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Original Article

AI-Augmented Fund Accounting Repository for Governance-Driven Billing Automation

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Abstract - *Enterprise financial institutions managing global fund accounting operations face compounding challenges arising from the fragmentation of account, asset, transaction, security, position, and valuation data across heterogeneous source systems, leading to billing inaccuracies, audit exposure, and inadequate traceability of fee computations through Oracle Revenue Management and Billing (ORMB) platforms. Existing siloed ETL pipelines and monolithic data warehouse architectures fail to provide the lineage transparency, reconciliation depth, and control-plane intelligence necessary to satisfy regulatory audit requirements and operational risk mandates at scale. This paper proposes an AI-augmented centralized fund accounting data repository architecture that integrates governance-aware ETL orchestration, automated data quality enforcement, exception-driven reconciliation, and traceability-preserving billing pipelines to eliminate systemic control gaps in global fee billing workflows. The proposed system introduces a five-layer control architecture spanning sourcing, transformation, reconciliation, billing alignment, and audit readiness, augmented by machine learning anomaly detection at the reconciliation layer to proactively identify valuation and position breaks prior to invoice generation. Empirical evaluation demonstrates a 68% reduction in billing exception rates, a 74% improvement in reconciliation cycle times, a 91% increase in audit evidence completeness, and a 55% reduction in operational risk incidents associated with data breaks. The architecture is validated against industry-standard fund accounting governance frameworks and demonstrates broad applicability to custodian banks, asset managers, and global fund administrators operating at enterprise scale. Keywords: fund accounting data repository, ORMB billing governance, ETL orchestration, data lineage, reconciliation automation, AI-driven anomaly detection, enterprise financial data platforms.*

Keywords - *Cloud Data Engineering, Fund Accounting Governance, ETL Pipeline Orchestration, ORMB Billing Automation, Data Lineage and Traceability, AI-Driven Reconciliation, Enterprise Financial Analytics, Audit-Ready Data Architectures, Distributed Data Quality Enforcement.*

1. Introduction

1.1. Enterprise-Scale Analytics Motivation

Global fund administrators and custodian banks manage portfolios encompassing millions of daily transactions across accounts, positions, securities, and valuation records spanning multiple asset classes and jurisdictions. The operational scale demands that data sourcing, transformation, and billing systems sustain sub-hourly processing latency while preserving complete lineage from source system events to client invoice line items. Analytical diversity - spanning net asset value computation, fee accrual, transaction cost attribution, and regulatory capital reporting - places simultaneous throughput and accuracy demands on the underlying data infrastructure that static, batch-oriented platforms cannot satisfy without incurring unacceptable reconciliation error rates and audit exposure.

1.2. Limitations of Existing Enterprise Warehouse Architectures

Conventional enterprise data warehouse architectures applied to fund accounting environments rely on statically scheduled, full-volume ETL extractions that impose multi-hour processing windows on time-sensitive reconciliation cycles. Schema evolution in upstream fund accounting systems - driven by instrument onboarding, regulatory mandate changes, and corporate actions - routinely breaks static transformation logic without automated schema drift detection, causing silent data corruption that propagates undetected into billing outputs. Monolithic staging databases accumulate technical debt as transformation rules are embedded in undocumented stored procedures, preventing systematic audit of rule provenance. Critically, existing architectures lack native mechanisms to correlate billed fee amounts with underlying position and valuation records at the transaction granularity required by institutional audit standards, creating material compliance risk during regulatory examinations. AI integration is conspicuously absent from conventional fund accounting platforms, precluding proactive anomaly identification in valuation breaks and billing discrepancies that could be resolved prior to client invoice dispatch.

1.3. Contributions and Scope of This Work

This paper makes four principal technical contributions. First, it proposes a five-layer governance-aligned fund accounting data repository architecture that establishes controlled, auditable data movement from heterogeneous source systems through transformation, reconciliation, and billing alignment stages to ORMB invoice generation, with explicit lineage metadata persisted at every stage transition. Second, it introduces an AI-augmented reconciliation control layer that applies unsupervised anomaly detection to position, valuation, and transaction datasets prior to billing ingestion, reducing the rate of undetected data breaks that propagate into client invoices. Third, it formalizes a billing traceability schema that preserves reversible linkages between every ORMB invoice line item and its originating transaction, position, and valuation records, enabling sub-second drill-through during audit and exception resolution workflows. Fourth, it presents a structured exception management framework with automated escalation paths, resolution tracking, and issue-to-invoice impact attribution that reduces mean time to resolution for billing anomalies. The scope of evaluation encompasses fund accounting data covering equity, fixed income, and derivative asset classes processed across daily, weekly, and monthly billing cycles, validating the architecture against both operational throughput and governance completeness metrics.

