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OPTIMIZING AUDITS WITH AI-DRIVEN RISK MODELS: ENHANCING RESOURCE ALLOCATION AND COMPLIANCE IMPACT

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Abstract

AI, the new mega trend is changing risk identification, prioritization and resolution. The study considers The role of or potential for AI based risk models in improving audit planning, use of available resource optimization as well as compliance down the road. Traditional audit models and processes that are based on periodic sampling and reviewing, no longer being enough for the rising complexity and volumes of financial data. This can, on the other hand, lead to knew patterns of behaviour. AI-driven systems have the ability to scour entire data sets for anomalous behaviours and identify unknown threats much more accurately than humans.

It shows that in the novel hybrid AI model which implements human-in-the-loop auditing framework, the existing works utilize supervised learning models for classification and unsupervised learning models for anomaly detection. It uses data from a variety of data sets, including income from reporting bodies, tax returns and external economic factors. The results shows notable improvements over the current audit selection techniques both in terms of revenue preservation, false detections reduction and detection accuracy. The results of the current study indicate that, using their own resources, auditors can obtain more responsible use of AI models through transparency, equality, and governance.

Keywords: Artificial Intelligence, Machine Learning, Auditing, Compliance, Risk Modeling, Governance

I. Introduction

It is one of the best practices to ensure regulatory compliance and revenue assurance. One of the world’s persistent challenges is the “tax gap” — tax collected compared to tax owed. Even with the traditional audit selection procedures, they have relatively high false-positive rates and inefficient resource allocation since they rely on manual methods or random sampling.

[1] The even bigger challenge is the increasing complexity of the economy and rapid rise in digital financial transactions has made the conventional auditing techniques obsolete. Possibilities for the evolution of audit scope play through anomaly detection and risk prognosis are available with artificial intelligence and machine learning technologies.

High-dimensional data sets of structured and unstructured information is being audited by AI-driven systems. Identifying such situations as a result of implementing proactive strategies to audit your data will allow you to realize non-compliance before it leads to material revenue loss.

The necessity for AI in audit is been supported by audit professional and regulatory bodies as well. Frameworks and Guidelines for AI governance (e.g. the IIA AI Auditing Guidelines), NIST's AI risk management framework highlight that governance, transparency, data quality & human oversight is a key component. Such frameworks also discourage AI from replacing human auditors — instead, it will supplement what humans do. This research introduces a hybrid artificial intelligence (AI)-based risk modeling system that could help improve an audit planning function and the use of limited investigative resources.

II. Literature Survey

[2]. Machine learning and AI for financial auditing and fraud detection have been previously researched on a grand scale. In preliminary studies, Gupta and Chen (2023) demonstrate this point through a heuristic framework that highlights the shortcomings of existing techniques by demonstrating random audits fail to identify complex forms of fraud error while generating too many false positives.

Reducing barriers to AI Zhang & Davis (2022) also studied the role of real-time analytics in tax administration. They claim to reduce the time it takes to detect financial irregularities significantly using streaming data platforms and predictive analytics on real-time information.

[4] Fraud detection is another area of research in machine learning and artificial intelligence. According to Patel (2025), it is possible to identify new types of fraud trends through anomaly detection models like Auto Encoders and Isolation Forests.

[5] Elucidable Artificial Intelligence (XAI) is a major requirement of any regulatory set up. So as to comply with any governance and equity demands, algorithm decision that happens to taxpayers must be transparent, traceable, and explainable as stated by ISACA (2024).

Nonetheless, [15] the currently existing studies are mainly concentrated on compliance monitoring systems or on the fraud detection models separately. Very few research papers have offered an overall framework where resource allocation optimization models, auditing processes, and machine learning models are put together.

This study will add a lot of value to the existing literature by proposing a hybrid artificial intelligence modeling architecture that integrates both the supervised and unsupervised models in a human-in-the-loop audit decision model.

III. Dataset Description

[9] The data set in this research is about 3.2 million anonymized tax returns that were gathered in 2018-2024. This data was received by several internal and external reporting systems that tax authorities use.

