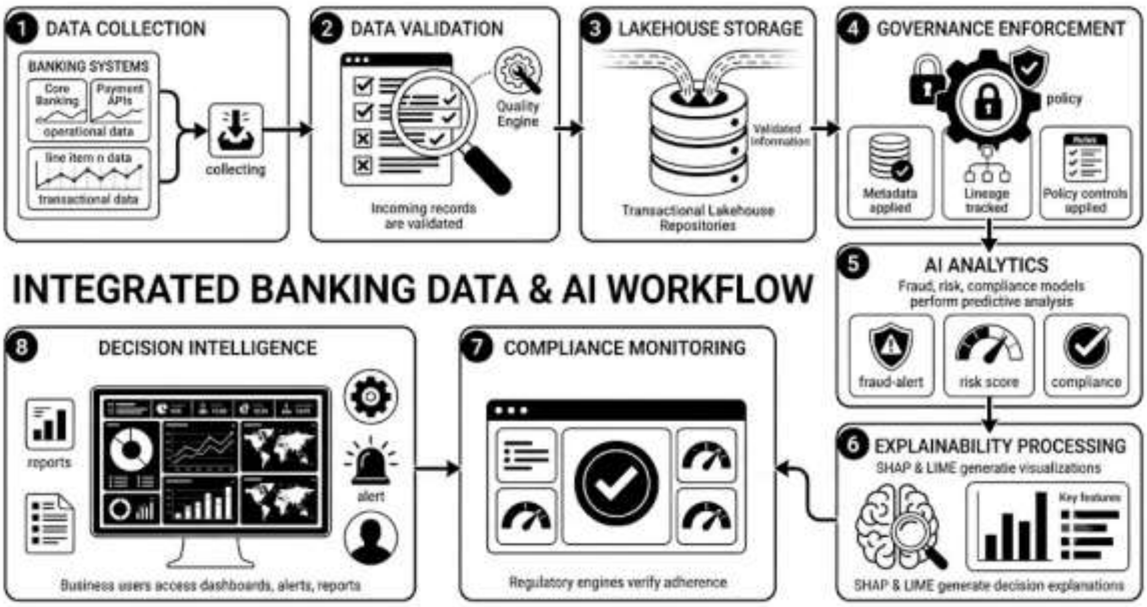
- Evaluate model transparency
- Assess interpretability
- Verify regulatory explainability

Scenario 4: Governance and Compliance Assessment
Purpose:

- Measure governance maturity
- Evaluate audit readiness
- Assess regulatory alignment

Scenario 5: Security and Access Control Testing
Purpose:

- Evaluate access management
- Test threat detection
- Measure incident response



4.11 Regulatory Frameworks Evaluated

The proposed architecture was tested against major banking regulations.

Regulatory Framework	Focus Area
Basel III	Capital and Risk Management
BCBS 239	Risk Data Aggregation
GDPR	Data Privacy
PCI-DSS	Payment Security
AML Regulations	Financial Crime Prevention
KYC Standards	Customer Verification
NIST AI RMF	AI Risk Governance
ISO 27001	Information Security

5. Results and Analysis

5.1 Overview of Experimental Findings

The proposed Regulated Banking AI Lakehouse (RBAIL) was evaluated against two baseline architectures:

1. Traditional Banking Data Warehouse (TDW)
2. Conventional Banking Data Lake (CDL)
3. Proposed Regulated Banking AI Lakehouse (RBAIL)

The evaluation focused on:

