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Responsible AI in Government Tax Analytics and Compliance Systems

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Abstract: Artificial intelligence (AI), mixed with advanced big data analytics methods, has the potential to play a pivotal role in enhancing efficiency and accuracy in multiple tax processes, from data management and fraud detection to pricing optimisation and performance assessments. However, the use of these new technologies must respect the ethical principles of transparency, accountability, and explainability in order to secure their acceptance by both internal and external stakeholders, ensure compliance with increasingly stringent financial regulations and well-founded tax decisions, and ultimately facilitate a more equitable tax regime. A Responsible AI framework is articulated for an area typically overlooked in the discussion of the ethical use of AI in other fields: its application in government analytics and compliance systems for tax agencies, natural and legal persons subjected to taxation, and internationally coordinated data-sharing agreements.

These institutions frequently combine their own datasets with information sourced externally through digital interceptions, companies and organisations mandated to carry out withholdings or disseminate internationally belonging to third parties, data of a fiscal nature of a different nature that guarantees compatibility in the absence of a tax treaty, and other types of financial data. Given the sensitive nature of tax-administrative data and the legal obligations in force for tax agencies, the AI systems developed should respond adequately to the three dimensions of Responsible AI: securing ownership of data and results; avoiding biases during the design stage and in the response stage; and guaranteeing control and security of the systems' outputs.

Keywords: Responsible Artificial Intelligence, Tax Analytics Systems, Government AI Governance, Ethical AI Frameworks, Tax Compliance Automation, Big Data Analytics In Taxation, Fraud Detection Technologies, Pricing Optimization Analytics, Performance Assessment Models, Transparency And Explainability, Accountability In AI Systems, Regulatory Compliance In Taxation, Equitable Tax Regimes, Public Sector AI Applications, International Data Sharing Agreements, Tax Administrative Data Management, Bias Mitigation In AI, Data Ownership And Stewardship, Secure AI Outputs, Trustworthy Government Analytics.

1. INTRODUCTION

Responsible Artificial Intelligence (AI) for Tax Administration encompasses its use in tax analytics and compliance systems, ensuring adherence to ethical principles throughout the complete lifecycle of the data analytics processes that support predictive models and machine-learning models. Preventing recidivism of systemic abuses against taxpayer rights and strengthening their voluntary compliance remain fundamental objectives for tax administration globally. Failure to obtain the desired results in predictive tax analytics may warrant the responsible use of compliance systems, subject to a regulatory framework and appropriate governance structures.

The ethical implementation of tax analytics applications has gained increasing attention in both the public and private sectors. Central to the responsible use of data analytics and machine-learning techniques is clear understanding of the institutional responsibilities of collecting, safeguarding, and administering taxpayer data on behalf of the citizenry. This governance model delineates the accountabilities of the respective roles assigned to data custodians, users, and decision-makers in the lifecycle of data analytics tools to mitigate actual, perceived, or potential discrimination against the taxpayer, as well as to preserve the enclaves of justice that should be guaranteed to all citizens.

1.1. Overview of Responsible AI in Tax Administration

Responsible AI describes government tax administration analytics and compliance systems developed and deployed in alignment with established ethical principles. For such uses, the attributes of transparency, accountability, and explainability are paramount. Ongoing investment in data integration and stewardship enables terabytes of tax administration data to be combined with third-party information for comprehensive analysis and highly predictive analytical models.

The denotation of tax analytics and compliance systems as Responsible AI underscores that fairness, equity, and safeguarding public trust are overriding design considerations. The deployment of tax analytics and compliance systems is thus underpinned by a robust legal basis, with legislative prohibitions against the malfeasance and bias experienced in

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non-governmental AI applications. The evolution in Responsible AI research methods, technologies, and applications further enhances public trust and confidence. The investment of the national tax authority in an independent data an-alysis centre is an obvious demonstration of such commitment, as is the cooperation with the national statistics agency.