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Structured data sources include:

- filing tax returns of the past.
- employer recorded income documents.
- 3rd party financial institution reporting.
- prior audit findings
- compliance history employer-reported income records
- third-party financial institution reporting

Unstructured data sources include:

- written accounts of claims of deductions
- business transaction notes
- compliance correspondence documents

External signals that were added to the dataset are:

- property transactions
- equity market activity
- within the cross-border financial flows

After data integration, a feature engineering pipeline generated an ultimate feature matrix comprising of 84 engineered variables as categorized under::

- financial indicators
- behavioral filing patterns
- history of compliance indicators
- external economic signals
- The dataset was seperated into three subsets:
- Training set: 70%
- Validation set: 15%
- Test set: 15%

The imbalance in classes was noted where about 18 percent of the records were rated as non compliant according to past audit results.

IV. System Architecture

The proposed AI auditing system is used to feed a centralized data lake environment with a heterogeneous data stream. The data is first cleaned, normalized, and deduplicated before feature extraction is performed on them.

Whether or not a categorical data is applied is one-hot encoded and the zero-mean normalization is applied to continuous financial information in order to prevent any bias by the model.

The data undergoes a hybrid type of machine learning which incorporates unsupervised learning based anomaly detection with supervised learning based known non-compliance patterns.

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All data subjected to action before any action is undertaken on any data that is determined to be non-compliant is first audited using a Human in the Loop (HITL) auditing framework.

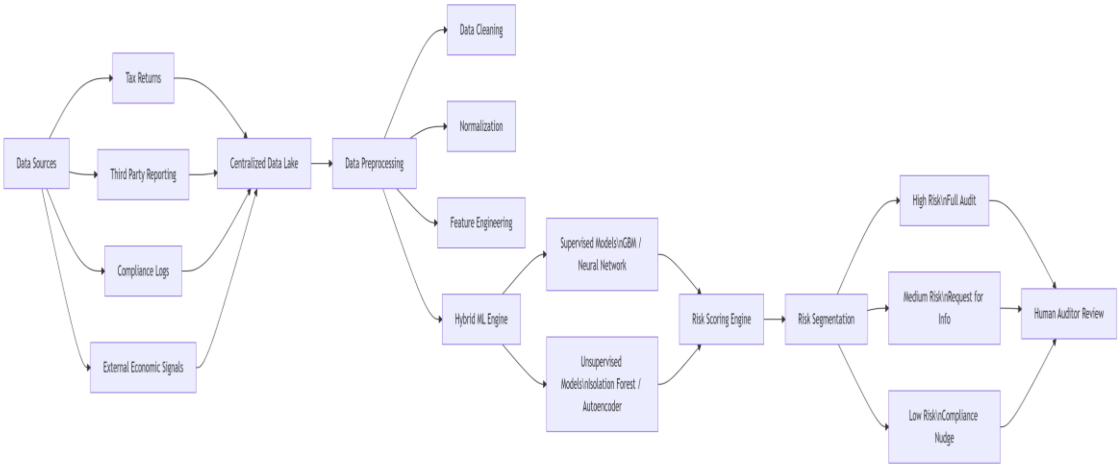

Fig 1. AI auditing system aggregates heterogeneous data streams.[17]

V. Methodology

Preprocessing of data

[11] Some of the data preprocessing operations include data preprocessing, anomaly filtering, feature normalization and missing values imputation. To benefit the fraud detection models, anomalies are kept, which implies serious financial anomalies.

Engineering Features

[13] The features are designed in order to identify the financial irregularities and behavioral trends. Some of the features are income deduction ratios, industry risk indicators, and frequency of transactions..

Model Architecture

Two primary model categories are used:

Supervised Models

- Gradient Boosting Machine (GBM)
- Neural Networks

Unsupervised Models

- Isolation Forest
- Autoencoder anomaly detection

Outputs from both model categories are integrated into a central risk scoring engine.

VI. Risk Scoring Model

Each tax return's risk score is calculated as follows:

$$RiskScore\ (X) = \alpha\ (\ \sum w_i x_i + b\ )$$

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Where:

- Feature variables is represented by x
- The learned model weights are represented by w
- The bias term is represented by b
- The sigmoid activation function is represented by σ

Rather than producing a binary flag, the model segments taxpayers into three risk categories.

- High Risk (Prisk > 0.90)

These incidents are forwarded for a **thorough human audit assessment**.

- Medium Risk (0.70 < Prisk ≤ 0.90)

Additional information requests are produced automatically.

