Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

AI-Driven Tax Fraud Detection and Tax Compliance Analytics: A Review of Methods, Challenges, and Responsible Deployment

Saidul Islam ✉[1], **Md Atiqur Rahman**[2], **Md Jahid Hasan**[3], **Farazi Ahsanul Islam**[4]

[1] *Master of Science in Information Technology (MSIT), Washington University of Science and Technology, Virginia, USA*

[2] *Doctor of Computer Science, University of the Potomac, Washington, DC, USA*

[3] *Master of Science in Information Technology (MSIT), Washington University of Science and Technology, Virginia, USA*

[4] *Master of Science in Information Technology (MSIT), Washington University of Science and Technology, Virginia, USA*

Corresponding Author: Saidul Islam**, E-mail:** saiislam.student@wust.edu

ABSTRACT

Tax authorities increasingly use artificial intelligence (AI) and machine learning (ML) to detect fraudulent refund claims, identity-related fraud, and anomalous financial reporting. This narrative review examines recent research on these methods and the problems that come with deploying them in tax administration. It covers supervised learning, unsupervised anomaly detection, graph neural networks, and privacy-preserving transformer models. It then discusses three groups of challenges: data quality and fragmented fiscal records, the black-box nature of complex models, and the ethical and legal duties of public agencies, including privacy, fairness, and accountability. The reviewed studies show that ML can improve audit selection and surface new fraud patterns, with one study of Italian audits reporting gains of up to 39% in detected evasion. They also show risks: audit selection that ignores race can still produce large racial disparities in the United States, and the Dutch childcare benefits case shows what happens when a risk model is opaque and unchecked. The review concludes that responsible deployment needs explainable models, fairness testing throughout development, privacy protections, and human oversight of final decisions. The article follows no formal search protocol, and future work should test these conclusions with a systematic review.

KEYWORDS

Tax fraud detection; machine learning; tax compliance analytics; explainable AI; algorithmic fairness; graph neural networks; privacy-preserving AI; tax administration.

ARTICLE INFORMATION

ACCEPTED: 30 September 2026 **PUBLISHED:** 31 October 2026 **DOI:** 10.32996/jcsts.2026.8.12.3

1. Introduction

Digital financial systems have changed how national tax administrations handle enforcement and compliance. Manual reviews and basic rule-based systems, long the core of tax auditing, no longer keep pace with large-scale financial crime. Tax filings have grown more complex as economies have become more interconnected, and fraudulent refund claims and identity-related fraud have grown with them. Fiscal authorities have responded by adopting Artificial Intelligence (AI) and Machine Learning (ML). The OECD reports that tax administrations use AI mostly to detect fraud and evasion, profile risk, classify documents, and support taxpayers through chatbots . These tools can process very large datasets, identify subtle patterns of non-compliance, and predict fraudulent behavior more precisely than earlier methods . Banks already use similar tools against fraud, and research on AI-driven fraud detection in the U.S. banking sector has examined the mediating roles of explainable AI trust and real-time fraud response capability . A 2024 systematic review of machine learning in taxation noted that systematic studies of the topic were still relatively scarce . This literature review adds to that work by covering the methods in use, the problems of data quality and explainability, and the ethical obligations that come with deploying these systems in public administration.

Copyright: © 2026 the Author(s). This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC-BY) 4.0 license (https://creativecommons.org/licenses/by/4.0/). Published by Al-Kindi Centre for Research and Development, London, United Kingdom.

Protecting public revenue and keeping the fiscal system fair are the main reasons for adopting AI in tax administration. Tax fraud, from simple under-reporting to cross-border VAT carousels, takes billions from national budgets every year . Machine learning applied to suspicious filings and anomalous financial reporting lets governments act before losses occur instead of after . The move to AI-based systems brings legal, ethical, and operational problems as well as technical ones. Papadimitriou and Giannopoulos note that implementing these systems requires a systematic understanding of what the algorithms can do and which research gaps remain. This review covers recent work such as multimodal graph neural networks and zero-knowledge transformers, and it treats transparency and algorithmic accountability in fiscal administration as necessary conditions for using them.

This article is a narrative review, not a systematic one. It covers studies of machine learning methods for detecting suspicious tax filings, fraudulent refund claims, identity-related fraud, and anomalous financial reporting, along with work on data quality, explainability, fairness, privacy, and deployment in tax administration. It draws mainly on recent peer-reviewed articles and preprints, and on reports from international organizations and human rights bodies where they documented how systems performed in practice. The review followed no formal search protocol, so it does not claim to cover every relevant study.

