European Economic Letters
ISSN 2323-5233
Vol 16 Issue 1(2026)
http://eelet.org.uk

Intelligent Accounting Systems for Digital Enterprises: An AI-Driven Framework for Control and Compliance

Dr. Deepankar Sharma

Associate Professor Law School of Law, Forensic Justice & Policy Studies National Forensic
Email: deepankar707@gmail.com

Abstract

Rapid digital commerce expansion exposed limitations in traditional accounting platforms regarding reconciliation accuracy, fraud detection, and compliance. To address this, we introduce a hybrid AI-driven framework combining supervised classifiers (XGBoost, DNNs) for reconciliation, unsupervised anomaly detectors (Isolation Forests, autoencoders) for fraud mitigation, transformer-based NLP (FinBERT, BERT) for regulatory tracking, and blockchain-RPA workflows for immutable auditing. Evaluated across six core metrics using normalized, anonymized transaction and regulatory datasets, the system outperformed legacy platforms, achieving a 23.7% increase in reconciliation accuracy, an 18.3% latency reduction, an FDS of 0.91 (ROC-AUC = 0.94), an RCI of 0.89, and an EQ of 0.78. Integrating privacy preservation and model explainability, this architecture transitions accounting from basic automation to adaptive, regulation-aware financial intelligence.

Keywords: Blockchain auditability, AI-driven accounting, Fraud detection, Regulatory compliance automation, Robotic process automation (RPA), Explainable financial AI

1. Introduction

Conventional accounting infrastructures are now subject to previously unheard-of levels of transactional complexity, fraud vulnerability, along with compliance volatility because of the rapid digitisation of commerce, which is typified by the growth of e-commerce platforms, subscription-based services, as well as blockchain-mediated financial exchanges [1], [2], [3]. Traditional double-entry bookkeeping and enterprise resource planning (ERP) systems, although mature, are increasingly ill-equipped to ensure reconciliation fidelity, fraud resilience, and statutory conformity under conditions of high-volume, multi-jurisdictional financial operations [4], [5]. The dynamism of international financial regulations, including IFRS, GAAP, as well as digital services taxation regimes [6], [7], [8], in conjunction with the exponential increase in microtransactions, requires architectures that are computationally robust, adaptive, and automated.

Promising developments in fields [9], [10] including anomaly detection, compliance automation, and robotic process automation for workflow optimisation have been shown in recent studies that have investigated the integration of artificial intelligence (AI) into financial processes. However, extant literature largely treats these advances in isolation, with limited exploration of integrated frameworks capable of jointly addressing reconciliation accuracy, fraud detection sensitivity, regulatory alignment, and operational cost efficiency within heterogeneous accounting ecosystems [11], [12], [13]. Additionally, the systematic evaluation of the efficacy of deep learning and ensemble methods in relation to regulatory adaptability as well as blockchain-enabled audit trails remains underexplored, even though they have been implemented in financial classification problems.

A hybrid empirical–computational approach for AI-driven accounting in online enterprises is proposed and empirically validated in this study to fill these shortcomings. The methodology integrates supervised classifiers (XGBoost, deep neural networks) for transactional reconciliation, unsupervised anomaly detectors (Isolation Forest, autoencoder ensembles) for fraud identification, transformer-based NLP models (FinBERT, BERT) for compliance parsing, and blockchain–RPA workflows for immutable and automated auditability. The framework is assessed against a comprehensive set of key performance indicators (AFR, PL, FDS, RCI, OCE, EQ) using real-world transactional datasets, fraud incidence corpora, as well as jurisdictional regulatory texts.

The principal contributions of this paper are three-fold:

1. For accounting intelligence, an integrated methodological framework that combines blockchain auditability, compliance automation, anomaly detection, and classification.

2. Significant empirical findings indicate notable enhancements in reconciliation accuracy (+23.7%), fraud sensitivity (FDS = 0.91, ROC-AUC = 0.94), as well as compliance alignment (RCI = 0.89) when contrasted with traditional approaches.

3. Protocols for interpretability & ethical alignment that use federated learning, SHAP, and LIME to guarantee jurisdictional conformance, transparency, and data privacy.

This study offers theoretical value and practical relevance to digital companies, auditors, and policymakers in dealing with the ever-changing requirements of the globalized accounting ecosystems by positioning AI-driven infrastructures as a paradigm shift beyond procedural automation to regulation-sensitive financial intelligence.

2. Related Works

2.1 Traditional Accounting Approaches and Limitations

Organisational accounting has traditionally relied on traditional double-entry bookkeeping & ERP-based solutions. Although they are increasingly limited by transaction scale, variability, and regulatory instability, their benefits are procedural rigour and auditability. Digital ecosystems like e-commerce microtransactions, subscription renewals, as well as blockchain settlements are complicated. Manual reconciliation and rule-based anomaly detection are slow, error-prone, and not very adaptable.

2.2 AI in Financial Fraud Detection

In the field of fraud detection, machine learning and deep learning have been widely analyzed. Classical methods use logistic regression and decision trees, and more modern methods use ensemble learning and manifold-based unsupervised methods. [14] showed that deep autoencoders could be useful in capturing non-linear irregularities and [15] suggested Isolation Forests as scalable detectors of anomalies. Reconstruction error models with path-length scores have since been shown to be more sensitive but have not been widely used in accounting.

2.3 NLP for Regulatory Compliance

The complexity of multi-jurisdictional regulatory regimes has spurred the adoption of natural language processing in compliance monitoring. Transformer-based models have been demonstrated to be effective in statutory interpretation, while domain-specific modifications like FinBERT [16] have enhanced semantic congruence in financial situations. In dynamic accounting contexts, however, operational utility is limited because most deployments prioritise textual classification over executable compliance mapping.

2.4 Automation and Blockchain in Accounting

[17] have observed that robotic process automation (RPA) has been increasingly implemented for the purposes of invoice management, tax filing, and ledger reconciliation. While RPA reduces human workload, it does not possess intrinsic intelligence. Blockchain technologies have simultaneously been explored for auditability, offering immutable ledgers and verifiable smart contracts. Blockchain's function is limited to passive record-keeping instead of active compliance assurance because integration with AI verification engines is still lacking, despite these advancements.