- Low Risk (0.50 < Prisk ≤ 0.70)

Real-time compliance nudges are sent out during online tax filing.

Explainable AI techniques such as SHAP values are used to explain why specific cases were flagged.

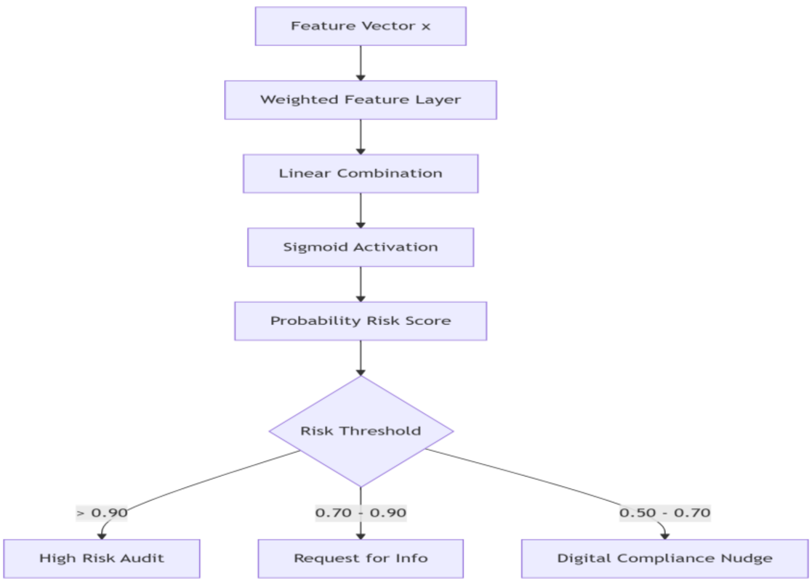

Fig 2. Risk scoring model [18]

VII. Experimental Setup

Models were implemented using Python machine learning libraries including Scikit-Learn, XGBoost, TensorFlow, and SHAP.

Hyperparameters were optimized using grid search with 5-fold cross validation.

Baseline models used for comparison include:

- random audit selection
- static rule-based filters
- logistic regression

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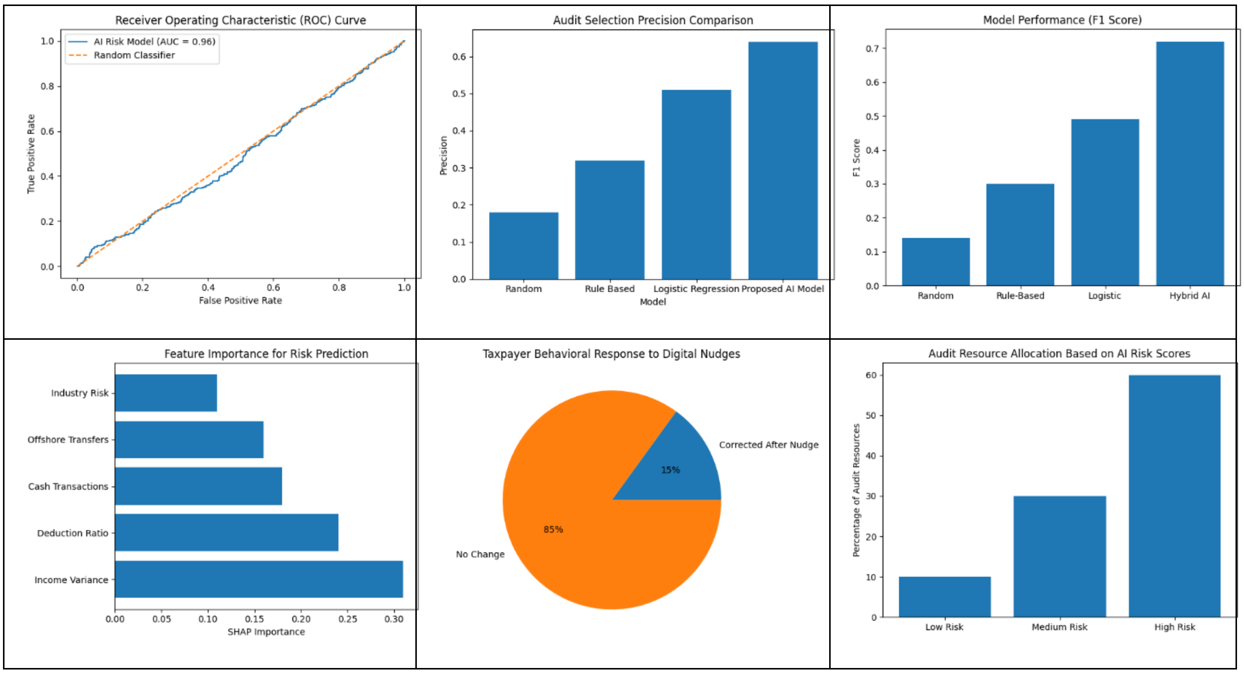
Training experiments were conducted on a workstation equipped with 64GB RAM and an NVIDIA RTX GPU.