2. Machine Learning Methods for Tax Fraud Detection

2.1 Supervised and Unsupervised Learning in Tax Analytics

Supervised learning in tax fraud detection usually means training models on historical cases labeled as fraudulent or not. Random Forests have performed best among several supervised classifiers in identifying non-compliant taxpayers . Frina et al. show how machine learning systems can raise tax revenue in a developing economy like Cameroon by finding high-risk taxpayers early. They report that supervised models can be tuned to regional economic behavior, so authorities can rank audits by the probability of non-compliance. In Italy, replacing the least promising 10% of audits with taxpayers chosen by a trained algorithm raised detected tax evasion by as much as 39% and evasion actually paid back by 29% . The reliance on labeled data also limits these models: supervised methods need training sets of previously identified cases , and they struggle to adapt to evolving fraud tactics . Related work on AI-driven business intelligence applies machine learning techniques to financial market analysis .

Unsupervised learning and anomaly detection address that limitation by looking for "unknown unknowns." These methods need no labeled outcomes. They study the underlying distribution of the data and flag outliers that depart sharply from the norm. Papadimitriou and Giannopoulos review artificial intelligence and machine learning approaches to tax fraud detection. Clustering algorithms and autoencoders let tax administrations flag anomalous financial reporting that may point to new fraud tactics . Supervised models then handle known threats while unsupervised models act as a safety net for new evasion strategies, which protects the integrity of the tax system as the financial environment changes.

2.2 Advanced Architectures: Graph Neural Networks and Transformers

Recent research has moved past tabular data toward architectures that capture relational and sequential dependencies. Graph Neural Networks (GNNs) suit tax fraud detection because transactions and taxpayer relationships form networks. Jing et al. introduced MM-TFDX, a multimodal graph neural network for dynamic cross-border tax fraud detection. It accounts for interactions between entities in different jurisdictions. Treating taxpayers and transactions as nodes and edges lets a GNN find suspicious subgraphs, such as circular invoicing . Network analysis of Mexican invoice data points the same way: invoicing loops between known tax evaders and their clients were over-represented, and deep neural networks and random forests built on that insight classified further contributors as suspects .

Transformer-based architectures add ways to process textual declarations and sequential financial data. Liu studies zero-knowledge transformer inference for privacy-preserving, auditable tax fraud detection. The approach addresses a conflict between the predictive power of deep learning and the strict confidentiality of tax data. Transformers can read the content of tax filings and spot inconsistencies in narrative descriptions that may signal fraudulent intent . Combined with the relational information from GNNs, these architectures give a fuller picture of taxpayer behavior. Jing et al. also point to "regulation-aware" explainability in deep learning frameworks, so that outputs are accurate and can also be justified under existing tax law.