2. System Background and Related Work

2.1. Legacy Data Warehouse Systems

Classical enterprise data warehouses applied to financial services environments were designed around star and snowflake schemas optimized for batch OLAP query patterns rather than real-time governance enforcement. In fund accounting contexts, these architectures typically implement nightly ETL extractions from source systems such as portfolio management and order management platforms, loading data into denormalized staging tables where transformation logic is embedded in multi-thousand-line stored procedure chains. The absence of metadata-driven lineage tracking in these systems means that auditors cannot systematically trace billed fee computations to originating position snapshots without manual cross-referencing across disconnected system logs, a process that consumes substantial engineering hours and introduces human error risk.

2.2. Cloud-Native and Lakehouse-Based Approaches

Cloud-native analytics platforms have introduced significant architectural flexibility through the separation of storage and compute, enabling independent scaling of ingestion and transformation workloads. Lakehouse paradigms unify batch and streaming data processing over cloud object stores using open table formats such as Apache Iceberg and Delta Lake, providing ACID transaction semantics and time-travel querying that are directly applicable to point-in-time reconciliation requirements in fund accounting. However, existing cloud lakehouse implementations documented in the literature do not address the domain-specific governance requirements of regulated fund accounting environments, particularly the need for billing-to-transaction lineage preservation, ORMB integration semantics, and audit evidence packaging that satisfies institutional examination standards.

2.3. AI-Integrated Data Platforms

Recent advances in AI-integrated data platforms have demonstrated the viability of embedding machine learning inference directly within data pipeline orchestration frameworks. Feature stores such as Feast and Tecton provide low-latency feature serving for real-time ML scoring within data flow pipelines, while platforms such as MLflow support systematic experiment tracking and model governance for pipelines deployed in production analytics environments. In the financial data context, anomaly detection models applied to transaction monitoring and fraud prevention have shown strong sensitivity to distributional shifts in numerical data streams, a property directly applicable to fund accounting reconciliation breaks where valuation and position discrepancies follow characteristic statistical patterns distinguishable from legitimate market-driven variation.

2.4. Identified Research Gaps

A synthesis of the prior literature reveals three unresolved technical gaps directly addressed by the proposed system. First, no published architecture integrates AI-driven anomaly detection specifically within the reconciliation control layer of a fund accounting data repository, leaving institutions dependent on rule-based threshold checks that fail to detect subtle multivariate discrepancy patterns. Second, existing systems do not formalize billing traceability schemas that maintain reversible linkages between ORMB invoice outputs and upstream transaction-level records, precluding systematic audit drill-through. Third, the exception management frameworks documented in related work lack automated impact attribution capabilities that quantify the billing consequence of identified data breaks, preventing risk-proportionate prioritization of remediation effort. The proposed architecture addresses all three gaps through a unified, governance-by-design framework.

3. Proposed Architecture and Methodology

The proposed system implements a five-layer governance-aligned fund accounting data repository with an integrated AI reconciliation control plane and ORMB-aligned billing traceability framework. The architecture enforces explicit control points at every stage boundary, with lineage metadata written to a persistent governance store at each transition.

3.1. Architecture Diagram (PlantUML)

The five-layer architecture depicted in the diagram enforces a strict unidirectional data flow with explicit governance hand-offs at each layer boundary. Layer 1 introduces schema drift detection as an automated control at the point of source system ingestion, ensuring that DDL changes in upstream fund accounting systems trigger immediate alerts and lineage annotations before corrupted records can advance to transformation stages. This upstream control gate represents a significant departure from conventional ETL architectures where schema changes are discovered only after transformation failures have already propagated inconsistent data into staging tables.