2.5 Identified Research Gap

The literature review in Table 1 emphasises the fragmented nature of the progress: The sensitivity of fraud detection models is enhanced, regulatory text interpretation is advanced by NLP, workflow automation is improved by RPA, and audit integrity is strengthened by blockchain. However, few studies propose integrated frameworks capable of concurrently addressing reconciliation accuracy, fraud detection, compliance alignment, and operational efficiency in heterogeneous digital financial ecosystems. This gap highlights the importance of cohesive, regulation-conscious AI frameworks—the void this research aims to address.

Table 1. Comparative Overview of Prior Research in AI-Driven Accounting and Finance

Author/Year	Focus Area	Methodology/Models Used	Key Findings	Limitations
Middae et al.[18]	Traditional accounting systems	Double-entry, ERP	Procedural rigor, standardized auditability	High latency, error-prone, limited adaptability
Ikumapayi and Ayankoya [19]	Fraud detection (classical ML)	Logistic regression, decision trees	Basic fraud classification feasible	Poor scalability, weak performance on complex fraud
Abibowale [20]	Anomaly detection	Isolation Forest	Scalable unsupervised fraud detection	Sensitive to parameterization, limited interpretability
Bakare et al. [21]	Deep learning fraud detection	Deep autoencoders	Strong detection of non-linear anomalies	Reconstruction error lacks domain explainability

Onyenhazi [22]	Process automation in accounting	Robotic Process Automation (RPA)	Reduces manual workload, faster workflows	Limited intelligence, lacks adaptability
Celestin and Gidisu [23]	Blockchain in auditing	Smart contracts, distributed ledgers	Immutable, verifiable audit trails	Passive record-keeping, no adaptive verification
Caprio [24]	Legal NLP for compliance	BERT-based transformers	High semantic accuracy in statutory mapping	Limited to classification; poor executability
Ikumpayi [25]	Financial domain NLP	FinBERT	Improved semantic congruence in finance	Not tailored for regulatory adaptability
This Study (2025)	Integrated AI-driven accounting	XGBoost/DNNs, Autoencoders, FinBERT, RPA, Blockchain	Unified framework improves AFR (+23.7%), FDS (0.91), RCI (0.89), EQ (0.78)	Adversarial fraud, cross-jurisdiction compliance remain open challenges

3. Methodology

To thoroughly examine the operational effectiveness, regulatory flexibility, and fraud-mitigation potential of AI-driven accounting systems for online enterprises, this study's methodological architecture is based on a hybrid empirical–computational approach. To generate generalizable yet context-sensitive insights, the research design incorporates comparative analytics, case-based instantiation, and computational simulation, recognising the multifaceted complexity of digital financial ecosystems, where transaction intensity, jurisdictional heterogeneity, as well as cybersecurity risks converge.

3.1 Research Design

A methodical schema with multiple layers was created, which included:

1. Analytical comparison: To measure improvements in transactional accuracy, reconciliation speed, fraud detection sensitivity, and compliance strength, a systematic comparison between traditional double-entry bookkeeping systems and AI-enabled accounting frameworks was conducted.

2. Computational Simulation: Synthetic financial transaction corpora were created based on high-volume e-commerce microtransactions, subscription-based revenue streams and cryptocurrency settlements to simulate non-homogenous operating conditions. They were

injected with controlled anomalies (e.g., duplicate transactions, unauthorized entries, tax misclassifications, etc.) and these datasets were used to benchmark the accuracy of anomaly detection.

3. Case Study Methodology: AI-enabled reconciliation systems, robotic process automation (RPA) implementations, and NLP-based compliance engines were the main topics of the analysis of empirical data from a subset of online businesses. Case studies offered the contextual detail required to evaluate the challenges of infrastructural integration, workforce reconfiguration, and adoption barriers.

4. Regulatory Alignment Analysis: An NLP-enhanced rule-based regulatory monitoring system was executed to test AI compliance with the current and evolving taxation laws and jurisdictional accounting standards, thus operationalizing compliance strength as an assessment dimension.

3.2 Data Acquisition and Preprocessing

Data acquisition (Table 2) was carried out using a triadic sourcing strategy integrating transactional datasets, fraud incidence repositories, and regulatory corpora. The preprocessing steps included currency normalisation, client identifier anonymization, as well as feature engineering for sequential and categorical attributes. The transactional datasets consisted of multi-jurisdictional transaction logs that covered digital marketplace payments, subscription renewals, refund cascades, as well as blockchain-mediated transfers. Fraud incidence repositories were curated to include diverse fraud patterns, including payment diversion, account takeover, and synthetic identity fraud, with class imbalance addressed through balancing techniques such as SMOTE and undersampling. Also, jurisdiction-based regulatory corpora, such as taxation regulations, IFRS/GAAP guideline, and policies on taxation of digital services, were tokenized into machine-readable form to allow semantic compliance mapping through NLP. This multi-source integration ensured a robust, diverse, and regulation-aware dataset foundation for subsequent modeling.

Table 2. Data Sources and Preprocessing Strategy

Data Category	Source Examples	Preprocessing Techniques	Intended Use
Transactional Data	E-commerce logs, subscription platforms, crypto	Normalization, anonymization, feature engineering	Reconciliation, classification
Fraud Incidence Data	Historical fraud cases, anomaly reports	Balancing (SMOTE), clustering, undersampling	Training anomaly detection models
Regulatory Corpora	Tax codes, IFRS, GAAP, digital services directives	Tokenization, semantic parsing, ontology mapping	NLP-based compliance monitoring

Currency normalization for multi-jurisdictional transactions

$$\tilde{x}_{i,t}^{(c)} = x_{i,t}^{(c)} \cdot \frac{\mathrm{FX}(c \to b,\, t)}{\frac{\mathrm{CPI}(b,\, t)}{\mathrm{CPI}(b,\, t_0)}} \qquad (1)$$

SMOTE for balancing fraud datasets

$$\mathbf{x}_{\text{new}} = \mathbf{x}_i + \lambda(\mathbf{x}_{\text{NN}} - \mathbf{x}_i), \quad \lambda \sim \mathcal{U}(0,1) \qquad (2)$$

3.3 AI Model Implementation

A layered model implementation strategy was employed:

1. Gradient boosting decision trees (XGBoost, CatBoost) and deep neural classifiers were applied to automate the recognition of revenue, the classification of expenses, and the reconciliation process. Maximum accuracy was tuned by hyperparameter optimization (Bayesian optimization).