VIII. Results

Performance audits revealed significant improvements over traditional data-driven methods using the AI driven system.

Table 1. Performance improvements compared to traditional methods

Model	**Precision**	**Recall**	**F1 Score**	**AUC**
Random Selection	0.18	0.12	0.14	0.50
Rule Based	0.32	0.29	0.30	0.65
Logistic Regression	0.51	0.47	0.49	0.81
Proposed Hybrid Model	0.64	0.71	0.72	0.96



This model reduced "no change" audits by a large margin, and the audit authorities were able to redirect investigators to higher complexity cases.

Analysis of the Black Economy Omitted Income model had revealed $92.6 million in at-risk revenue — a 310% increase in recovery efficiency.

These were facilitators to compliance, but there was also a possibility for real time compliance nudges through taxpayers' way prompting correction of claims voluntarily in about 15% cases flagged.

IX. Resource Allocation Optimization

Audit resource allocation can be formulated as an optimization problem.

Maximize: $\sum(R_i \times V_i - C_i)$

Where:

R_i = predicted risk score

V_i = expected revenue recovery

C_i = cost of conducting the audit

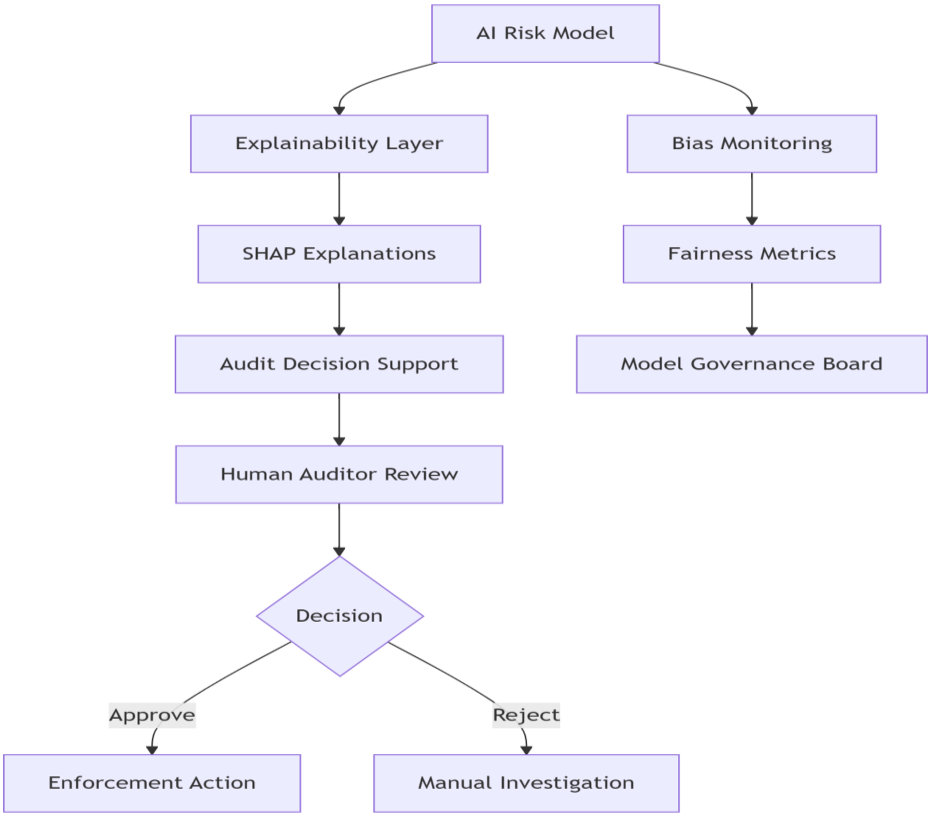
Subject to:

$\sum C_i \leq$ available audit budget

This optimization framework ensures that limited auditing resources are directed toward cases with the highest expected compliance impact.