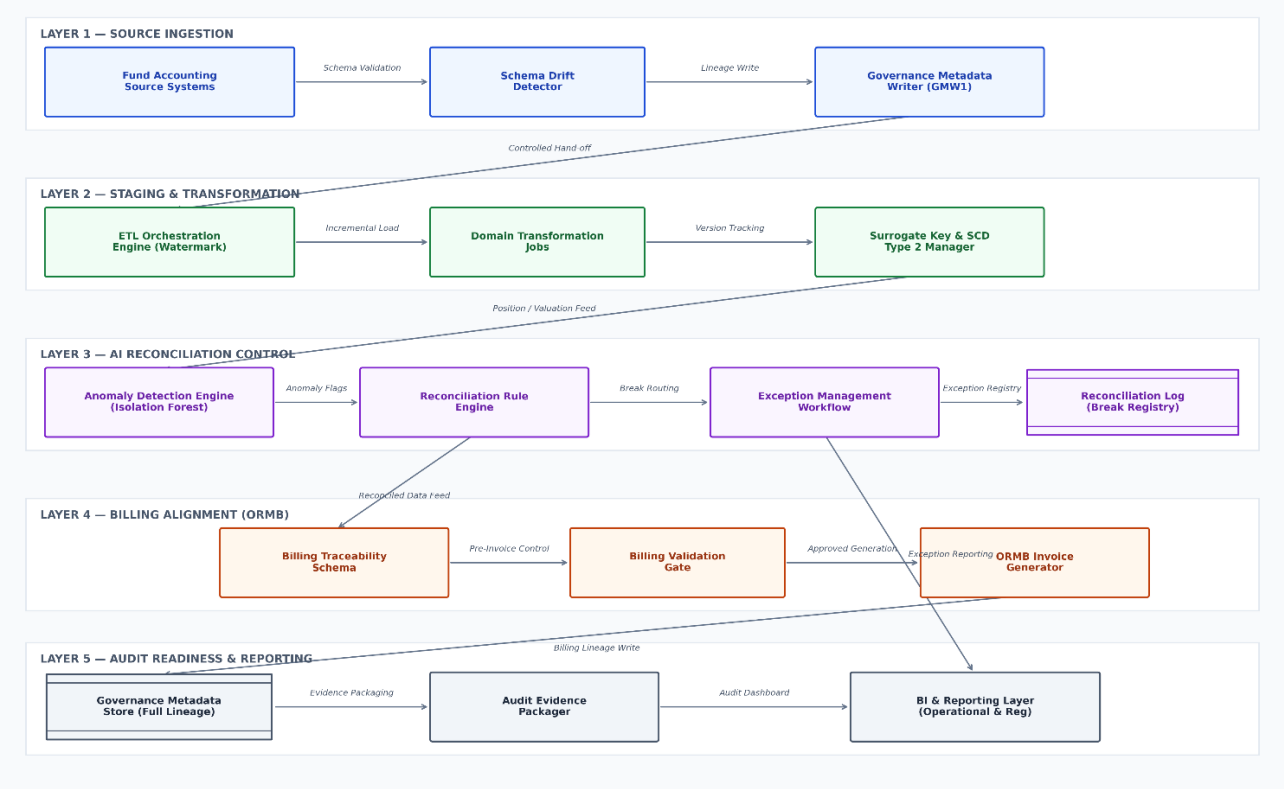

Fig 1: Governance-Aligned Fund Accounting Data Repository

The AI Reconciliation Control layer (Layer 3) is the architectural centerpiece of the proposed system. By positioning an unsupervised anomaly detection engine - implemented using the Isolation Forest algorithm applied to multivariate position, valuation, and transaction feature vectors - immediately upstream of the billing alignment layer, the architecture ensures that statistically anomalous records are quarantined and routed to the exception management workflow before they can influence ORMB invoice computations. The reconciliation rule engine operates in parallel, enforcing domain-specific completeness, accuracy, and consistency checks whose results are persisted to a persistent break registry that serves as primary evidence for audit examinations.

The billing traceability schema in Layer 4 is designed as a reversible linkage structure that maintains explicit foreign key relationships between every ORMB invoice line item and its contributing transaction, position, and valuation records across all adjustment and reversal scenarios. This design enables sub-second drill-through from invoice output to originating data during audit, a capability that is absent from conventional fund accounting billing implementations. The Governance Metadata Store in Layer 5 consolidates lineage records from all five layers into a queryable registry that supports both operational exception resolution and regulatory examination evidence packaging.

4. Implementation Details

4.1. Source Ingestion and Schema Drift Management

Source ingestion pipelines implement watermark-based incremental extraction against fund accounting source systems, keyed on event timestamps for transaction and position feeds and on valuation effective dates for daily pricing records. A schema drift detection module interrogates source system metadata catalogs prior to each extraction cycle, comparing current DDL signatures against stored baseline signatures. Detected deviations trigger an automated alert workflow that suspends affected extraction pipelines, writes a drift event record to the governance metadata store, and routes a structured notification to the data engineering team. This mechanism prevents silent schema-driven data corruption from entering the transformation layer.