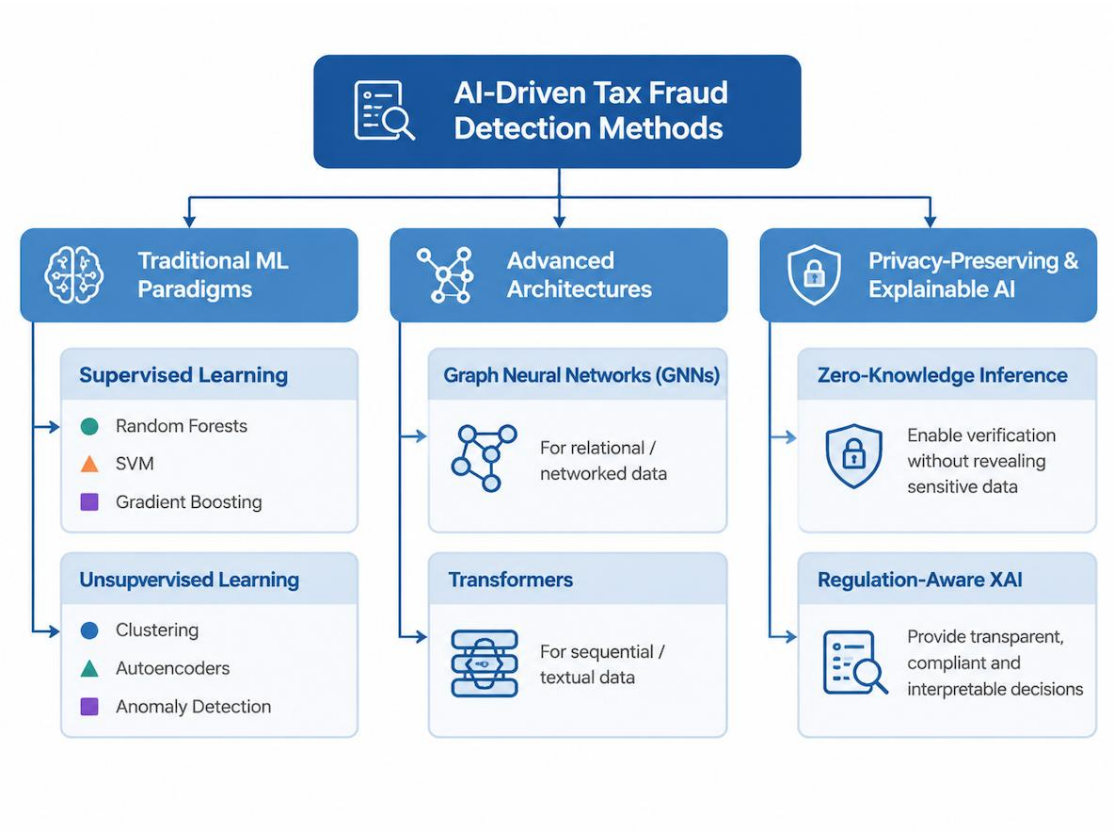


Figure 1. Taxonomy of machine learning methodologies and advanced architectures in modern tax fraud detection.

3. Challenges in AI-Driven Tax Administration

3.1 Data Quality, Availability, and Multimodality

Data quality and fragmented fiscal information are among the most persistent obstacles to deploying AI for tax fraud detection. Tax authorities often hold data that is incomplete, inconsistent, or siloed across departments and jurisdictions. Papadimitriou and Giannopoulos identify dependence on data quality as a widespread problem that can produce biased or inaccurate model outcomes. If the inputs, from income statements to third-party financial reports, are flawed, even a sophisticated model gives unreliable results. In a fiscal setting, this "garbage in, garbage out" problem has a real cost: a wrong fraud flag can lead to legal action against an innocent taxpayer, and a missed one can cost the state significant revenue. Pulling data from separate systems into one analytical store is an engineering task of its own, and a mixed-method study of workload-aware ETL pipeline architecture compares SQL Server Integration Services and Azure Data Factory for enterprise data warehousing .

Multimodal data sources add to the difficulty. Modern tax fraud detection must combine structured data such as numerical tax returns with unstructured data such as legal contracts or social media activity. Jing et al. note that MM-TFDX assumes textual declarations are available. A model that copes with this variety is better placed to detect identity-related fraud and complex corporate schemes. Financial data also changes constantly, so models need regular updating to reflect current economic conditions. Without high-quality, real-time data streams, AI systems in tax administration risk becoming obsolete as fraudsters adapt to new loopholes and digital weaknesses.

3.2 Explainability and the "Black Box" Problem

Many advanced AI models, particularly deep learning and ensemble methods, work as "black boxes." That is a problem for tax administrations, which must operate under principles of transparency and due process. When an AI system flags a filing as fraudulent, the authority has to explain the decision, especially when it leads to an audit or a penalty. Frina et al. stress that machine learning systems need to be explainable to work in settings like Cameroon. An explainable AI (XAI) approach shows auditors which features, such as particular income ratios or deduction patterns, contributed to a high risk score. Explainability is a technical requirement and also a condition for legal and social acceptance of AI in the public sector. Banking research treats trust in explainable AI as a mediating factor in how fraud detection translates into cybersecurity resilience .

Without explainability, a "trust deficit" can emerge between government and citizens. Radhi and Hassan argue that automated tax audits and AI-driven compliance need legal safeguards that ensure algorithmic accountability. An opaque

system is hard to challenge in court, potentially violating the taxpayer's right to a fair hearing. The Dutch childcare benefits case shows the cost of opacity: Amnesty International reported that the tax authority's lack of transparency and accountability left affected parents without effective remedies . Researchers are therefore building explainability mechanisms directly into model architectures. The MM-TFDX framework of Jing et al. , for example, includes regulation-aware explainability that links its explanations to statutory tax rules. When algorithmic outputs come with human-readable justifications, tax authorities can use AI and still meet the accountability standards that fiscal administration requires.