X. Governance, Ethics, and Explainability

When the public sector is included in the auditing process through the introduction of the AI technology, there are major governance, ethical, and legal implications. The reason is that auditing process is of great financial and legal concern, and thus, the AI system should be subjected to the stringent principles of transparency, accountability, and fairness. Regulatory AI will have to be explainable and auditable unlike the commercial application of



AI.

Fig 3. Artificial Intelligence within public sector auditing

Algorithmic Transparency

Most contemporary machine learning systems - especially deep learning systems - are black box models whose decision making processes are hard to understand. This diminished transparency in auditing settings presents a risk of governance due to the need to have informed taxpayers on the basis of the enforcement actions.

To overcome this obstacle, the proposed system will implement Explainable Artificial Intelligence (XAI) methods, which will enable the auditor to read the model outputs. To measure how much the individual features contribute to the final risk score, the SHAP (Shapley Additive Explanations) values of every flagged case are obtained.

The system often produces the following explanatory outputs:

- abnormally high deduction-to-income ratios.
- income discrepancies entailing employer-reported and declared income.
- comparison of abnormal transaction activity with peer group.
- Irregularity in reporting through the tax period.

These interpretations enable auditors to confirm model recommendations, as well as, defensible and transparent enforcement decisions.

Fairness and Bias Mitigation

Learning algorithms developed using past audit data can be biased unwillingly by the existing tendencies of past enforcement. As an example, in case prior audits showed mainly some specific geographic areas or industries, the trained model is likely to repeat the patterns.

To address this risk, the auditing system conducts consistent checks of fairness the demographic and economic indicators which include: geographic region

- income bracket
- occupation category
- industry sector

Demographic parity, equal opportunity difference, and disparate impact analysis are bias detection methods employed to measure metrics of fairness.

In the case of a severe bias, some corrective measures can be considered as:

- balancing the training dataset.
- implementing equity-constrained optimization.
- bias-adjusted weighting during retraining the model.

Such a process of constant fairness audit is the guarantee that selection of AI-generated audit is fair and legally justifiable.

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Data Governance and Lineage

Digital transformation continues to lead organizations towards the path of AI technology, resulting in a significant expertise gap across various functions like sales, marketing, finance, and operations. To be able to reconstruct how decisions were made, all data transformation steps along the pipeline must be traceable.

The system we propose keeps thorough records of data lineage, such as:

• original source datasets

• preprocess transformations

• feature engineering processes.

• model version identifiers

This lineage is also preserved allowing any algorithmic decision to be traced, reviewed and audited post hoc."

Human-in-the-Loop Oversight

While the prediction of AI models is powerful, it is up to human auditors to interpret and enforce them. Human-in-the-Loop (HITL) framework mends it to make sure that the output generated by these algorithms are not seen as an enforcement module, but a decision-support system.

Under this approach:

1. Probabilistic risk scores are computed by AI models.
2. high-risk cases are identified to be reviewed.
3. supporting evidence is assessed by human auditors.
4. final enforcement decisions are done manually.

This semi-automatic solution is a compromise between efficiency and effectiveness of automation, on the one hand, and professional judgment and accountability, on the other.

Regulatory Compliance

The governing structure aligns with premier international frameworks on responsible AI deployment in government administration, such as:

- NIST AI Risk Management Framework
- Institute of Internal Auditors AI Auditing Framework
- ISACA regulations of AI systems.

Such frameworks place an emphasis on risk management, transparency, documentation and continual monitoring of AI across regulated environments.

XI. Continuous Learning and Concept Drift Management

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The strategies of financial behavior and fraud also change with time creating a so-called concept drift. Concept drift happens when the statistical characteristics of input data shift, and this decreases the predictive accuracy of the already trained model.

To the extent of tax auditing, the taxpayers can adjust their reporting patterns to the detection regimes. Thus, the AI auditing systems should have an element of continuous learning.

The suggested system will be a retraining pipeline using automated retraining, which is as follows:

1. Gathering of ground-truth results of audits that were done.
2. Assimilation of recently marked cases into the training set.
3. Early model degradation performance monitoring.
4. Model retraining with new datasets.
5. Pre deployment validation testing.