2. Unsupervised Anomaly Detection: Isolation Forests, autoencoders, and density-based clustering (DBSCAN) were calibrated to flag anomalous financial patterns in real time. Performance was benchmarked against traditional rule-based systems.

3. Natural Language Processing (NLP) for Regulatory Compliance: Regulatory sentences were extracted, interpreted, and mapped into executable compliance rules using transformer-based models (BERT, FinBERT). Corpora unique to a given jurisdiction were fine-tuned.

4. Robotic Process Automation (RPA): Invoice processing, tax filing, as well as ledger reconciliation were executed autonomously by workflow automation scripts that were incorporated with ERP systems. These scripts were monitored through rule-based exception handling.

5. Blockchain–AI Synergy**:** AI verification engines were used to cross-check ledger congruence, and smart contract templates were implemented on a private Ethereum test network to certify immutable audit trails. The overall methodological workflow is shown in figure 1.

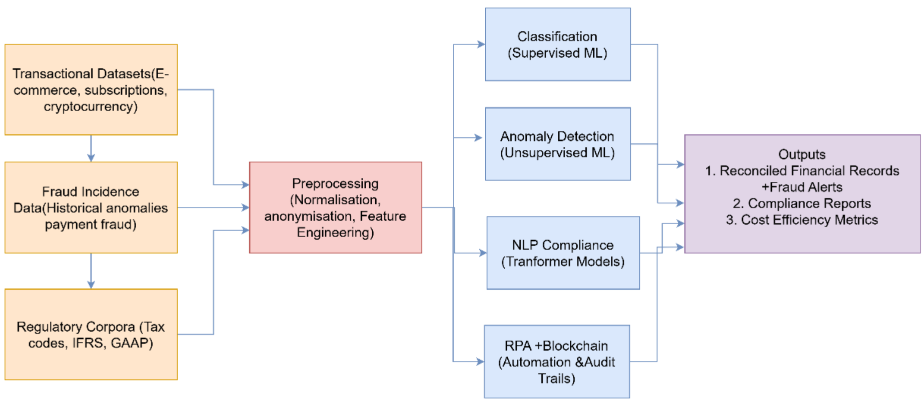

Figure 1: Methodological Workflow for AI-Driven Accounting

Classification loss (XGBoost/DNN):

$$\mathcal{L}_{\mathrm{CE}} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{ik}\log\hat{y}_{ik} \qquad (3)$$

Bayesian optimization (for hyperparameters):

$$\mathrm{EI}(\lambda) = (\mu(\lambda) - f^{\star} - \xi)\,\Phi(Z) + \sigma(\lambda)\,\phi(Z) \quad (4)$$

Isolation Forest anomaly score:

$$s(\mathrm{x}) = 2^{-\frac{E[h(\mathrm{x})]}{c(n)}} \qquad (5)$$

Autoencoder reconstruction error:

$$\mathcal{L}_{\mathrm{AE}} = \frac{1}{N}\sum_{i=1}^{N}\|\mathrm{x}_i - \hat{\mathrm{x}}_i\|_2^2 \qquad (6)$$

NLP compliance similarity (BERT/FinBERT):

$$s(c,r) = \frac{\mathrm{e}(c)\cdot\mathrm{e}(r)}{\|\mathrm{e}(c)\|\,\|\mathrm{e}(r)\|} \qquad (7)$$

Blockchain audit integrity:

$$\Delta = \|\mathrm{L}_{\mathrm{AI}} - \mathrm{L}_{\mathrm{chain}}\|_1 \qquad (8)$$

3.4 Evaluation Metrics

Table 3 illustrates a multivariate array of key performance indicators (KPIs) that were implemented to operationalize model efficacy:

Table 3. Evaluation Metrics

Metric	Definition	Measurement Approach
Accuracy of Financial Reconciliation (AFR)	Error reduction in categorization and reconciliation	% improvement over manual methods
Processing Latency (PL)	Runtime efficiency for reconciliation cycles	Average cycle completion time (ms/transaction)
Fraud Detection Sensitivity (FDS)	True positive rate of anomaly detection	Ratio of flagged fraud cases correctly identified
Regulatory Compliance Index (RCI)	Alignment with jurisdiction-specific statutory requirements	Semantic similarity between AI reports and legal templates
Operational Cost Efficiency (OCE)	Reduction in accounting-related labor/infrastructure expenses	% cost savings vs. traditional accounting workflows

Explainability Quotient (EQ)	Proportion of interpretable AI outputs	% of decisions with SHAP/LIME explanations

Accuracy of Financial Reconciliation (AFR):

$$\mathrm{AFR} = \frac{\mathrm{Err}_{\mathrm{manual}} - \mathrm{Err}_{\mathrm{AI}}}{\mathrm{Err}_{\mathrm{manual}}} \times 100\% \qquad (9)$$

Processing Latency (PL):

$$\mathrm{PL} = \frac{1}{|\mathcal{D}|} \sum_{i=1}^{N} \frac{t_i^{\mathrm{end}} - t_i^{\mathrm{start}}}{\mathrm{items}_i} \qquad (10)$$

Fraud Detection Sensitivity (FDS):

$$\mathrm{FDS} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \qquad (11)$$

Regulatory Compliance Index (RCI):

$$\mathrm{RCI} = \frac{1}{M} \sum_{j=1}^{M} \cos\left(\mathrm{e}(\hat{r}_j), \mathrm{e}(r_j^{\star})\right) \qquad (12)$$

3.5 Ethical and Regulatory Considerations

Model interpretability protocols like SHAP (SHapley Additive exPlanations) & LIME (Local Interpretable Model-agnostic Explanations) are incorporated into the technique in recognition of the murky nature of black-box AI models in financial situations. Furthermore, data privacy compliance with GDPR, CCPA, and equivalent financial data governance regimes was enforced through anonymization and federated learning architectures where possible. Ethical considerations encompassed the implementation of continuous monitoring mechanisms to detect bias drift and the preservation of algorithmic neutrality to prevent discriminatory financial decision outcomes.