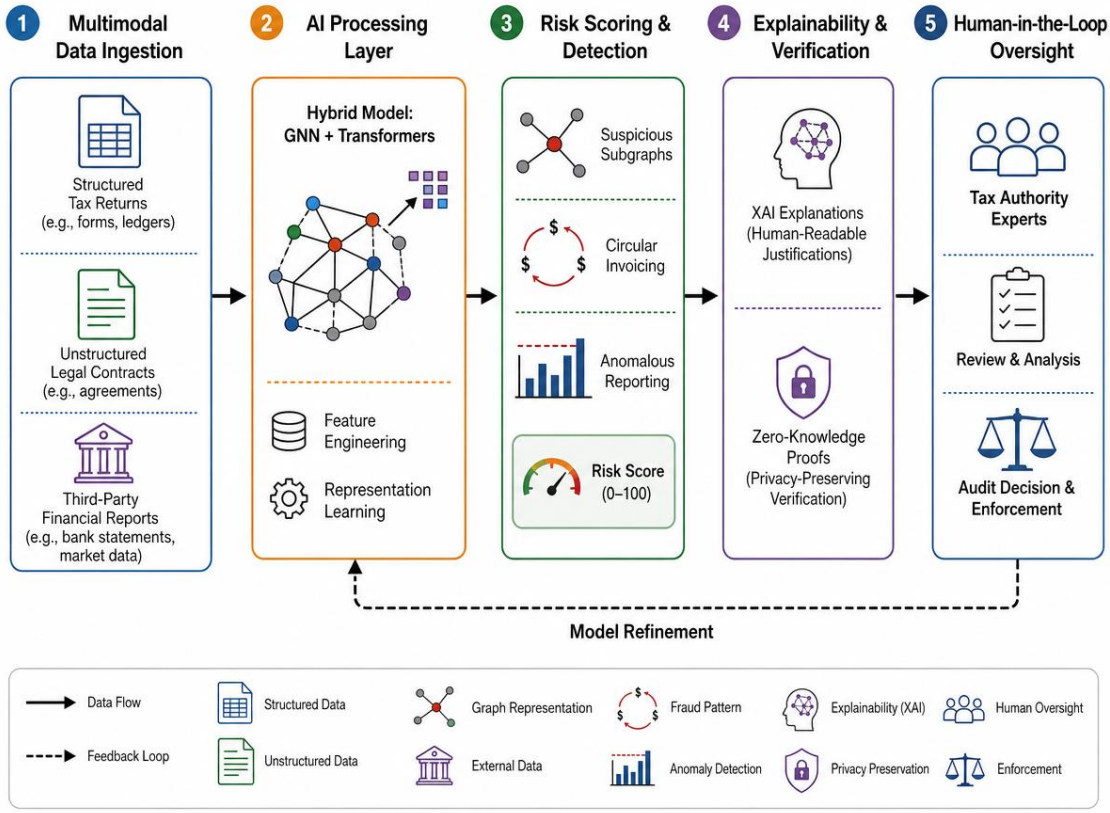


Figure 2. The end-to-end process of AI-integrated tax administration, from raw data to accountable enforcement.

4. Responsible Deployment and Ethical Considerations

4.1 Privacy, Confidentiality, and Computational Integrity

Using AI for tax fraud detection means processing highly sensitive personal and financial information, which raises serious privacy and data protection concerns. Tax authorities are legally bound to protect taxpayer confidentiality, yet AI models need large volumes of data to work well. Liu addresses this conflict with zero-knowledge transformer inference, which verifies a model's output without exposing the sensitive data used during inference. Privacy-preserving techniques like this help build trust and guard against unauthorized surveillance and data breaches. Verifying model outputs without exposing the underlying data could let tax administrations run complex analytics while limiting exposure of taxpayer information .

Ethical deployment also requires balancing state interests against individual rights. Radhi and Hassan stress legal safeguards and transparency in fiscal administration. They warn that as tax processes become more automated, human discretion and empathy may be lost. Responsible deployment means building systems that are technically sound and consistent with democratic values. That includes training on representative data and checking that algorithms do not penalize vulnerable populations inadvertently. The privacy-preserving technologies Liu describes could support an "auditable" AI ecosystem in which the state's power to monitor and enforce tax laws is constrained by technical and legal limits. Agencies also need a way to judge whether a candidate technology fits their needs before adopting it, and a structured technology-selection framework, such as the hybrid human–machine consensus approach for SME technology selection, offers one starting point .