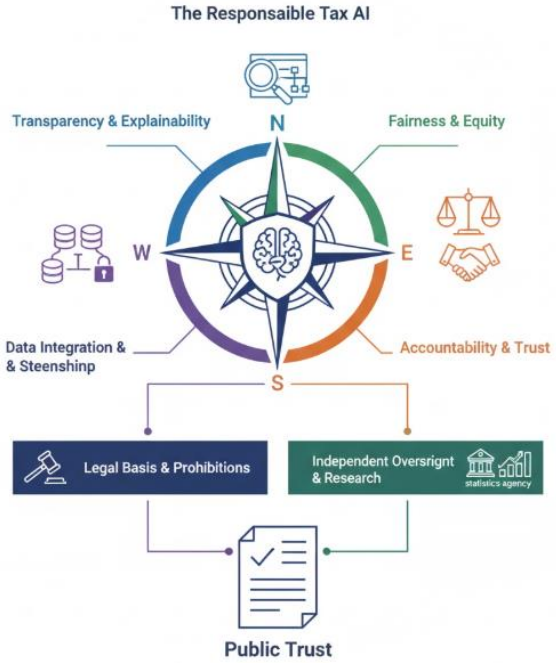
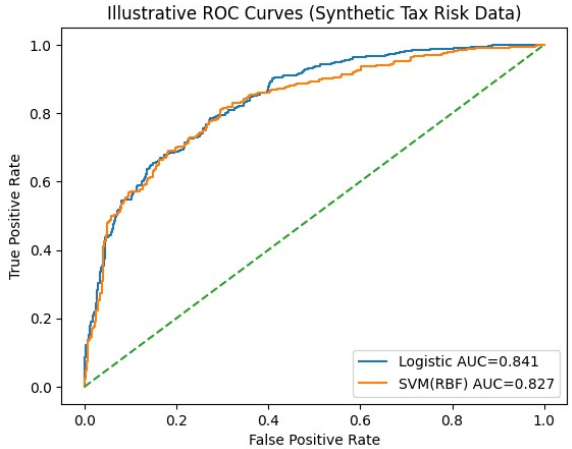


Fig 1: Architecting Public Trust: A Framework for Responsible AI in Tax Administration through Ethical Governance and Data Stewardship

2. FOUNDATIONS OF RESPONSIBLE AI IN TAX ADMINISTRATION

Underlying Responsible AI in government tax administration systems are key ethical principles and governance structures that facilitate the implementation and use of methods based on artificial intelligence and machine learning. These principles include fairness, equity, and inclusiveness; reliability, safety and security; and transparency, accessibility and transferability; notably accountability and auditability; effectiveness and efficiency; and responsiveness and timeliness. Transparency, accountability and explainability are especially valuable for government tax authorities.
Use of tax analytics and subsequent application in compliance systems are supported by respective sets of methods, technologies, architecture, data governance and stewardship, and model validation and testing. In tax analytics, data from multiple sources is integrated with advanced analytical methods to detect taxpayer risk and nested behaviour. Within compliance systems, these risks are translated into regulatory interventions and deployed through automated decision support systems or rule-based expert systems, guided by process control procedures that incorporate regulatory law and frameworks. The result is a post-validated A|I|M solution that follows the logic “if you produce it, people will pay, and the tax office detects it, then you assess and collect”.



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Equation 1: Risk score → threshold → compliance action

Notation

- Features: $x_i \in \mathbb{R}^d$
- Label: $y_i \in \{0,1\}$ (1 = "risk/non-compliance")
- Model score (probability-like): $s(x) \in [0,1]$
- Threshold: τ

Decision rule

$$y_{\text{hat}}(x) = \begin{cases} 1 & \text{if } s(x) \geq \tau \\ 0 & \text{otherwise} \end{cases}$$

Cost-based thresholding (typical in compliance systems)

Let c_{FP} = cost of false positive, c_{FN} = cost of false negative.

$$\mathbb{E}[C] = c_{FP}\, P(y_{\text{hat}} = 1, y = 0) + c_{FN}\, P(y_{\text{hat}} = 0, y = 1)$$

2.1. Ethical Principles and Governance

Guided by a commitment to Responsible AI, the application of artificial intelligence (AI) for tax analytics and compliance systems is governed by a framework defined by three core principles: the responsible and ethical use of technology, public transparency and engagement, and the promotion of social equity. The responsible and ethical use of AI refers to the application of integrity-informed practices in the development, deployment and provision of tax analytics and compliance solutions. Hence, social trust and public confidentiality are guarded and public concern mitigated, while prospects for justice, proportionality and fairness in the design and implementation of products and services are bolstered. Conforming with the ethical principles and governance foundation for AI in government, the Tax Administration Act establishes a framework for the adoption and deployment of solutions using advanced and predictive analytics. Obligations and responsibilities apply to both the entire tax agency and to agency staff, serving to enhance the overall quality and performance of all predictive analytical products and services, not just those employing AI techniques.