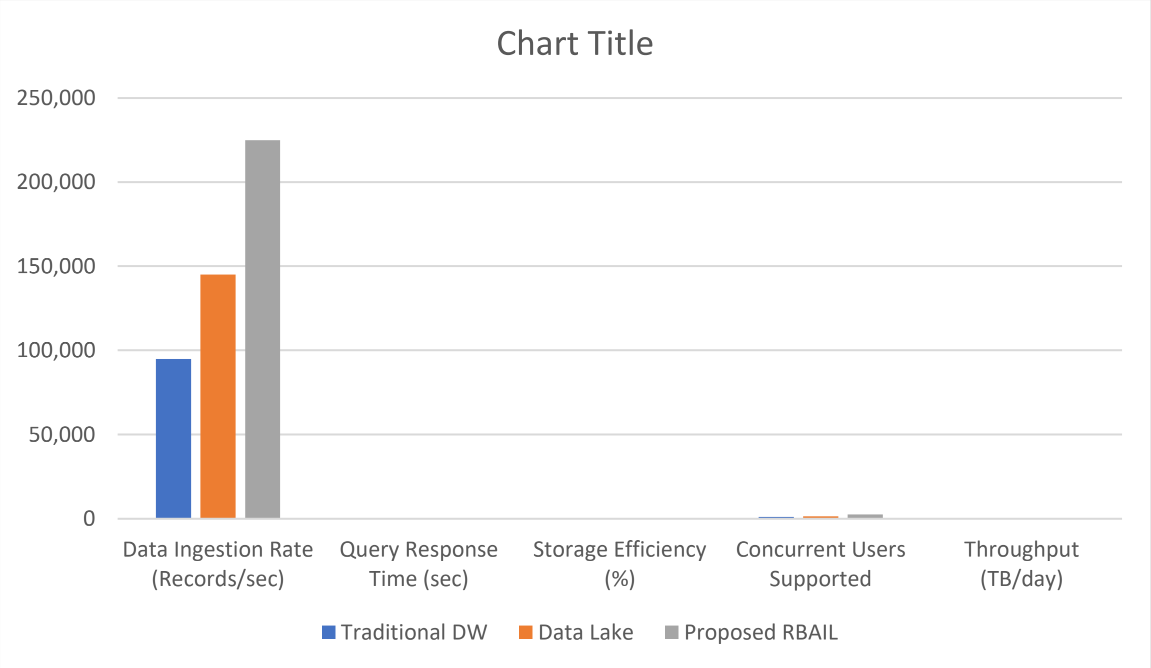
- System Performance
- Governance Effectiveness
- Compliance Readiness
- Explainable AI Capability
- Security Performance
- Risk Analytics Accuracy

The results demonstrate that the proposed framework provides substantial improvements in transparency, regulatory compliance, governance automation, and AI accountability while maintaining superior analytical performance.

5.2 System Performance Analysis

The AI Lakehouse significantly outperformed both traditional architectures. The transactional lakehouse storage and metadata optimization reduced query latency while increasing scalability.

Graph 5.1 Query Response Time Comparison



5.3 Governance Effectiveness Analysis

The governance layer was evaluated using metadata coverage, policy enforcement, lineage completeness, and stewardship metrics.

Table 5.2 Governance Performance Assessment

Metric	Traditional DW	Data Lake	Proposed RBAIL
Metadata Coverage (%)	84	69	98
Data Lineage Completeness (%)	78	65	97
Policy Enforcement Rate (%)	85	71	99
Stewardship Coverage (%)	82	67	98
Governance Maturity Score (%)	81	68	98