4.2 Fairness, Bias, and Algorithmic Accountability

Fairness is a central concern in AI-driven tax systems because biased algorithms can discriminate systematically against certain groups of taxpayers. A model trained on historical audit data that reflects past bias, such as over-auditing particular industries or demographic groups, will likely repeat and even amplify it. Papadimitriou and Giannopoulos call for a research agenda that prioritizes fairness and the mitigation of algorithmic bias. Cases from practice show the risk. Elzayn et al. found

that IRS audit selection that did not use race still audited Black taxpayers at 2.9 to 4.7 times the rate of non-Black taxpayers, mainly through audits of Earned Income Tax Credit claimants . In the Netherlands, the tax authority's childcare benefits risk model used Dutch nationality as a risk factor, so non-Dutch nationals received higher risk scores, which Amnesty International described as racial profiling . Fair systems require rigorous testing and fairness metrics throughout the model development lifecycle. Tax authorities need to find and correct biases that lead to unfair targeting of taxpayers, since such targeting undermines the perceived legitimacy of the tax system.

Accountability also needs a framework for oversight and redress. Radhi and Hassan discuss transparency and accountability in machine-learning-based compliance infrastructures. That calls for the technical ability to explain a model's decision and also the institutional capacity to handle appeals and corrections. When an AI system makes an error, the taxpayer needs a clear path to contest the finding and the authority needs one to fix the mistake. Frina et al. suggest that explainable systems help administrations see where a model fails or shows bias, and Gupta and Bansal argue that explainability mitigates ethical risks such as bias and discrimination in automated tax audits. The aim of responsible deployment is a "human-in-the-loop" system in which AI assists human auditors instead of replacing them, so that final decisions remain subject to human judgment and ethical oversight.

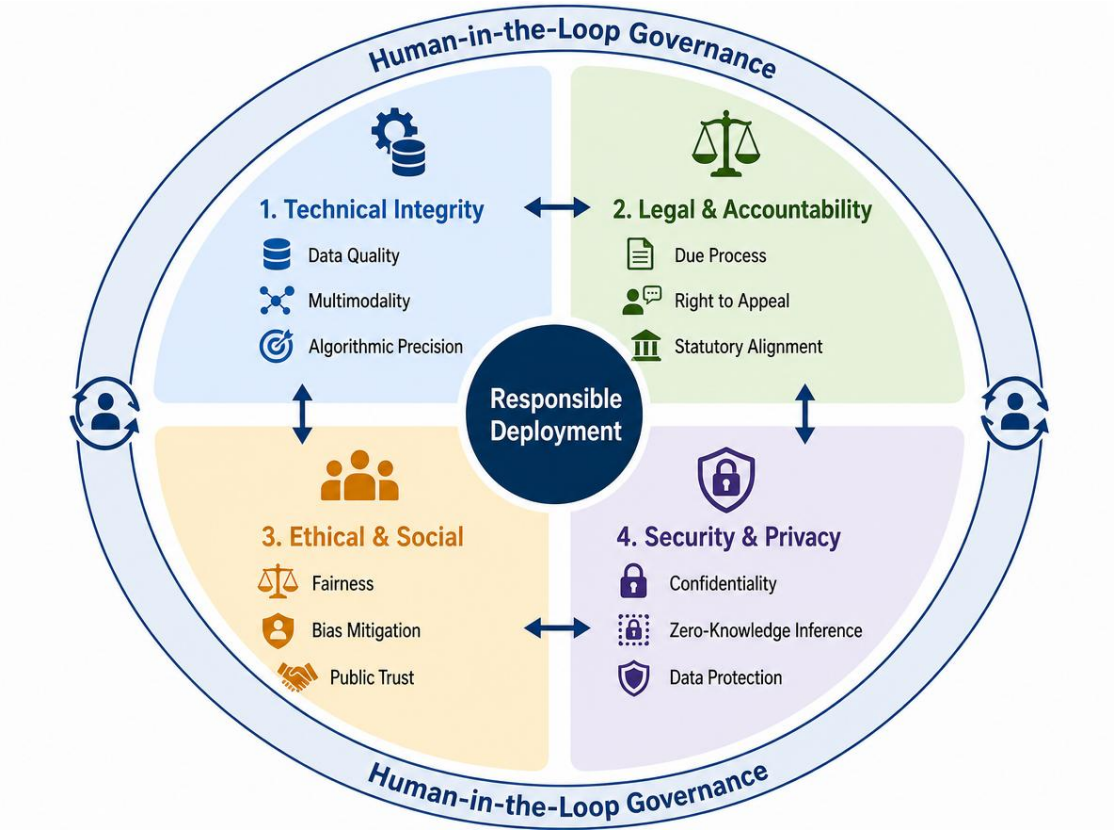


Figure 3. Conceptual framework for the ethical and responsible deployment of AI systems within national tax administrations.