2.2. Transparency, Accountability, and Explainability

Transparency, accountability, and explainability are guiding principles for Responsible AI used in tax analytics and compliance systems. Adopted to reduce the risk of data breach and invasive surveillance, these principles help ensure that the predicted results from an agency's analytics and compliance systems are made explicitly available to the affected parties to the degree possible.

Compliance systems rooted in predictive analytics introduce new risks: one party processing personal data may rely on another, resulting in profound consequences—for society and for the individuals affected. For example, a bank may be liable for unwarranted suspicious transaction reports generated based on an incomplete PEP (politically exposed persons) database because the inaccurate information was supplied by a government agency. Ultimately, the accountability automatically shifts to some third-party institution, the role of which was not adequately scrutinized by the first party when it engaged the service of an external provider. As one of the affected parties, the undertaking making the transaction cannot contest the prediction automation process. When its performance is swayed by factors that are beyond the undertaking's control and that the compliance system could address through mitigation or internal machine-learning monitoring processes, predictive analytics loses its preventive nature. These situations call for sensitive management, either through data sharing agreements or by having automated detection checks in place.

While transparency about the output of predictive models is required, the overall process must remain secret to safeguard sensitive data. Therefore, stakeholders potentially affected by a decision based on the predicted outcome should be informed of the source and the threshold values. It is essential to specify the rationale for defining those threshold values and the criteria for allowing or disallowing model reprocessing in dedicated control environments. In the risk domain, a strong interaction between the adaptive decision-making, prevention, and compliance components should be in place, establishing feedback loops shared with the community either by a dedicated structure or in liaison with industry association platforms. Data providers should also be properly shielded by mathematical guides detailing the risk and damage exposure data elements and the associated scope of responsibility.

3. TAX ANALYTICS: METHODOLOGIES AND TECHNOLOGIES

A range of methodologies is used in tax analytics that categorise, confirm, analyse, and refine, often through iterations. Key algorithms include support vector machines, unsupervised clustering, and graph analytics. Predictive models are

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used to anticipate risk and improve operations; misclassification is always a risk. Predictive modelling shares data across hierarchies to anticipate risk. Predictive techniques frequently use unsupervised learning to determine relationships and allocate likely behaviours to segments. Predictive analytics plus external data leads to more accurate insights, processed via model risk management.

AI-based compliance systems that use AI, ML, or neural nets directly touch taxpayers, analysing behaviour, generating communications, recommending audits, and identifying tax fraud. Communication generation can take in structured and unstructured data across multiple formats. Model risk management oversight is applied to ML and similar models. Linked compliance systems apply multiple AI-based modules in the same case, progressing proposals from tax agency to machine, taxpayer, and decision-maker. Tax agency expertise defines business rules for each ML module. Supervised ML techniques designed for text summarisation ensure audit recommendations are easy, accurate, valid, and valuable.

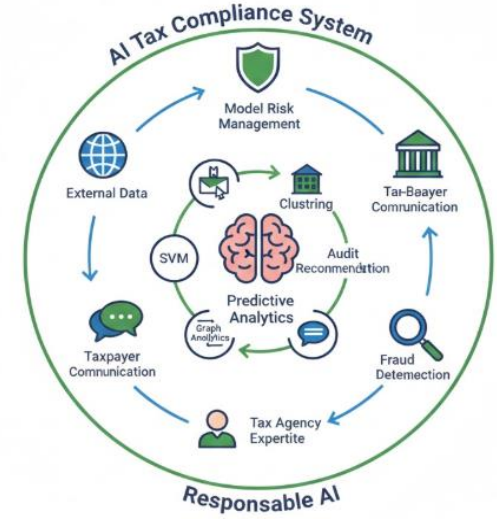

Fig 2: Algorithmic Integrity in Fiscal Oversight: A Multi-Modular AI Framework for Predictive Compliance and Model Risk Management in Tax Administration