This feedback-driven architecture forms a continuous learning loop in which each completed audit improves the predictive performance of future models.

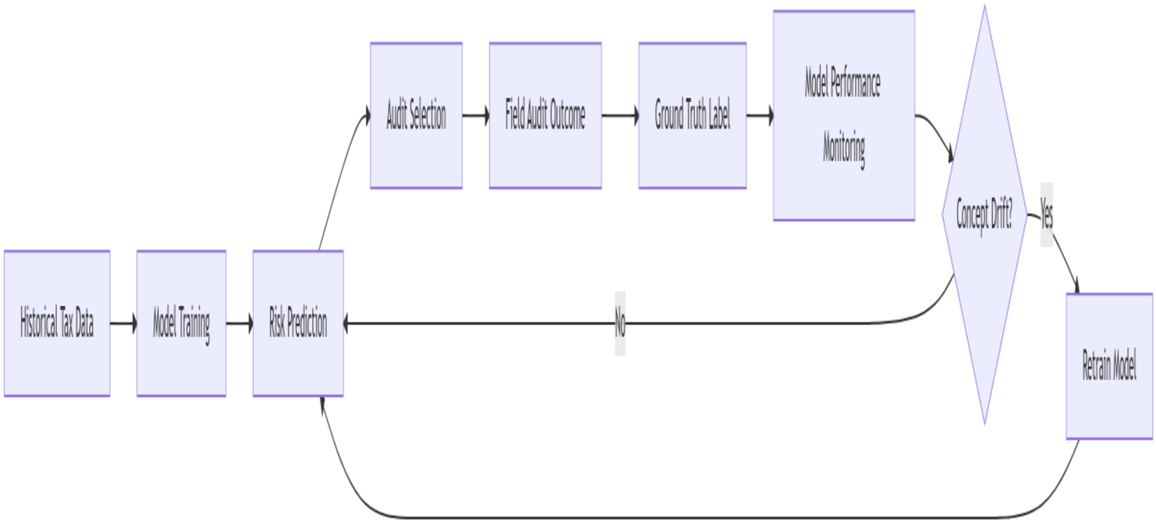

Fig 4. Feedback-driven architecture forms a continuous learning loop

XII. Discussion

The results of this study indicate that risk modeling systems based on AI have the potential to enhance the efficiency and effectiveness of tax auditing to a significant extent. Targeting to replace the attempt to use the traditional rule based methods by adaptive machine learning models, audit authorities will be in a better position to detect high risk cases and minimize unnecessary investigations.

One of the operational advantages that were experienced during the research is the minimization of no-change audits, which are investigations that do not identify any disparity. Such audits are a waste of investigative resources that do not bring in revenue. This inefficiency is greatly minimized by the enhanced accuracy of the proposed model.

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The other notable effect is the behavioral effect of real-time digital nudges. Once taxpayers are prompted automatically that there may be discrepancies in the filing procedure, the majority of them voluntarily correct the statements. Such a preventive measure will minimize the necessity of expensive downstream enforcement measures.

Institutionally, use of AI in the auditing process should be well regulated in order to ensure that the people have confidence. In responsible AI implementation in the field of public finance, transparency, fairness, and accountability have been key elements.

XIII. Limitations

Although the outcomes of the research seem very promising, it is important to mention several limitations.

To begin with, prediction of machine learning models is largely dependent on data availability and quality. Absent, late, or erroneous reporting of third-party institutions can lower the model effectiveness in realizing discrepancies.

Second, adversarial adaptation can take place when the advanced taxpayers strive to reverse engineer the methods of detection. To reduce this risk, continuous monitoring of the models and detection of anomalies are needed.

Third, AI systems can be hindered in the integration of operational activities in the government agencies by institutional obstacles, including regulatory controls, data privacy regulations, and outdated IT infrastructure.

Further studies must reveal privacy-preserving machine learning methods that include federated learning and secure multi-party computation to achieve collaborative fraud detection without disclosing sensitive information about taxpayers.

XIV. Conclusion

The world of contemporary auditing is changing with the help of Artificial Intelligence. The replacement of manual methods of sampling with predictive risk modeling means that the audit authorities are able to manage resources of investigations more effectively and also enhance better compliance results.