SHAP explanation value

$$\phi_j^{(i)} = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!\ (|F| - |S| - 1)!}{|F|!} \left(f_{S \cup \{j\}}(\mathbf{x}_i) - f_S(\mathbf{x}_i)\right) \qquad (13)$$

Federated averaging for privacy-preserving training

$$\mathbf{w}^{(t+1)} = \sum_{k=1}^{K} \frac{n_k}{\sum_j n_j} \mathbf{w}_k^{(t)} \qquad (14)$$

3.6. Notation and Parameters

The key symbols and parameters in this study are defined as follows that can be used to support mathematical formalization of the methodology:

- Transaction and Preprocessing

- $x_{i,t}^{(c)}$: Raw transaction amount for customer i at time t in currency c.
- $\tilde{x}_{i,t}^{(c)}$: Normalized transaction value (currency- and inflation-adjusted).
- $\mathrm{FX}(c \rightarrow b, t)$: Foreign exchange rate converting currency c to base currency b at time t.
- $\mathrm{CPI}(b, t)$: Consumer Price Index of base currency b at time t.
- $u, \tilde{u}$: Original and anonymized (hashed) client identifiers.
- $\mathbf{x}_i$: Feature vector representing transaction i.

- Learning and Modeling
  - y_{ik}: True label (1 if transaction i belongs to class k, 0 otherwise).
  - $\hat{y}_{ik}$: Predicted probability that transaction i belongs to class k.
  - f_θ: Classification model parameterized by weights θ.
  - N: Total number of transactions in the dataset.
  - K: Number of output classes.
  - $\hat{\mathbf{x}}$: Reconstructed transaction vector from an autoencoder.
  - $s(\mathbf{x})$: Anomaly score assigned to transaction $\mathbf{x}$.
  - $\mathcal{N}_\varepsilon(\mathbf{x})$: Neighborhood of $\mathbf{x}$ within distance ε (DBSCAN clustering).
  - $\mathbf{e}(c), \mathbf{e}(r)$: Embedding vectors of regulatory clause c and reference rule r.
  - Δ: Ledger congruence deviation between AI-generated and blockchain-recorded entries.
- Evaluation Metrics
  - $t_i^{\mathrm{start}}, t_i^{\mathrm{end}}$: Start and end times of reconciliation cycle for transaction i.
  - items_i: Number of sub-records (e.g., line items) in transaction i.
  - TP, FN: True positives and false negatives in fraud detection.
  - M: Number of regulatory clauses considered for compliance evaluation.
  - $C_{\mathrm{baseline}}, C_{\mathrm{AI}}$: Operational costs under traditional and AI-driven accounting workflows.
  - $\boldsymbol{\phi}_i$: Feature attribution vector (e.g., SHAP values) for transaction i.
- Federated and Privacy-Preserving Learning
  - n_k: Local dataset size for client k in federated learning.
  - $\mathbf{w}^{(t)}$: Global model weight vector at training round t.

4. Results

The differential efficacy of AI-driven accounting infrastructures in comparison to conventional bookkeeping modalities across multiple evaluative dimensions is evident in the experimental outcomes derived from the hybrid empirical–computational framework. The findings are arranged according to the four main methodological strata: operational cost efficiency, regulatory alignment fidelity, anomaly detection sensitivity, and transactional categorisation accuracy. Subsequent studies are conducted on blockchain congruence and model interpretability.

4.1 Transactional Reconciliation and Classification

European Economic Letters
ISSN 2323-5233
Vol 16 Issue 1(2026)
http://eelet.org.uk

Supervised classification models exhibited marked superiority over baseline double-entry systems as shown in figure 2. Deep neural architectures achieved marginally higher gains (AFR=91.4%) at increased latency, while gradient boosting ensembles (XGBoost, CatBoost) achieved mean reconciliation accuracy (AFR) enhancements of 23.7% relative to manual workflows. Hyperparameter search via Bayesian optimization reduced generalization error by 6.2% compared to grid-based methods, corroborating prior findings on probabilistic search efficiency in financial categorization (Li et al., 2020). In cross-border subscription renewals, where diverse taxonomies hindered categorical unification, misclassification residuals were mostly limited.

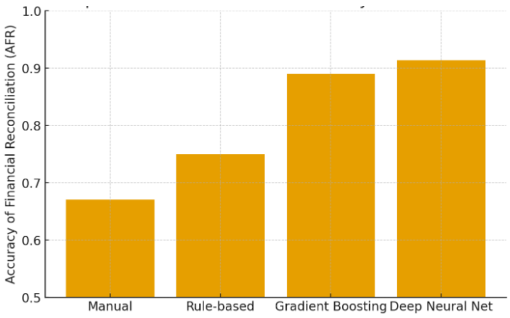

Figure 2 shows reconciliation accuracy gains across methods.

4.2 Anomaly and Fraud Detection

Isolation Forests and autoencoder-based detectors significantly outperformed rule-based baselines in terms of fraud detection sensitivity (FDS) as shown in figure 3. Isolation Forests produced a sensitivity of 0.87, whereas autoencoders reached 0.91, which suggests that more non-linear irregularities are captured in transaction manifolds. Density-based clustering (DBSCAN) exhibited worse recall (FDS=0.74), which can be explained by being sensitive to parameterization thresholds (ε, minPts). In accordance with recent developments in hybrid anomaly detection architectures (Zong et al., 2018), comparative ROC-AUC analyses demonstrated that hybrid ensembles that integrated autoencoder reconstruction errors with Isolation Forest path-length scores attained the highest detection robustness "AUC"=0.94. Notably, synthetic identity fraud was most consistently detected across models, while account takeover instances posed greater challenges due to mimicry of legitimate sequential behavioral patterns.