3.1. Data Integration and Stewardship

Responsible AI in government tax analytics and compliance systems incorporates the use of modern data stewardship by ensuring that the data used in Tax Analytics and Compliance systems deployed by National Tax Authorities (NTAs) is processed in accordance with regulatory requirements by an established Data Stewardship process at the NTA with oversight by designated jurisdictions/territories, ensuring the data used is accurate, kept up to date at all times throughout the life of the models, that data retention and deletion policies are exercised as directed by Law and Regulations using appropriate application and information provisioning controls. The data versions applied for the creation and deployment of models and the additional controlled parameters such as pre-defined Measurable Indicators of Success (MIS), Minimum Acceptable Compliance Level (MACL) for the Analytical Models maintained under Controlled Environment is made visible to all stakeholders, including the Judiciary, Public and Advisors. NTAs disclose the data versions used in compliance systems and misuse of these systems is made a criminal offense.

The model versioning applied in the Compliance Systems Application is clearly defined. The Enabling Feature Extraction Pipeline (EFx) is responsible for ingestion of data, generation of features, detection of data drift and generation of stage-level reports for compliance systems analytical models. These reports consist of the status summary at data quality, distributional homogeneity, data drift monitoring, and feature set status (addition, modification, removal, deprecation) levels making possible the type assurance for the application. Data integration and stewardship for tax analytics also comprises Redressal Desk Control Analysis (RDCA) – a non-revenue cost and risk control analysis investigation of documents seeking redressals on tax-processing-detection agencies scrutiny.

3.2. Analytical Models and Predictive Techniques

Tax analytics encompass the development of models for data analysis and prediction. Models developed for tax analytics may include descriptive models (such as segmentation models or cluster analysis) to assist revenue authorities in understanding taxpayer behaviours, as well as diagnostic models used to describe the reasons that bring out certain behaviours of taxpayers, such as determent behaviours by some tax payers to comply with tax regulations.

Predictive models (including machine learning methods) are increasingly used by revenue authorities all over the world. Many revenue authorities have also implemented models to predict taxpayer behaviour using large amounts of data. Instead of conducting surveys to determine what triggers taxpayers to comply or deter from taxing regulations, tax

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analytics have enabled revenue authorities to better understand these effects. Prescriptive models, seldom available, support revenue authorities in defining the best course of action. Promising prescriptive models exist, but only in research contexts. For instance, optimal fraud audit sampling, evidence or litigation allocation, or punishment strategy allocation have been studied.

Machine learning models for predicting or classifying behaviours of fraud or not-fraud tax payers are ubiquitous among revenue authorities. Such models have been widely applied and much documented in the literature, with an evident trend toward the investigation of ensemble prediction methods combining a variety of approaches. Simple cheque-detection and credit-card fraud-detection methods, based on a well-selected set of features, supply an entryway for exploring more sophisticated detection tools.

4. COMPLIANCE SYSTEMS: IMPLEMENTATION AND OVERSIGHT

The use of AI-based solutions in tax enforcement raises significant issues well beyond issues of methodology or technology. Such systems must be designed not only to ensure transparency, accountability, or explainability of predictions, but also to ensure that the decisions they support comply with applicable laws. Public authorities are responsible for enforcing a wide variety of legal norms and enforcing statutory and constitutional principles such as respect for the presumption of innocence, protection from unreasonable searches and seizures, the right to contest the decisions of government agencies, and free speech.

An effective Re-AI approach to compliance systems therefore requires the establishment of state-of-the-art domestic and international regulatory frameworks and standards for all types of tax enforcement systems, with guidance from relevant international organizations and oversight by independent regulatory agencies acting within the scope of their respective mandates. Such important measures and recommendations are widely recognized but not necessarily applied in all jurisdictions. They include standards for the legal use of facial recognition and other biometric identification technologies; demand-clearance safeguards; recognition of the limits of models, scores, and alerts; explicit constraints on deterrence and preventive measures; enhanced training for tax law enforcement officials; and ongoing oversight, assessment, and evaluation by independent regulatory authorities with the necessary expertise.