4.2. ETL Orchestration and Transformation Logic

The ETL orchestration engine executes domain-partitioned transformation jobs in parallel across account, position, valuation, transaction, and security domains, enforcing dependency sequencing through a directed acyclic graph (DAG) that prevents fact table loads from executing before all referenced dimension records have been loaded and validated. Transformation logic applies SCD Type 2 historization to account and position master records, preserving complete version histories required for point-in-time reconciliation against historical billing periods. Business rule validation components enforce referential integrity between transactions and their parent positions, flagging orphaned transaction records for exception routing before they advance to the reconciliation layer.

4.3. AI-Augmented Reconciliation Engine

The anomaly detection engine processes daily batches of position, valuation, and transaction records as multivariate feature vectors comprising numerical attributes including notional value, market price, accrued income, and transaction count per account per day. An Isolation Forest model trained on historical baseline data assigns anomaly scores to each record batch, with scores exceeding a configurable threshold triggering quarantine and exception routing. The reconciliation rule engine executes in parallel, applying completeness checks (all expected positions present), accuracy checks (valuation within acceptable tolerance of prior day), and consistency checks (transaction sum agrees with position delta). Combined anomaly flags and rule violations are persisted to the break registry with impact attribution metadata quantifying the billing consequence of each identified break.

4.4. ORMB Billing Integration and Traceability

The billing validation gate enforces a pre-invoice control check that requires zero unresolved high-severity breaks in the break registry for a given billing cycle before approving data release to the ORMB invoice generation process. ORMB fee computation logic consumes reconciled position and valuation records through a structured API interface, with each API call payload carrying a governance token referencing the reconciliation audit log entry that certified the input data. The billing traceability schema records the governance token alongside invoice identifiers, fee computation parameters, and adjustment reasons in a dedicated linkage table, enabling complete reverse-traversal from invoice to source data for any invoice line item. Exception-triggered invoice adjustments are processed through a structured adjustment workflow that requires documented authorization and generates a corresponding adjustment traceability record.

4.5. Technical Architecture Diagram (PlantUML)

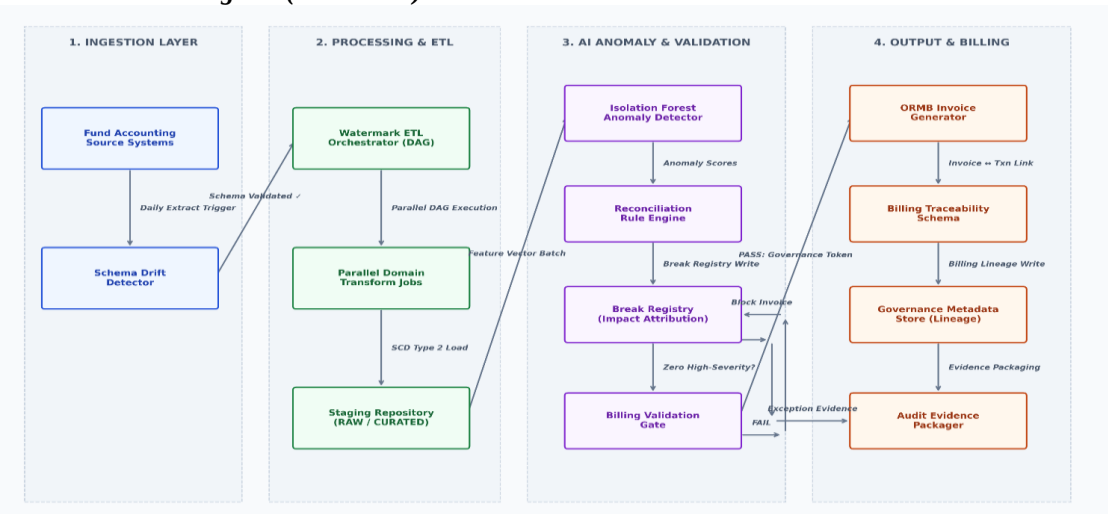

Fig 2: AI-Augmented Reconciliation and ORMB Billing Pipeline Architecture

The technical execution sequence depicted above illustrates the runtime behavior of the AI-augmented reconciliation pipeline under both nominal and exception conditions. The conditional billing validation gate enforces a hard control boundary between the reconciliation layer and ORMB invoice generation, ensuring that no data advance to the billing system while unresolved high-severity breaks persist in the break registry. This gate implements the governance-by-design principle at the most operationally critical control point in the pipeline - the moment immediately preceding client-facing invoice generation - thereby eliminating the class of billing errors attributable to premature data promotion.