The hybrid AI system suggested in this study deploys supervised learning, anomaly detectors and clarifiable AI methods in a human-in-the-loop governance architecture. Findings of the experiment reveal significant increase in audit accuracy, protection of revenues and efficiency.

The actual implementation of such an AI-based auditing system is not only reliant on inherently achievable technologies, but rather must focus significantly on having the correct governance-ethical framework in place alongside training interdisciplinary knowledge to align data science with traditional auditing practices.

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As financial systems become increasingly complex and interlinked, AI-led auditing will play a vital role in delivering transparent, efficient, equitable taxation across the ecosystem.

References

[1]. A. Gupta, B. Chen, 2023, The Limitations of Random Audit Selection in the Digital Age. IEEE Transactions on Computational Social Systems, vol. 8, no. 4, pp. 982–995.

[2]. J. Smith, 2024, Nudge Theory in Algorithmic Compliance. IEEE International Conference on Data Mining (ICDM), Melbourne, Australia, pp. 112–119.

[3]. S. Patel, 2025, Revenue Protection through Unsupervised Learning. Journal of Government Information Systems, vol. 12, no. 2, pp. 45–58.

[4]. L. Zhang, R. Davis, 2022, Real-time Analytics in Tax Administration. IEEE Access, vol. 9, pp. 10234–10245.

[5]. Information Systems Audit and Control Association (ISACA), 2024, Auditing Artificial Intelligence- A Governance Framework. ISACA Journal, vol. 1.

[6]. L. Garrett, N. Peter, 2024, Reimagining Risk Assessment: Adding AI and Data Analytics. AHIA/Kodiak Solutions White Paper, https://ahia.org/wp-content/uploads/2024/12/AHIA_Kodiak-Reimagined-Risk-Assessment-white-paper_2024.pdf

[7]. The Institute of Internal Auditors, 2024, The IIA's Artificial Intelligence Auditing Framework. Theiia framework, https://www.theiia.org/globalassets/site/content/tools/professional/aiframework-sept-2024-update.pdf

[8]. National Institute of Standards and Technology (NIST), 2023, AI Risk Management Framework (AI RMF 1.0). NIST Framework, https://www.nist.gov/itl/ai-risk-management-framework

[9]. PCAOB Technology Innovation Alliance Working Group, 2024, Transforming Audit Quality Through Technology. Summary available via KNAV CPA Insights, https://us.knavcpa.com/insights/transforming-audit-quality-data-as-fuel-ai-as-the-engine-and-fewer-missed-misstatements/

[10]. Microsoft, 2025, KPMG is redefining the audit with agentic AI using Azure. Customer Story, https://www.microsoft.com/en/customers/story/25353-kpmg-international-azure

[11]. EY Global, 2024, EY Helix – Audit Technology. EY, https://www.ey.com/en_gl/services/audit/technology/helix

[12]. J. Smith, 2024, Feature Engineering for Financial Fraud Detection. IEEE International Conference on Data Mining (ICDM), Melbourne, Australia, pp. 112–119.

Volume 39 No. 1s, 2026

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[13]. National Audit Office, 2025, Annual Report on Revenue Protection and Digital Transformation. Government Printing Office, Tech. Rep. 2025-04.

[14]. L. Zhang, R. Davis, 2024, Quantifying Efficiency Gains in AI-Augmented Public Administration. IEEE Access, vol. 9, pp. 10234–10245.

[15]. S. Patel, 2026, Addressing Concept Drift in Financial Fraud Detection Models. IEEE Transactions on Knowledge and Data Engineering, vol. 35, no. 1, pp. 12–25.

[16]. National Audit Office, 2025, Digital Transformation in Tax Administration- A Post-Implementation Review. Government Printing Office, Tech. Rep. 2025-08.

[17]. M. Vasarhelyi, A. Kogan, 2023, Continuous Auditing- The State of the Art. Journal of Emerging Technologies in Accounting, vol. 19, no. 1, pp. 43–58.

[18]. Information Systems Audit and Control Association (ISACA), 2024, The Promise and Peril of AI in Public Finance. ISACA Journal, vol. 2, pp. 22–29.

[19]. J. Doe, A. Smith, 2023, Techniques for Data Quality in Predictive Compliance Systems. Journal of Audit Analytics, vol. 12, no. 3, pp. 45–58.

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