5. Conclusion

AI and machine learning are changing fiscal administration through tax fraud detection and compliance analytics. This review covered methods from traditional supervised and unsupervised learning to multimodal graph neural networks and privacy-preserving transformers . These methods offer new ways to identify suspicious tax filings, fraudulent refund claims, and anomalous financial reporting. The research also shows obstacles to full implementation. Data quality remains a fundamental challenge , and the black-box nature of complex models calls for sustained work on explainability and transparency , an issue that banking fraud research also addresses by examining trust in explainable AI .

Successful deployment depends on ethical and legal integrity as well as algorithmic precision. Radhi and Hassan call for algorithmic accountability and legal safeguards to protect taxpayer rights. Liu's work on zero-knowledge proofs offers a technical way to reconcile data utility with privacy. As tax authorities adopt these tools, they should build "regulation-aware" systems that follow existing legal frameworks.

AI-driven tax fraud detection can raise tax revenue and make the fiscal system fairer, but only if technical, ethical, and operational challenges are addressed together. Future research should improve model explainability, reduce algorithmic

bias, and develop privacy-preserving frameworks that are effective in practice. Audit selection studies show that design choices carry policy trade-offs , so fairness checks belong in the development process and not only after deployment. A research agenda built around responsible deployment can help tax administrations develop systems that are efficient and also trusted by the public they serve. Adoption is still under way and will need continued collaboration among data scientists, legal experts, and policy makers.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

References

[1] A comprehensive framework for evaluating software engineering technologies. (n.d.). https://scholar.google.com/citations?view_op=view_citation&hl=en&user=uZgMlskAAAAJ&citation_for_view=uZgMlskAAAAJ:BUYA1_V_uYcC

[2] Advancing Computational Intelligence: AI-Based algorithm design and optimization in programming. (n.d.). https://scholar.google.com/citations?view_op=view_citation&hl=en&user=uZgMlskAAAAJ&citation_for_view=uZgMlskAAAAJ:u_35RYKgDlwC

[3] AI-Driven Fraud Detection and Cybersecurity Resilience in the U.S. Banking sector: The Mediating roles of Explainable AI Trust and Real-Time Fraud Response Capability. (n.d.). https://scholar.google.com/citations?view_op=view_citation&hl=en&user=uZgMlskAAAAJ&citation_for_view=uZgMlskAAAAJ:ML0RJ9NH7IQC

[4] Amnesty International. Xenophobic Machines: Discrimination through Unregulated Use of Algorithms in the Dutch Childcare Benefits Scandal. 25 October 2021

[5] Artificial intelligence-driven business intelligence: Machine learning techniques for financial market analysis. (n.d.). https://scholar.google.com/citations?view_op=view_citation&hl=en&user=uZgMlskAAAAJ&citation_for_view=uZgMlskAAAAJ:Z5m8FVwuT1cC

[6] D Jayanti, S Sulistyo, PI Santosa. Application of Machine Learning in Taxation: A Systematic Literature Review. 2024 International Seminar on Intelligent Technology and Its Applications (ISITIA), Mataram, Indonesia, 10-12 July 2024

[7] D Papadimitriou, V Giannopoulos. Artificial Intelligence and Machine Learning Approaches for Tax Fraud Detection: A Systematic Literature Review and Research Agenda. mdpi.com, 2026

[8] H Elzayn, E Smith, T Hertz, C Guage, A Ramesh, R Fisher, DE Ho, J Goldin. Measuring and Mitigating Racial Disparities in Tax Audits. Quarterly Journal of Economics, 140(1):113-163, 2025. https://doi.org/10.1093/qje/qjae027

[9] M Battaglini, L Guiso, C Lacava, DL Miller, E Patacchini. Refining public policies with machine learning: The case of tax auditing. Journal of Econometrics, 2024. https://doi.org/10.1016/j.jeconom.2024.105847

[10] M Zumaya, R Guerrero, E Islas, O Pineda, C Gershenson, G Iniguez, C Pineda. Identifying tax evasion in Mexico with tools from network science and machine learning. arXiv:2104.13353, 2021

[11] MD Frina, JRK Kamdjoug, DRK Menou. Optimizing Tax Revenue Through Machine Learning-Driven Fraud Detection: An Explainable Approach for Cameroon. Springer, 2026

[12] MK Radhi, NF Hassan. Automated Tax Audits and AI-Driven Compliance: Legal Safeguards, Transparency, and Algorithmic Accountability in Fiscal Administration. Springer, 2026

[13] OECD. Governing with Artificial Intelligence: The State of Play and Way Forward in Core Government Functions. OECD Publishing, 2025

[14] S Jing, L Zhang, X Wang. MM-TFDX: a multimodal graph neural network framework for dynamic cross-border tax fraud detection with regulation-aware explainability. nature.com, 2026