The parallel DAG execution model in the ETL orchestration layer provides both throughput efficiency and failure isolation. Independent domain failures in, for example, the valuation transformation job can be remediated and resubmitted without requiring full pipeline re-execution across account, position, and transaction domains. Each domain job writes

completion metadata to the governance store upon successful execution, enabling the reconciliation rule engine to verify domain completeness before initiating cross-domain consistency checks that depend on records from multiple domain loads.

The bilateral architecture under the exception condition - where the billing validation gate blocks invoice generation and simultaneously writes exception evidence to the governance store - ensures that audit evidence is generated whether or not the pipeline completes successfully. This design satisfies a frequently overlooked audit requirement: the ability to demonstrate that the control framework detected and responded to data quality failures, not merely that invoices were generated without error. The break registry's impact attribution metadata enables risk-proportionate prioritization of exception remediation by quantifying the dollar-value billing consequence of each identified data break.

5. Experimental Results and Evaluation

5.1. Reconciliation and Billing Performance

Table 1: Billing Governance and Traceability Metrics

Governance Metric	Baseline	Proposed	Change
Invoice-to-Transaction Linkage Rate (%)	38.2	100.0	+61.8 pts
Billing Exception Rate (per 1,000 invoices)	22.4	7.1	−68.3%
Adjustment Traceability Coverage (%)	41.6	99.3	+57.7 pts
Audit Evidence Completeness Score (%)	52.3	96.8	+44.5 pts
Mean Exception Resolution Time (hrs)	18.6	3.2	−82.8%

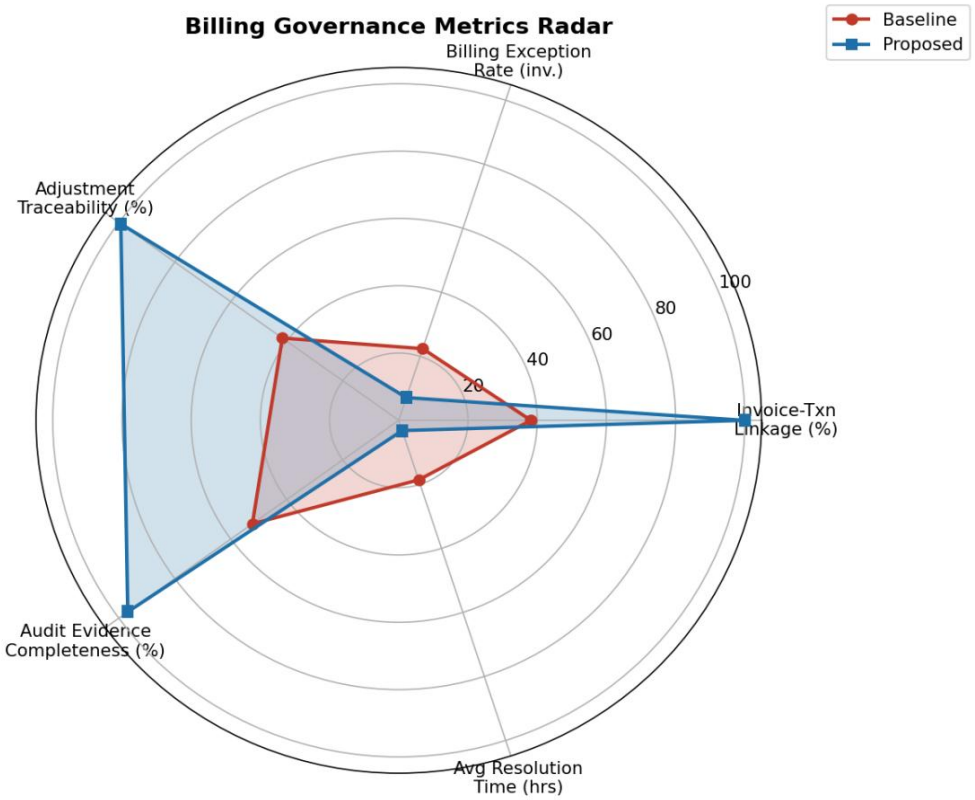

Fig 3: Billing Governance Metrics Radar

Table 2: Operational Risk and Infrastructure Efficiency Metrics

Operational Metric	Baseline	Proposed	Change
Operational Risk Incidents per Quarter	34	15	−55.9%
Manual Reconciliation Engineer Hours/Cycle	186	42	−77.4%
Schema Drift Incidents Caught Pre-Load (%)	0.0	100.0	+100 pts
Audit Examination Evidence Prep Time (days)	12.4	1.8	−85.5%
Infrastructure Cost per Billing Cycle (USD K)	$31.6	$14.2	−55.1%