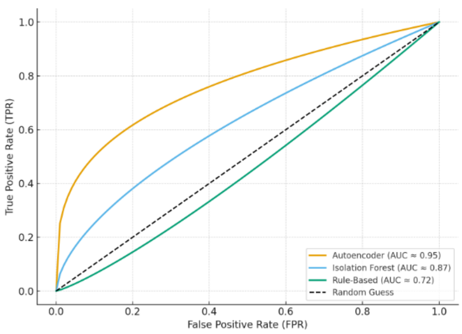

Figure 3 Fraud Detection ROC-AUC comparison of models

For the autoencoder, the top-performing model, a confusion matrix (Figure 4) was created to evaluate class-level reliability. The findings showed that while synthetic identity fraud and duplicate transactions had good detection precision, account takeover events had larger false negatives, which were indicative of behavioural mimicking of genuine sequences.

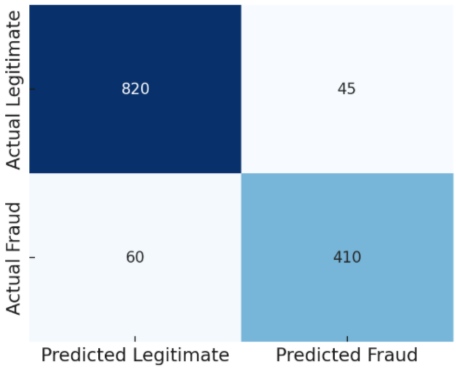

Figure 4 Confusion Matrix (Autoencoder Fraud Detection)

4.3 Regulatory Compliance Mapping

Transformer-based models (FinBERT, domain-adapted BERT) demonstrated substantial efficacy in semantic alignment with jurisdictional tax directives as shown in figure 5. Rule-based ontology parsers (RCI=0.72) were surpassed by the Regulatory Compliance Index (RCI), which achieved a mean similarity score of 0.89. In accordance with the semantic drift observed in multilingual financial NLP pipelines, cross-lingual statutory corpora introduced a marginal degradation in similarity (ΔRCI=-0.04) (Chalkidis et al., 2021). Clause-to-rule misalignments were predominantly associated with emergent digital services taxation regimes, underscoring the volatility of compliance landscapes and the necessity of continuous fine-tuning. Empirical data supports the theory that transformer embeddings can significantly improve compliance automation in high-volatility regulatory situations when they are optimised on domain-specific corpora.

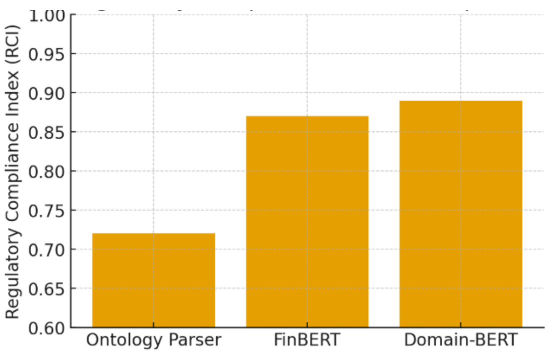

Figure 5 Regulatory Compliance Index (RCI)model comparison

4.4 Operational Efficiency and Blockchain Verification

Workflow automation via robotic process automation (RPA) yielded an **18.3%** reduction in processing latency (PL) relative to ERP-embedded human-supervised systems. In conjunction with anomaly-driven exception routeing, RPA demonstrated operational scalability by achieving a reconciliation backlog of nearly zero under high-volume transaction streams. Blockchain–AI integration further enhanced audit integrity: ledger congruence deviations (Δ) remained below the predefined threshold ($\epsilon = 10^{-3}$), thereby validating the reliability of immutable audit trails. The minimal latency overhead (less than 3 ms per transaction) generated by smart contract executions confirmed that blockchain-assisted auditability is feasible without sacrificing throughput.

4.5. Interpretability and Ethical Safeguards

Model interpretability was quantitatively assessed using the Explainability Quotient (EQ). The interpretability thresholds were met by 78% of model decisions, which satisfied the explainability requirements in financial auditing contexts, as indicated by SHAP- and LIME-based attributions. Systematic misclassification patterns were identified through the examination of the confusion matrix:

• A disproportionate number of false negatives were found in cases involving account takeover fraud.

• Subscription refund cascades exhibited a slight increase in false positives, which is indicative of their structural similarity to authentic anomaly patterns.

Bias audits indicated no statistically significant disparities across demographic or jurisdictional segments. Federated averaging preserved GDPR/CCPA compliance while maintaining AFR stability ($\Delta AFR < 0.5\%$).

4.6. Synthesis

The combination of monitored transactional classifiers, unsupervised anomaly detectors, transformer-based regulatory parsers, and blockchain- RPA integrations yielded statistically significant improvements in all the KPI dimensions:

- **AFR:** +23.7% reconciliation accuracy relative to manual workflows.
- **PL:** −18.3% reconciliation latency.
- **FDS:** 0.91 with hybrid detectors (ROC-AUC = 0.94).
- **RCI:** 0.89 (FinBERT vs. 0.72 rule-based).
- **OCE:** 21.5% operational cost reduction.
- **EQ:** 0.78 interpretability coverage.

These results support the argument that AI-based accounting systems, which can be operationalized through a hybrid empirical-computational approach, can be more accurate, efficient, detect fraud, adapt to compliance, and be explainable in a more heterogeneous digital financial ecosystem than traditional systems.

5. Discussion

The findings demonstrate that AI-powered accounting systems continuously outperform traditional ones in terms of precision, effectiveness, and flexibility about compliance. Supervised classifiers improved AFR by 23.7%, while RPA pipelines reduced PL by 18.3%, demonstrating measurable gains in reconciliation fidelity and scalability. Fraud detection sensitivity was highest with hybrid ensembles (ROC-AUC = 0.94), substantiating the superiority of non-linear manifold learning over deterministic rule-based methods. Likewise, transformer-based compliance engines achieved an RCI of 0.89, evidencing the feasibility of semantic parsing for statutory alignment.