[15] Workload-Aware ETL Pipeline Architecture for Enterprise data warehousing: A mixed-method study of SQL Server Integration Services and Azure Data Factory. (n.d.). https://scholar.google.com/citations?view_op=view_citation&hl=en&user=uZgMlskAAAAJ&citation_for_view=uZgMlskAAAAJ:4MWp96NkSFoC

[16] Y Liu. Privacy preserving and auditable tax fraud detection using zero knowledge transformer inference. Springer, 2026

[17] Adebayo, F., Haslam, B., Ikumapayi, O., Bezditnyi, V., U, E., Wolf, S., Adeniji, E., Reinikka, R., Svensson, J., Noah, G., Wong, C., Azfar, O., Kahkonen, S., Lanyi, A., Meagher, P., Rutherford, D., Joseph, C., Dolapo, S. H., Bachner, G., … Jones, N. (2025). *Securing Government Revenue: A Cloud-Based AI Model for Predictive Detection of Tax-Related Financial Crimes*. International Journal of Computer Applications Technology and Research. https://doi.org/10.7753/ijcatr1405.1007

[18] Adelakun, B. O., Onwubuariri, E. R., Adeniran, G. A., & Ntiakoh, A. (2024). Enhancing fraud detection in accounting through AI: Techniques and case studies. *Finance & Accounting Research Journal*, *6*(6), 978–999. https://doi.org/10.51594/farj.v6i6.1232

[19] Ali, K. M. Y., Akter, S., Islam, S., & Mridha, M. F. (2025). Advancing Computational Intelligence: AI-Based Algorithm Design and Optimization in Programming. *Journal of Computer Science and Technology Studies*, *7*(1), 122–138. https://doi.org/10.32996/jcsts.2025.7.1.10

[20] Ariyibi, K. O., Bello, O. F., Ekundayo, T. F., Oladepo, O. I., Wada, I. U., & Makinde, E. O. (2024). Leveraging Artificial Intelligence for enhanced tax fraud detection in modern fiscal systems. *GSC Advanced Research and Reviews*, *21*(2), 129–137. https://doi.org/10.30574/gscarr.2024.21.2.0415

[21] Battaglini, M., Guiso, L., Lacava, C., Miller, D. L., & Patacchini, E. (2024). Refining public policies with machine learning: The case of tax auditing. *Journal of Econometrics*, *249*, 105847. https://doi.org/10.1016/j.jeconom.2024.105847

[22] BOLOȘ, C., & HERCZEG, L. (2025). *ANALYSIS OF THE TYPE OF COMPANIES INVOLVED IN TAX FRAUD*. The Annals of the University of Oradea Economic Sciences. https://doi.org/10.47535/1991auoes34(1)011

[23] Elzayn, H., Smith, E., Hertz, T., Guage, C., Ramesh, A., Fisher, R., Ho, D. E., & Goldin, J. S. (2024). Measuring and Mitigating Racial Disparities in Tax Audits. *The Quarterly Journal of Economics*, *140*(1), 113–163. https://doi.org/10.1093/qje/qjae027

[24] Frina, M. D., Kamdjoug, J. R. K., & Menou, D. R. K. (2026). *Optimizing Tax Revenue Through Machine Learning-Driven Fraud Detection: An Explainable Approach for Cameroon*. Lecture Notes in Networks and Systems, 252–266. https://doi.org/10.1007/978-3-032-32023-0_22

[25] Gupta, C., & Gupta, V. (2025). Hybrid Human–Machine Consensus Framework for SME Technology Selection: Integrating Machine Learning and Planning Poker. *Systems*, *14*(1), 42. https://doi.org/10.3390/systems14010042

[26] Gupta, T., & Bansal, S. K. (2026). Explainable AI and Automated Tax Audits: Implications for Taxpayer Trust, Legal Accountability, and Ethical Compliance. *International Journal For Multidisciplinary Research*, *8*(1). https://doi.org/10.36948/ijfmr.2026.v08i01.67578

[27] Hridoy, S. M. A. S., Rahman, S. M., Rishad, S. M. S. I., Bhuiyan, M. S., Islam, S., & Raihan, M. J. (2023). *A Comprehensive Framework for Evaluating Software Engineering Technologies. In SSRN Electronic Journal*. RELX Group (Netherlands). https://doi.org/10.2139/ssrn.4650826

[28] International, A. (2021). Xenophobic Machines: Discrimination through Unregulated Use of Algorithms in the Dutch Childcare Benefits Scandal.