Equation 2: Logistic regression (risk scoring) from maximum likelihood

This is a standard "predictive model → score" backbone for tax risk scoring.

Step 1: model

$$s(x) = \sigma(z), \quad z = w^{\top}x + b, \quad \sigma(z) = \frac{1}{1+e^{-z}}$$

Step 2: Bernoulli likelihood

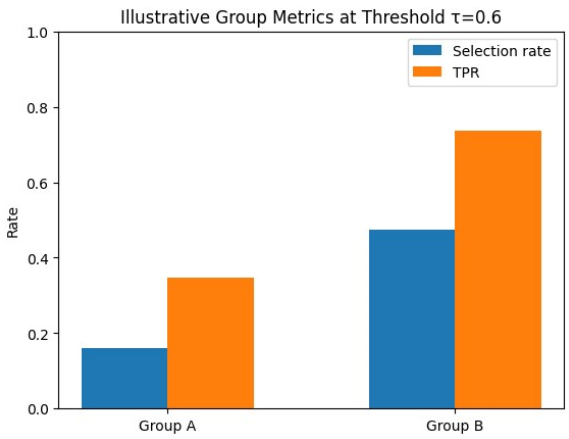
$$P(y_i \mid x_i) = s(x_i)^{y_i}\big(1 - s(x_i)\big)^{1-y_i}$$

Step 3: log-likelihood

$$LL(w,b) = \sum_i \big[y_i \log s(x_i) + (1-y_i)\log\big(1 - s(x_i)\big)\big]$$

Step 4: minimize negative log-likelihood (plus regularization)

$$\min_{w,b} J(w,b) = -LL(w,b) + \frac{\lambda}{2} \| w \|^2$$



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4.1. Regulatory Frameworks and Standards

A strong regulatory framework establishes the collective expectation and public confidence that the administration of laws will be fair, effective, and efficient. Regulations set boundaries and frameworks within which government agencies must operate. Governments can introduce laws, regulations, and guidance to support the responsible use of AI in tax administration and compliance systems.

Essentially, laws are legally binding, can impose criminal penalties for violations, and are generally less readable than non-legally binding regulations and guidance. Non-legally binding regulations – such as requirements to undertake a risk management assessment – are issued by external authorities, such as information and privacy commissions. Governments can also issue less formal guidance to agencies on how to interpret laws and regulations. Tax policy and legal frameworks should include these principles and implement them through alignment of regulatory powers and responsibilities.

Further, tax authorities should consider the use of impact assessments to support compliance with the principles. Impact assessments can assist management in understanding how technology is being applied and provide an opportunity to highlight potential risks to those developing, implementing, and overseeing AI within the agencies. International assessments of regulations governing AI can provide insights about the depth and clarity of these laws and if they are sufficient to ensure public confidence regarding the use of AI in government operations.

5. GOVERNANCE STRUCTURES FOR RESPONSIBLE AI IN TAX AGENCIES

Governance structures for responsibly applying AI methods in government tax analytics and compliance systems are essential to engendering public trust and ensuring compliance with ethical principles that place people at the center of government operations. Therefore, scrutiny, process management, and oversight responsibilities are essential ingredients to the design and operation of tax systems capable of integrating, processing, and analyzing sensitive information about—and potentially affecting the lives of—millions of taxpayers. To guide, oversee, and articulate the management of these systems, a Governance Board is a natural "go-to" entity, especially in established national tax authorities where dedicated internal units or departments of analytical methodologies and tax compliance are in place (consider commonly known tax-enforcement units). In government organizations immune from electoral change, the board's role is to provide direction about the tax analytics methodologic foundation deployed in national tax systems and make opinions in, or approve, planned changes.