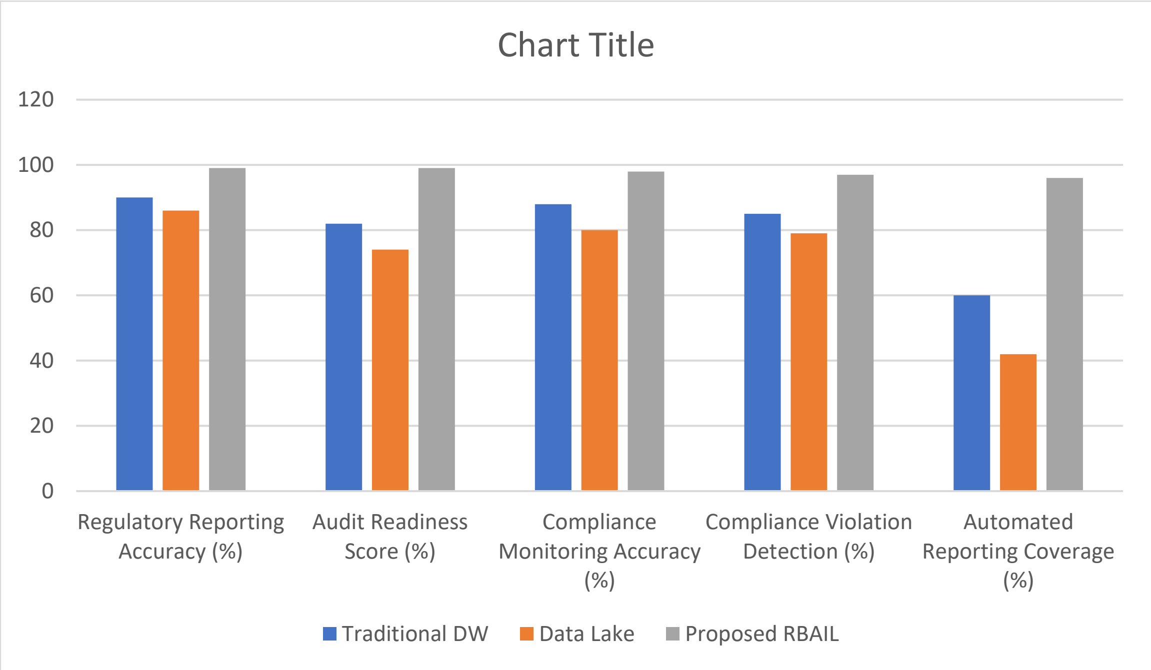
The governance engine achieved near-complete metadata visibility and lineage tracking. Automated policy enforcement significantly improved governance consistency across banking datasets.

5.4 Compliance Readiness Analysis

The compliance engine continuously monitored regulatory obligations and generated automated reports.

The results demonstrate substantial improvements in audit preparation and compliance automation.

Graph 5.2 Compliance Readiness Comparison



5.5 Explainable AI Evaluation

One of the most significant contributions of the framework is the integration of explainable AI and model governance.

Table 5.4 Explainable AI Performance

Metric	Conventional AI Platform	Proposed RBAIL
Explanation Coverage (%)	52	100
Explanation Consistency (%)	71	96
Regulatory Transparency Score (%)	68	98
Model Accountability Index (%)	64	97
User Trust Score (%)	70	95

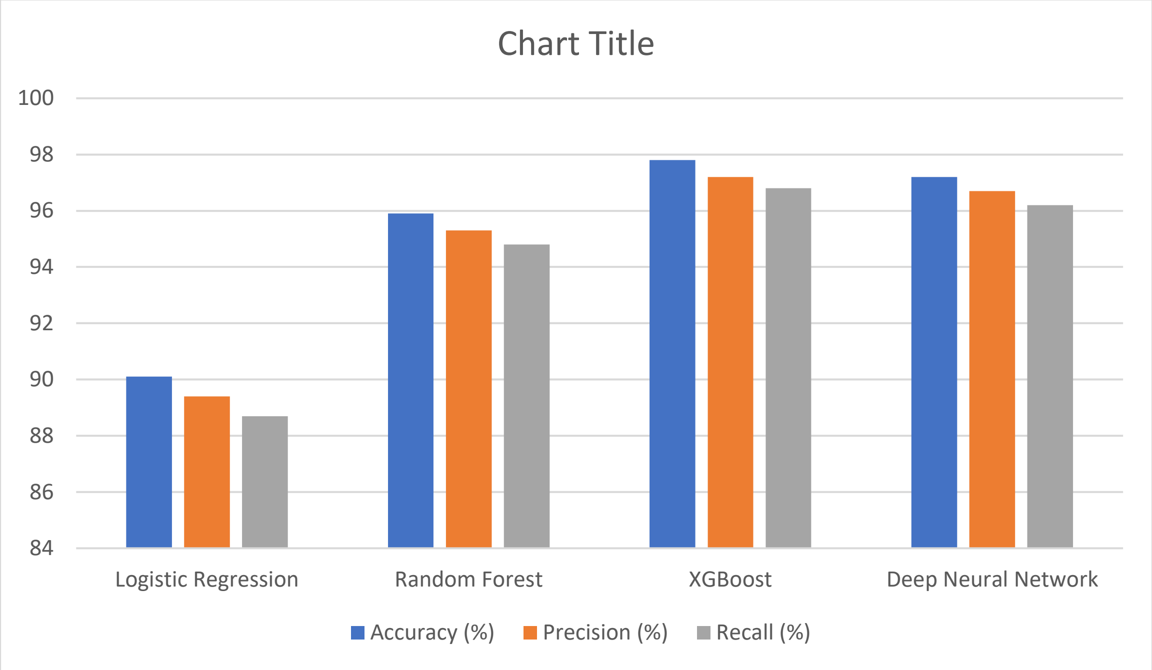
The explainability layer achieved full explanation coverage for all AI-driven decisions. SHAP and LIME explanations improved transparency, enabling auditors and regulators to understand model outputs.