[29] Islam, S., Rahman, M. A., & Hasan, M. J. (2026). *Workload-Aware ETL Pipeline Architecture for Enterprise Data Warehousing: A Mixed-Method Study of SQL Server Integration Services and Azure Data Factory*. Figshare. https://doi.org/10.6084/m9.figshare.34625415

[30] Jayanti, D., Sulistyo, S., & Santosa, P. I. (2024). *Application of Machine Learning in Taxation: A Systematic Literature Review*. International Seminar on Intelligent Technology and Its Applications, 687–691. https://doi.org/10.1109/isitia63062.2024.10668268

[31] Jing, S., Zhang, L., & Wang, X. (2026). *MM-TFDX: a multimodal graph neural network framework for dynamic cross-border tax fraud detection with regulation-aware explainability*. Scientific Reports. https://doi.org/10.1038/s41598-026-64839-4

[32] Kamoun, A., Boujelbane, R., & Boujelben, S. (2024). A prediction model to detect non-compliant taxpayers using a supervised machine learning approach: evidence from Tunisia. *Journal of Business Analytics*, *8*(2), 116–133. https://doi.org/10.1080/2573234x.2024.2438195

[33] Liang, J., Fan, J., Feng, Z., & Jing, X. (2025). Anomaly Detection in Tax Filing Documents Using Natural Language Processing Techniques. *Applied and Computational Engineering*, *144*(1), 80–89. https://doi.org/10.54254/2755-2721/2025.21736

[34] Liu, Y. (2026). Privacy preserving and auditable tax fraud detection using zero knowledge transformer inference. *Discover Artificial Intelligence*, *6*(1). https://doi.org/10.1007/s44163-026-01882-0

[35] Mehta, P., Bhargava, S., Kumar, S., Kumar, R., & Babu, Ch. S. (2022). Representation Learning on Graphs to Identifying Circular Trading in Goods and Services Tax. *2022 IEEE International Conference on Big Data (Big Data)*, *40*, 2323–2326. https://doi.org/10.1109/bigdata55660.2022.10020707

[36] OECD. (2025). *Governing with Artificial Intelligence*. In OECD eBooks. Organization for Economic Cooperation and Development. https://doi.org/10.1787/795de142-en

[37] Papadimitriou, D., Giannopoulos, V., Dimitropoulos, P. E., Nikolaidis, V. N., Stavroyiannis, S., & Dimitrakopoulos, P. (2026). Artificial Intelligence and Machine Learning Approaches for Tax Fraud Detection: A Systematic Literature Review and Research Agenda. *Journal of Risk and Financial Management*, *19*(9), 673. https://doi.org/10.3390/jrfm19090673

[38] Radhi, M. K., & Hassan, N. F. (2026). *Automated Tax Audits and AI-Driven Compliance: Legal Safeguards, Transparency, and Algorithmic Accountability in Fiscal Administration*. Communications in Computer and Information Science, 150–177. https://doi.org/10.1007/978-3-032-39720-1_6

[39] Rahman, M. A., Khan, M. H., -, S. I., -, K. S. A. M., & -, M. F. K. (2025). Artificial Intelligence-Driven Business Intelligence: Machine Learning Techniques for Financial Market Analysis. *International Journal on Science and Technology*, *16*(1). https://doi.org/10.71097/ijsat.v16.i1.2420

[40] Rimi, N. N. (2025). *AI-Driven Fraud Detection and Cybersecurity Resilience in the U.S. Banking Sector: The Mediating Roles of Explainable AI Trust and Real-Time Fraud Response Capability*. Communications on Applied Nonlinear Analysis. https://doi.org/10.52710/cana.jrnl.v32.7478

[41] Savić, M., Atanasijević, J., Jakovetić, D., & Krejić, N. (2022). Tax evasion risk management using a Hybrid Unsupervised Outlier Detection method. *Expert Systems with Applications*, *193*, 116409. https://doi.org/10.1016/j.eswa.2021.116409

[42] Zhang, T. (2025). A Knowledge Graph-Enhanced Multimodal AI Framework for Intelligent Tax Data Integration and Compliance Enhancement. *Frontiers in Business and Finance*, *2*(2), 247–261. https://doi.org/10.71465/fbf384

[43] Zumaya, M., Guerrero, R., Islas, E., Pineda, O., Gershenson, C., Íñiguez, G., & Pineda, C. (2021). *Identifying Tax Evasion in Mexico with Tools from Network Science and Machine Learning. In Understanding complex systems (pp. 89–113)*. Springer Nature. https://doi.org/10.1007/978-3-030-81484-7_6