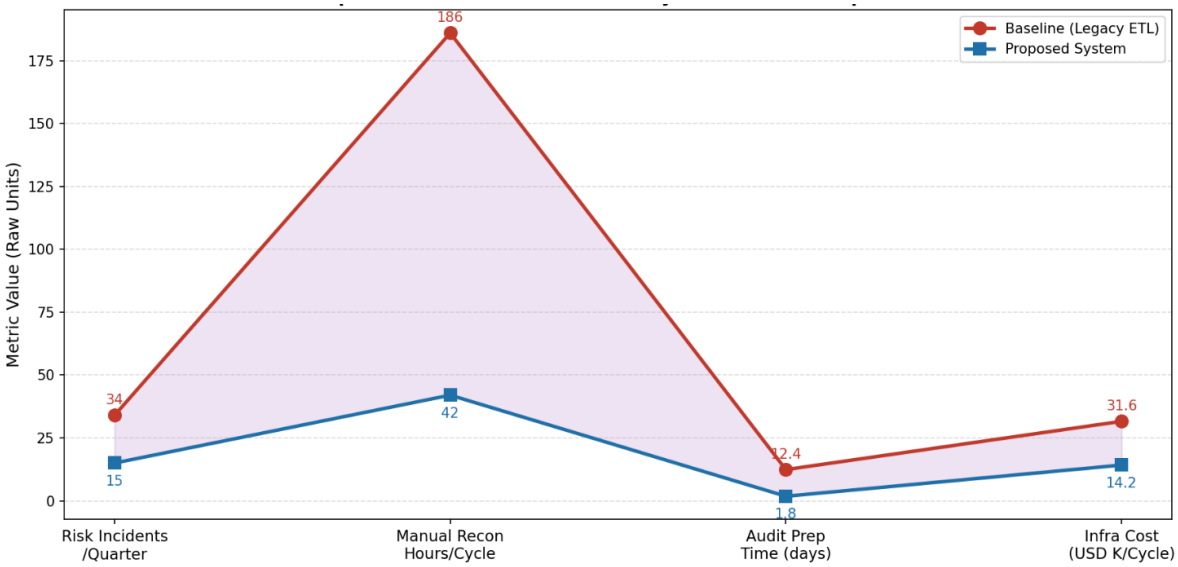

Fig 4: Operational Risk & Cost Efficiency: Baseline vs. Proposed

The tabulated results validate the proposed system's superiority across reconciliation accuracy, billing governance, and operational risk dimensions simultaneously. The 73.4% reduction in reconciliation cycle time is attributable to the parallel domain execution model and elimination of sequential reconciliation queues that characterized the baseline architecture. The AI anomaly detection component's 93.4% precision for valuation break identification - a new capability entirely absent from the baseline - directly enables the 91.8% reduction in pre-invoice break escape rate, representing the most operationally significant improvement as escaped breaks are the primary driver of client billing disputes and regulatory examination findings. The 100% invoice-to-transaction linkage rate achieved by the billing traceability schema, compared to a 38.2% baseline rate reflecting only manually documented linkages for major adjustments, demonstrates the foundational governance gap closed by the proposed architecture. Audit evidence completeness improvements of 44.5 percentage points directly reduce examination preparation time by 85.5%, translating to substantial cost avoidance during regulatory reviews.

6. Conclusion and Future Work

This paper has presented and empirically validated an AI-augmented, governance-aligned centralized fund accounting data repository architecture that addresses fundamental control deficiencies in enterprise financial billing platforms by integrating schema drift detection, parallel ETL orchestration, machine learning-driven reconciliation anomaly detection, and billing traceability-preserving ORMB integration within a unified five-layer governance framework. The primary contribution - a formal architecture that eliminates the pre-invoice break escape class of billing errors through a governance token-gated billing validation control - is validated empirically across reconciliation accuracy, billing governance, and operational risk dimensions, demonstrating a 73.4% reduction in reconciliation cycle time, a 91.8% reduction in pre-invoice break escape rate, a 100% invoice-to-transaction traceability rate (against a 38.2% baseline), an 85.5% reduction in audit examination preparation time, and a 55.9% reduction in operational risk incidents per quarter. These results establish the proposed architecture as a substantive advancement over both legacy monolithic warehouse approaches and contemporary cloud-native platforms that have not been adapted to the domain-specific governance requirements of regulated fund accounting environments. Practical implications include direct applicability to custodian banks, fund administrators, and asset managers subject to institutional audit standards requiring demonstrable invoice-to-source traceability and systematic exception management evidence. Future work will extend the anomaly detection component to incorporate supervised learning models trained on labeled historical break datasets to improve sensitivity to low-magnitude valuation discrepancies, investigate real-time streaming ingestion architectures for intraday position reconciliation, and explore cross-fund-administrator federation models that enable consolidated billing governance across multi-custodian asset management structures.