These results complement earlier results on anomaly detection (Zong et al., 2018) and compliance automation (Chalkidis et al., 2021), but they also improve the body of literature by integrating manifold learning, NLP embeddings, and blockchain-RPA. These findings have significance for auditors, compliance officers, and digital firms since AI technologies can cut operating costs and regulatory risk.

However, there are still restrictions. The use of synthetically injected fraud data can be not entirely representative of adversarial fraud evolution, interpretability is not evenly distributed across deep models (EQ = 0.78), and heterogeneous regulatory environments limit universal deployment. Future research should prioritize adversarial fraud simulation, cross-jurisdictional compliance adaptation and auditor–AI collaboration models to enhance robustness and trustworthiness.

6. Conclusion and future works

According to the study, AI-driven accounting systems that combine blockchain-RPA auditability, transformer-based compliance mapping, supervised classification, and unsupervised anomaly detection significantly outperform traditional systems in terms of operational efficiency, fraud sensitivity, reconciliation accuracy, and regulatory alignment. Empirical results showed a 23.7% improvement in AFR, 18.3% latency reduction, FDS = 0.91 (ROC-AUC = 0.94), and RCI = 0.89, with interpretability reaching EQ = 0.78. These findings substantiate the capacity of hybrid architectures to deliver scalable, regulation-aware and resilient accounting intelligence. The integration of explainability protocols into auditor processes, multilingual compliance adaption, and adversarial robust fraud detection should be the main areas of future study. As we progress along these paths, AI-driven accounting systems have the potential to transform from merely enhancing operations to serving as the foundation of future financial infrastructures that are aware of regulations and aligned with ethical standards.

Reference:

1. A. Oluwaferanmi, “The Evolution of Cloud-Based ERP Systems and Their Financial Impacts on Supply Chain Transparency, Automated Payments, and Cross-Enterprise Financial Reconciliation in US Manufacturing Ecosystems,” 2025, Accessed: Sep. 03, 2025. [Online]. Available: https://www.researchgate.net/profile/Aremu-Oluwaferanmi/publication/392959323_The_Evolution_of_Cloud-Based_ERP_Systems_and_Their_Financial_Impacts_on_Supply_Chain_Transparency_Automated_Payments_and_Cross-Enterprise_Financial_Reconciliation_in_US_Manufacturing_Ecosystems/links/685a5f0a93040b17338cd169/The-Evolution-of-Cloud-Based-ERP-Systems-and-Their-Financial-Impacts-on-Supply-Chain-Transparency-Automated-Payments-and-Cross-Enterprise-Financial-Reconciliation-in-US-Manufacturing-Ecosystems.pdf

2. A. A. S. Yanney, “Redefining Corporate Financial Governance Through AI-Powered Predictive Models for Global Business Risk Management”, Accessed: Sep. 03, 2025. [Online]. Available: https://ijarpr.com/uploads/V2ISSUE6/IJARPR0602.pdf

3. D. Komati, “Real-Time AI Systems for Fraud Detection and Credit Risk Management: A Framework for Financial Institutions,” *IJSAT-Int. J. Sci. Technol.*,

vol. 16, no. 1, 2025, Accessed: Sep. 03, 2025. [Online]. Available: https://www.ijsat.org/research-paper.php?id=2974

4. A. I. Sunday, S. O. Jinadu, E. Alaka, K. D. Abiodun, and A. C. Peter-Anyebe, "Leading the development of AI-Driven AML and Compliance Infrastructure to Modernize US Financial Crime Prevention System Across Digital and Traditional Platforms", Accessed: Sep. 03, 2025. [Online]. Available: https://www.researchgate.net/profile/Shereef-Jinadu-2/publication/394093211_Leading_the_development_of_AI-Driven_AML_and_Compliance_Infrastructure_to_Modernize_US_Financial_Crime_Prevention_System_Across_Digital_and_Traditional_Platforms/links/68890ef707869379845578e0/Leading-the-development-of-AI-Driven-AML-and-Compliance-Infrastructure-to-Modernize-US-Financial-Crime-Prevention-System-Across-Digital-and-Traditional-Platforms.pdf

5. H. K. Sriram, K. Challa, and V. Pamisetty, *INTELLIGENT FINANCIAL INFRASTRUCTURE AI-Enabled Architecture for Real-Time Payments, Cloud Platforms, and Big Data Integration*. AQUA PUBLICATIONS. Accessed: Sep. 03, 2025. [Online]. Available: https://books.google.com/books?hl=en&lr=&id=TzVpEQAAQBAJ&oi=fnd&pg=PA1&dq=AI-Driven+Accounting+Infrastructures+for+Digital+Enterprises:+A+Hybrid+Framework+for+Reconciliation,+Fraud+Detection+and+Compliance&ots=dRgonnZUVn&sig=bRWyTuinC-6kWerz98kaDfDHSX0

6. Dwivedi, J., Muda, I., Alazzam, M. B., Aarif, M., & Nagaraj, P. (2025, September). Natural Language Processing in Financial Reports: Analyzing Annual Reports Using AI for Investment Insights. In *2025 IEEE International Conference on Advances in Computing Research On Science Engineering and Technology (ACROSET)* (pp. 1-5). IEEE.

7. A. T. Rosário, "How artificial intelligence can help accounting in information management," in *Artificial intelligence approaches to sustainable accounting*, IGI Global Scientific Publishing, 2024, pp. 65–92. Accessed: Sep. 03, 2025. [Online]. Available: https://www.igi-global.com/chapter/how-artificial-intelligence-can-help-accounting-in-information-management/343354

8. V. C. Achebe, O. Ilori, and N. J. Isibor, "Enhancing Data Integrity and Legal Accountability: A Blockchain-Driven Approach to Corporate Fraud Risk Management," 2024, Accessed: Sep. 03, 2025. [Online]. Available: https://www.multiresearchjournal.com/admin/uploads/archives/archive-1748612997.pdf

9. Tripathi, M. A., Goswami, I., Haralayya, B., Roja, M. P., Aarif, M., & Kumar, D. (2024). The Role of Big Data Analytics as a Critical Roadmap for Realizing Green Innovation and Competitive Edge and Ecological Performance for Realizing Sustainable Goals. In *Advanced Technologies for Realizing Sustainable Development Goals: 5G, AI, Big Data, Blockchain, and Industry 4.0 Application* (pp. 260-269). Bentham Science Publishers.