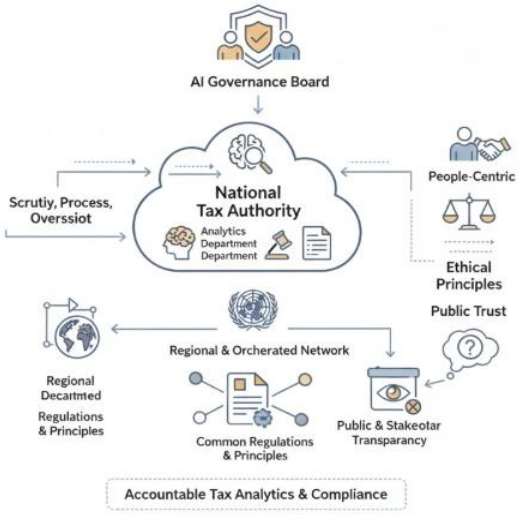

Fig 3: Ethical Orchestration: Multilevel Governance Frameworks for AI-Driven Tax Analytics and Institutional Trust

Structural governance arrangements mostly occur at the national level; cooperation and coordination of analyses may happen at regional and global levels through international organizations and forums open to sharing collective knowledge. Fundamental for such arrangements is the existence of common regulation and principles providing a common understanding for how tax information can be used for various purposes at various analytical levels. A principal-orchestrated network of government tax data, such as the United Nations' System of National Accounts, offers the foundation for external agency tax interaction. When supplying regulatory mandates, such public and stakeholder transparence minimize misuse or disharmony while tackling the dust-generated "but why not me?" syndrome.

5.1. Institutional Roles and Responsibilities

Roles and responsibilities within tax agencies are key to ensuring alignment of agency operations with expectations. Frequently, a dedicated unit within the tax agency is assigned a governance support role to newly developed AI systems.

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This unit's role can include AI oversight, review of the agency's training datasets for accuracy and privacy implications, conduct of external modelling reviews, guidance for ethical and regulatory compliance, and assessment of AI vendors. Such a role can help evaluate how tax agencies leverage model risk management concepts—including model validation, inventory management, observability, and oversight for outsourced models—across all models, including those created by third-party vendors. These responsibilities can also include a forward-looking aspect so that agencies monitor movements in applicable laws, guidance, and standards to identify future impacts on the agency's AI systems. Such a dedicated support unit provides a mechanism for surveillance of the different AI applications across all branches within the agency.

Tax agencies interacting with other arms of government that are involved in promoting ethical AI can adopt their work on ethical AI policies, risk frameworks, and audit guidelines to the context of tax operations. Such collaboration can include providing guidance to the development of a federal government-wide AI strategy that supports the nation's aim of a responsible and ethical AI ecosystem. The agency's work to prepare the workforce for AI models and the potential for adverse social outcomes can also inform other arms of government. In cases where tax agencies provide social safety nets, this support can inform the design and administration of social safety net programs in a manner that reduces discrimination and bias.

5.2. Stakeholder Engagement and Public Transparency

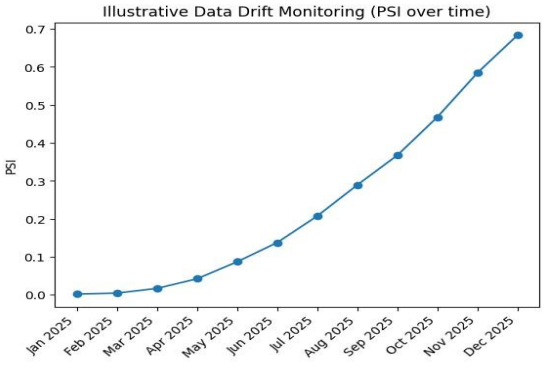
Transparent and accountable governance of tax analytics and automated compliance systems is critical not only for their effectiveness and efficiency but also for their social legitimacy. Consequently, credible and independent oversight of governance structures and artefacts used in implementing tax analytics and automated compliance systems is essential. Their technical soundness and the underlying data must be subject to quality-assurance processes. These activities typically take place in a trusted organisational, regulatory and legal context that also examines and rectifies unintended social, economic and financial consequences of using such information. Explicit policies for stakeholder engagement require independent research on emerging technology and its consequences.

Tax agencies operate risk-based compliance programs in the public interest. Such activities routinely involve sensitive policy decisions. Stakeholders, including business, civil society, taxpayers and media, are therefore keen to understand the reasoning behind tax-administered decisions and audit work. Transparent consultation mechanisms can facilitate understanding, proactive and responsive policy action, multidisciplinary engagement, and management of public sentiment. Institutions with regulatory oversight responsibilities need to adhere to rules and guidelines for public transparency. Stakeholders require access to processes used in creating and maintaining decision-support systems—to the data, algorithms, modelling, and testing of analytic products—as well as to provide data, validate models, and communicate results.