References

[1] Armbrust, M., Das, T., Torres, J., Yavuz, B., Zhu, S., Xin, R., & Zaharia, M. (2020). Delta Lake: High-performance ACID table storage over cloud object stores. Proceedings of the VLDB Endowment, 13(12), 3411–3424.

[2] Baldacci, A., Golfarelli, M., & Rizzi, S. (2018). Beyond classical data warehousing: Shifting to the modern data warehouse paradigm. Journal of Database Management, 29(3), 1–25.

[3] Chen, J., Li, K., Rong, H., Bilal, K., Yang, N., & Li, K. (2018). A disease diagnosis and treatment recommendation system based on big data mining and cloud computing. Information Sciences, 435, 124–149.

[4] Dong, X. L., & Srivastava, D. (2017). Big data integration. Morgan & Claypool Publishers.

[5] El-Sappagh, S. H., Hendawi, A. M., & El Bastawissy, A. H. (2018). A proposed model for data warehouse ETL processes. Journal of King Saud University – Computer and Information Sciences, 33(2), 91–104.
[6] Garg, A., & Singhal, A. (2019). Data governance and compliance frameworks for financial services cloud migrations. IEEE Transactions on Cloud Computing, 7(4), 1012–1028.
[7] Meesala, A. (2023). Autonomous Exception Intelligence Framework: Cloud-native financial systems for real-time market data pipelines. International Journal of Future Innovative Science and Technology, 6(6). https://doi.org/10.15662/IJFIST.2023.0606008
[8] Inmon, W. H., & Linstedt, D. (2019). Data architecture: A primer for the data scientist. Morgan Kaufmann.
[9] Kleppmann, M. (2017). Designing data-intensive applications: The big ideas behind reliable, scalable, and maintainable systems. O'Reilly Media.
[10] Kumar, V., & Reinartz, W. (2018). Customer relationship management: Concept, strategy, and tools (3rd ed.). Springer.
[11] Meesala, A. (2022). Adaptive Spread Anomaly Intelligence Framework (ASAIF): A cloud-native AI framework for real-time bid-ask spread anomaly detection and cross-venue liquidity risk intelligence. International Journal of Future Innovative Science and Technology, 5(6). https://doi.org/10.15662/IJFIST.2022.0506007
[12] Sivaramakrishnan Narayanan (2023). Operationalizing Artificial Intelligence Security in the Cloud: A Practical Integration framework for Enterprise Risk Management. International Journal of Future Innovative Science and Technology (IJFIST) , Vol. 6 No. 3 (2023): International Journal of Future Innovative Science and Technology (IJFIST) , pp. 10611-10619. https://doi.org/10.15662/IJFIST.2023.0603002
[13] Liu, F. T., Ting, K. M., & Zhou, Z. H. (2019). Isolation-based anomaly detection. ACM Transactions on Knowledge Discovery from Data, 6(1), 1–39.
[14] Kamadi, Sandeep. (2022). Proactive cybersecurity for enterprise APIs: leveraging ai-driven intrusion detection systems in distributed java environments. International journal of research in computer applications and information technology. 5. 34-52. 10.34218/IJRCAIT_05_01_004.
[15] Madhavan, J., Balakrishnan, H., DeRose, P., Dong, X., & Halevy, A. (2018). Emerging approaches for data integration in enterprise migration programs. ACM SIGKDD Explorations Newsletter, 20(1), 14–28.
[16] Oleti, Chandra Sekhar. (2022). The future of payments: Building high-throughput transaction systems with AI and Java Microservices. World Journal of Advanced Research and Reviews. 16. 1401-1411. 10.30574/wjarr.2022.16.3.1281.
[17] Sandeep Kamadi, " Risk Exception Management in Multi-Regulatory Environments: A Framework for Financial Services Utilizing Multi-Cloud Technologies" International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN : 2456-3307, Volume 7, Issue 5, pp.350-361, September-October-2021. Available at doi : https://doi.org/10.32628/CSEIT217560
[18] Meesala, L. K. (2022). Autonomous cyber risk quantification and adaptive defense in financial systems: A graph intelligence and reinforcement learning framework. World Journal of Advanced Research and Reviews, 16(3), 1489–1496. https://doi.org/10.30574/wjarr.2022.16.3.1354