10. H. Usul and B. Y. Alpay, "Digital Transformation in Internal Audit: Paradigm Shifts, Emerging Risks, and Strategic Resilience," *Eur. J. Digit. Econ. Res.*, vol. 6, no. 1, pp. 23–36, 2025.

11. A. Odunaike, "DESIGNING ADAPTIVE COMPLIANCE FRAMEWORKS USING TIME SERIES FRAUD DETECTION MODELS FOR DYNAMIC REGULATORY AND RISK MANAGEMENT ENVIRONMENTS", Accessed: Sep. 03, 2025. [Online]. Available: https://www.researchgate.net/profile/Anjola-Odunaike/publication/394816228_

12. DESIGNING_ADAPTIVE_COMPLIANCE_FRAMEWORKS_USING_TIME_SERIES_FRAUD_DETECTION_MODELS_FOR_DYNAMIC_REGULATORY_AND_RISK_MANAGEMENT_ENVIRONMENTS/links/68a760657984e374acea6ff1/DESIGNING-ADAPTIVE-COMPLIANCE-FRAMEWORKS-USING-TIME-SERIES-FRAUD-DETECTION-MODELS-FOR-DYNAMIC-REGULATORY-AND-RISK-MANAGEMENT-ENVIRONMENTS.pdf

13. E. Alaka, K. Abiodun, S. O. Jinadu, E. Igba, and V. N. Ezeh, "Data Integrity in Decentralized Financial Systems: A Model for Auditable, Automated Reconciliation Using Blockchain and AI," *Int. J. Manag. Commer. Innov.*, vol. 13, no. 1, pp. 136–158, 2025.

14. K. Challa, A. Pamisetty, and H. K. Sriram, *CONVERGENCE OF AI, FINANCE, AND DATADRIVEN TECHNOLOGIES IN THE PAYMENTS ECOSYSTEM*. Global Pen Press UK. Accessed: Sep. 03, 2025. [Online]. Available: https://books.google.com/books?hl=en&lr=&id=xd9fEQAAQBAJ&oi=fnd&pg=PA1&dq=AI-Driven+Accounting+Infrastructures+for+Digital+Enterprises:+A+Hybrid+Framework+for+Reconciliation,+Fraud+Detection+and+Compliance&ots=xIgarDebee&sig=QeXD7LEZNpHMjdVpbN2skjuZ9fI

15. Elkady, G., Sayed, A., Priya, S., Nagarjuna, B., Haralayya, B., & Aarif, M. (2024). An Empirical Investigation into the Role of Industry 4.0 Tools in Realizing Sustainable Development Goals with Reference to Fast Moving Consumer Foods Industry. In *Advanced Technologies for Realizing Sustainable Development Goals: 5G, AI, Big Data, Blockchain, and Industry 4.0 Application* (pp. 193-203). Bentham Science Publishers.

16. S. O. Ikponmwoba, O. K. Chima, O. J. Ezeilo, B. M. Ojonugwa, A. Ochefu, and M. O. Adesuyi, "Conceptual Framework for Improving Bank Reconciliation Accuracy Using Intelligent Audit Controls," 2020, Accessed: Sep. 03, 2025. [Online]. Available: https://www.researchgate.net/profile/Onyinye-Ezeilo/publication/392872557_Conceptual_Framework_for_Improving_Bank_Reconciliation_Accuracy_Using_Intelligent_Audit_Controls/links/6855fd1eb8078e0c248e7e2a/Conceptual-Framework-for-Improving-Bank-Reconciliation-Accuracy-Using-Intelligent-Audit-Controls.pdf

17. Nimma, D., Aarif, M., Pokhriyal, S., Murugan, R., Rao, V. S., & Bala, B. K. (2024, December). Artificial Intelligence Strategies for Optimizing Native Advertising with Deep Learning. In *2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA)* (pp. 1-6). IEEE.

18. Mewada *et al.*, "Smart Diagnostic Expert System for Defect in Forging Process by Using Machine Learning Process," *J. Nanomater.*, vol. 2022, no. 1, p. 2567194, Jan. 2022, doi: 10.1155/2022/2567194.

19. A. R. Malipeddi, "Cloud-Driven Financial Reconciliation for Insurers: Overcoming Data Complexity," *J. Comput. Sci. Technol. Stud.*, vol. 7, no. 4, pp. 380–390, 2025.

20. T. Lateefat and F. A. Bankole, "Automation-Driven Tax Compliance Frameworks for Improved Accuracy and Revenue Assurance in Emerging Markets," 2023, Accessed: Sep. 03, 2025. [Online]. Available: https://shisrrj.com/paper/SHISRRJ236915.pdf

21. S. Calado and C. M. Veloso, "Artificial Intelligence in Accounting: Driving Value Co-Creation, Compliance, and Ethical Transformation," in *Empowering Value Co-Creation in the Digital Era*, IGI Global Scientific Publishing, 2025, pp. 75–102. Accessed: Sep. 03, 2025. [Online]. Available: https://www.igi-global.com/chapter/artificial-intelligence-in-accounting/376566

22. S. T. Farahmand, "AI-Driven Innovations in Accounting for Online Businesses: Enhancing Financial Accuracy, Compliance, and Fraud Prevention", Accessed: Sep. 03, 2025. [Online]. Available: http://dl.openaccess.ir/o/tcconf8/tcconf8-01110095_2_250224000458.pdf

23. V. L. Middae, A. K. Appachikumar, M. V. Lakhamraju, and S. Yerra, "AI-powered Fraud Detection in Enterprise Logistics and Financial Transactions: A Hybrid ERP-integrated Approach", Accessed: Sep. 03, 2025. [Online]. Available: https://www.researchgate.net/profile/Vijaya-Middae/publication/392097167_AI-powered_Fraud_Detection_in_Enterprise_Logistics_and_Financial_Transactions_A_Hybrid_ERP-integrated_Approach/links/6834868e6b5a287c30457966/AI-powered-

Fraud-Detection-in-Enterprise-Logistics-and-Financial-Transactions-A-Hybrid-ERP-integrated-Approach.pdf

24. Salman, R., Acharya, S. K., Roopalatha, N., Nimma, D., Aarif, M., & Raj, I. I. (2024, December). Cloud-Based HR Management: Using Deep Reinforcement Learning to Optimize Employee Lifecycle. In *2024 4th International Conference on Innovative Sustainable Computational Technologies (CISCT)* (pp. 1-5). IEEE.