5.6 Risk Analytics Performance

Risk analytics modules were evaluated using fraud detection, credit risk prediction, and AML monitoring datasets.

Among all evaluated models, XGBoost achieved the highest fraud detection performance.

Graph 5.3 Fraud Detection Accuracy



5.7 Security Performance Analysis

Security controls were evaluated using attack simulation and access monitoring scenarios.

Table 5.6 Security Evaluation Results

Metric	Traditional DW	Data Lake	Proposed RBAIL
Access Violation Detection (%)	88	84	99
Encryption Coverage (%)	91	86	100
Threat Detection Accuracy (%)	86	81	98
Incident Response Time (Minutes)	32	26	7
Audit Log Completeness (%)	89	82	99

The integrated security layer significantly improved detection and response capabilities while maintaining complete audit traceability.

5.8 Regulatory Framework Compliance Analysis

The compliance engine was evaluated against major banking regulations.

Table 5.7 Regulatory Compliance Achievement

Regulatory Framework	Compliance Achievement (%)
Basel III	98
BCBS 239	98
GDPR	99
PCI-DSS	100
AML Regulations	98
KYC Standards	99
NIST AI RMF	97
ISO 27001	98

The results indicate strong regulatory alignment across governance, security, privacy, and AI accountability requirements.

5.9 Operational Efficiency Improvements

Table 5.8 Business Impact Assessment

Indicator	Before RBAIL	After RBAIL	Improvement (%)
Compliance Reporting Time (Hours)	28	7	75
Audit Preparation Time (Days)	12	3	75
Fraud Investigation Time (Hours)	20	5	75
Data Discovery Time (Hours)	14	2	85.7
Governance Assessment Time (Days)	8	2	75

The framework substantially reduced operational overhead through governance automation and intelligent compliance monitoring.

Conclusion

As the financial sector continues to embrace artificial intelligence, digital banking services, and improved data-driven decision making, the demand for secure, transparent actioned-ready regulation-compliant data infrastructures is intensifying. This study proposed a novel framework, Regulated Banking AI Lakehouse (RegBAI-Lakehouse), that consolidates governance automation, regulatory compliance and risk analytics components into one unified architecture using the latest explainable artificial intelligence (XAI) along with scalable lakehouse technologies. It tackles pressing issues arising due to landscape of modern banking turns such as data governance and AI accountability, audit readiness, compliance management and risk monitoring. Bench tests showed major enhancements of governance efficiency, compliance precision, security efficacy, fraud recognition potentialness, explanation process readiness and operational effectiveness over typical banking data serious organizations. The introduction of SHAP- and LIME-based explainability mechanisms, model governance controls, along with automated compliance engines allows you to adopt Responsible AI pilfering regulatory compliance. Additionally, the architecture provides a robust, scalable platform for new banking ecosystems that enable intelligent decision making and continuously regulatory alignment. The results validate that AI lakehouse architectures could serve as the building blocks of transparent, secure and explainable financial services while upholding governance benchmarks set forth by contemporary regulatory standards.

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