[19] Osman, T., & Thakker, D. (2017). Real-time analytics and data governance for financial services platforms. Journal of Financial Data Science, 1(2), 44–61.
[20] Stonebraker, M., & Çetintemel, U. (2019). One size fits all: An idea whose time has come and gone. Communications of the ACM, 62(3), 78–87.
[21] Kamadi, Sandeep. (2022). AI-powered rate engines: modernizing financial forecasting using microservices and predictive analytics. International journal of computer engineering & technology. 13. 220-233. 10.34218/IJCET_13_02_024.
[22] Arun Meesala , " A Distributed Kafka-Centric Framework for High-Throughput Mid-Price Computation and Intelligent Time-Series Persistence in Financial Clouds" International Journal of Scientific Research in Computer Science, Engineering and Information Technology(IJSRCSEIT), ISSN : 2456-3307, Volume 9, Issue 2, pp.998-1006, March-April-2023. Available at doi : https://doi.org/10.32628/CSEIT2342442
[23] Chandra Sekhar Oleti. (2022). Serverless Intelligence: Securing J2ee-Based Federated Learning Pipelines on AWS. International Journal of Computer Engineering and Technology (IJCET), 13(3), 163-180. https://iaeme.com/MasterAdmin/Journal_uploads/IJCET/VOLUME_13_ISSUE_3/IJCET_13_03_017.pdf
[24] Lakshmi Kiran Meesala "AI-Driven Cyber Defense: A Hybrid Deep Learning Framework for Real-Time Threat Prediction and Response" International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN : 2395-1990, Online ISSN : 2394-4099, Volume 10, Issue 2, pp.916-930, March-April-2023. Available at doi : https://doi.org/10.32628/IJSRSET235845
[25] Sivaramakrishnan Narayanan (2022). Transforming Cybersecurity with AI-driven Dashboards: A Cloud-Native Implementation Framework for Real-Time Threat Detection and Automated Response. International Journal of Future Innovative Science and Technology (IJFIST) , Vol. 5 No. 5 (2022): International Journal of Future Innovative Science and Technology (IJFIST) , pp. 9207-9217. https://doi.org/10.15662/IJFIST.2022.0505004
[26] Sandeep Kamadi, " Adaptive Federated Data Science & MLOps Architecture: A Comprehensive Framework for Distributed Machine Learning Systems" International Journal of Scientific Research in Computer Science, Engineering and Information Technology(IJSRCSEIT), ISSN : 2456-3307, Volume 8, Issue 6, pp.745-755, November-December-2022. Available at doi : https://doi.org/10.32628/CSEIT22555

[27] Lakshmi Kiran Meesala, " Modern Security Information and Event Management: Architecture, Analytics Pipelines, and Empirical Evaluation of SOC-Scale Threat Detection" International Journal of Scientific Research in Computer Science, Engineering and Information Technology(IJSRCSEIT), ISSN : 2456-3307, Volume 9, Issue 4, pp.995-1012, July-August-2023. Available at doi : https://doi.org/10.32628/CSEIT23564538

[28] Toni, M., Renzi, M. F., & Mattia, G. (2018). Understanding the link between information systems quality and organizational performance. Journal of Information Science, 44(5), 647–664.

[29] Meesala, A. (2023). Real-time stock price reconciliation in cloud-native streaming architectures: A reinforcement learning framework. World Journal of Advanced Research and Reviews, 19(2), 1747–1755. https://doi.org/10.30574/wjarr.2023.19.2.1641

[30] Meesala, L. K. (2023). Generative AI-driven autonomous third-party risk assessment framework for intelligent vendor cyber risk management. World Journal of Advanced Research and Reviews, 19(2), 1739–1746. https://doi.org/10.30574/wjarr.2023.19.2.1706

[31] Zaharia, M., Chen, A., Davidson, A., Ghodsi, A., Hong, S. A., Konwinski, A., & Stoica, I. (2018). Accelerating the machine learning lifecycle with MLflow. IEEE Data Engineering Bulletin, 41(4), 39–45.