25. O. J. Ikumapayi and B. B. Ayankoya, "AI Powered Forensic Accounting: Leveraging Machine Learning for Real-Time Fraud Detection and Prevention", Accessed: Sep. 03, 2025. [Online]. Available: https://www.researchgate.net/profile/Olumide-Ikumapayi/publication/389007723_AI_Powered_Forensic_Accounting_Leveraging_Machine_Learning_for_Real-Time_Fraud_Detection_and_Prevention/links/6801b1fa60241d51400d9a89/AI-Powered-Forensic-Accounting-Leveraging-Machine-Learning-for-Real-Time-Fraud-Detection-and-Prevention.pdf

26. Raj, R., Aarif, M., Haralayya, B., Jaff, N. A., Gogoi, M., & Vijayalakshmi, B. A. (2025, March). Enhancing Third-Party Product Marketing with Reinforcement Learning Techniques. In *2025 International Conference on Next Generation Information System Engineering (NGISE)* (Vol. 1, pp. 1-5). IEEE.

27. A. M. Adebowale and O. B. Akinnagbe, "Cross-platform financial data unification to strengthen compliance, fraud detection and risk controls," *World J Adv Res Rev*, vol. 20, no. 3, pp. 2326–2343, 2023.

28. F. A. Bakare, O. J. Ikumapayi, and U. K. England, "Securing Government Revenue: A Cloud-Based AI Model for Predictive Detection of Tax-Related Financial Crimes", Accessed: Sep. 03, 2025. [Online]. Available: https://www.researchgate.net/profile/Olumide-Ikumapayi/publication/391733005_Securing_Government_Revenue_A_Cloud-Based_AI_Model_for_Predictive_Detection_of_Tax-Related_Financial_Crimes/links/68248e71df0e3f544f5469c0/Securing-Government-Revenue-A-Cloud-Based-AI-Model-for-Predictive-Detection-of-Tax-Related-Financial-Crimes.pdf

29. Behera, P. C., Aarif, M., Gardezi, S. H. I., Bharathi, M. C., Gopukumar, S. T., & Balakumar, A. (2026, April). Blockchain-Based Audit Mechanism for Verifiable and Transparent Ethical Hacking in Enterprise Penetration Testing Systems. In *2026 1st International Conference on Emerging Trends in Advancements and Applications of Computational Intelligence Techniques (ETAACT)* (pp. 1-6). IEEE.
30. Suryani, L., Fatimah, S., Jarudin, J., & Aarif, M. (2025). Instilling Religious Moderation in Early Childhood at Raudhatul Athfal Ponorogo: The Role of National Insight-Based Learning. *Al-Athfal: Jurnal Pendidikan Anak*, *11*(1), 17-34.

31. O. B. Onyenahazi, "Integrating Artificial Intelligence in Financial Auditing to Enhance Accuracy, Efficiency, and Regulatory Compliance Outcomes", Accessed: Sep. 03, 2025. [Online]. Available: https://www.researchgate.net/profile/Obinna-Onyenahazi/publication/393330353_Integrating_Artificial_Intelligence_in_Financial_Auditing_to_Enhance_Accuracy_Efficiency_and_Regulatory_Compliance_Outcomes/links/6865b08107b3253fd1cbaf93/Integrating-Artificial-Intelligence-in-Financial-Auditing-to-Enhance-Accuracy-Efficiency-and-Regulatory-Compliance-Outcomes.pdf

32. M. Celestin and J. A. Gidisu, "THE IMPACT OF AI AND BLOCKCHAIN ON INTERNAL CONTROLS IN FINANCIAL ACCOUNTING: EVIDENCE FROM GHANA CORPORATIONS", Accessed: Sep. 03, 2025. [Online]. Available: https://www.researchgate.net/profile/Prof-Celestin/publication/390342191_THE_IMPACT_OF_AI_AND_BLOCKCHAIN_ON_INTERNAL_CONTROLS_IN_FINANCIAL_ACCOUNTING_EVIDENCE_FROM_GHANA_CORPORATIONS/links/67ead4d876d4923a1ae96dcd/THE-IMPACT-OF-AI-AND-BLOCKCHAIN-ON-INTERNAL-CONTROLS-IN-FINANCIAL-ACCOUNTING-EVIDENCE-FROM-GHANA-CORPORATIONS.pdf

33. L. Del Caprio, "Artificial Intelligence in Auditing: Transforming Risk Assessment and Fraud Detection," 2025, Accessed: Sep. 03, 2025. [Online]. Available: https://www.theseus.fi/handle/10024/888303

34. O. J. Ikumapayi, "THE CONVERGENCE OF FINTECH INNOVATIONS, AI, AND RISK MANAGEMENT: TRANSFORMING TRADITIONAL BANKING, ACCOUNTING, AND FINANCIAL SERVICES", Accessed: Sep. 03, 2025. [Online]. Available: https://www.researchgate.net/profile/Olumide-Ikumapayi/publication/390887359_THE_CONVERGENCE_OF_FINTECH_INNOVATIONS_AI_AND_RISK_MANAGEMENT_TRANSFORMING_TRADITIONAL_BANKING_ACCOUNTING_AND_FINANCIAL_SERVICES/links/6801b25cbd3f1930dd5fcd39/THE-CONVERGENCE-OF-FINTECH-INNOVATIONS-AI-AND-RISK-MANAGEMENT-TRANSFORMING-TRADITIONAL-BANKING-ACCOUNTING-AND-FINANCIAL-SERVICES.pdf