6. CASE STUDIES AND EMPIRICAL EVIDENCE

Responsible AI for government tax analytics and compliance systems is grounded in sound and comprehensive ethical principles that consider and address the concerns and needs of stakeholders, including citizens. Active governance frameworks incorporate their requirements within a clear and consistent regulatory framework adapted to the specificities of these systems. Engagement and co-development of tax analytics and compliance systems with the affected stakeholders maximises public acceptance when these systems require reallocation of tax compliance burdens. Continuous and proactive arrangements for institutional transparency mitigate concerns about citizens being subjected to automated decision-making or executory administrative acts without human intervention.

Insights from Responsible AI working groups at the Canadian Revenue Agency, the U.S. Internal Revenue Service, and the New Zealand, Australian, and United Kingdom's national tax authorities share empirical and practical cases, providing guidance grounded in experience for all national tax authorities that wish to adopt these analytics and compliance systems.



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Equation 3: Support Vector Machine (SVM): primal → dual (step-by-step)

Use labels $y_i \in \{-1, +1\}$.

Primal (soft margin)

$$\min_{w,b,\xi} \frac{1}{2} \| w \|^2 + C \sum_i \xi_i$$

subject to

$$y_i(w^\top x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0$$

Lagrangian

Introduce multipliers $\alpha_i \geq 0$ and $\mu_i \geq 0$:

$$L = \frac{1}{2} \| w \|^2 + C\sum\xi_i - \sum\alpha_i(y_i(w^\top x_i + b) - 1 + \xi_i) - \sum\mu_i\xi_i$$

Stationarity (set derivatives to 0)

- w.r.t. w:

$$\frac{\partial L}{\partial w} = 0 \Rightarrow w = \sum_i \alpha_i y_i x_i$$

- w.r.t. b:

$$\frac{\partial L}{\partial b} = 0 \Rightarrow \sum_i \alpha_i y_i = 0$$

- w.r.t. ξ_i:

$$\frac{\partial L}{\partial \xi_i} = 0 \Rightarrow C - \alpha_i - \mu_i = 0 \Rightarrow 0 \leq \alpha_i \leq C$$

Dual

Substitute back:

$$\max_\alpha \sum_i \alpha_i - \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j (x_i^\top x_j)$$

subject to

$$0 \leq \alpha_i \leq C, \quad \sum_i \alpha_i y_i = 0$$

Decision function (kernelized if needed):

$$f(x) = \sum_i \alpha_i y_i K(x_i, x) + b, \quad y_{\text{hat}} = \text{sign}(f(x))$$

6.1. National Tax Authority Applications

US Internal Revenue Service (IRS) compliance systems illustrate an integrated and hierarchically detailed approach to Responsible AI in government tax administration. Programs and systems, such as the Information Returns Program and the Fraud Detection System, rely on explanatory data integration and predictive modelling, supported by formal oversight and an extensive set of policies on machine learning. The IRS is committed to reviewing algorithm-based asset decisions, such as underpaying loans, ensuring transparency and fairness for all stakeholders.

At the Massachusetts Department of Revenue, published research identifies racially biased associations inherent in Assessment models produced by commercial firms, calling important discrimination questions into the debate. Agency governance sends positive signals given considerations for public privacy, future modeling decisions, proposed fairness practices and statement support for including disparate impact assessment as part of the broader equity and fairness bucket of considerations. Evidence for tax return AI implementation at Sweden's Skatteverket also aligns with the described Responsible AI framework for analytic applications.

7. CONCLUSION

As the concept of Responsible AI gains traction, the application of AI technologies for social good—a focus on how governments and the public sector deploy AI for fairness, equity, and inclusion—is critical. For tax agencies, deploying AI technologies to comply with democratic standards, processes, and governance principles is essential. The ethical principles underpinning Responsible AI—fairness, reliability, safety, privacy, security, inclusiveness, transparency, and

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accountability—provide a foundation for the use of AI in national tax administration, ensuring fairness in the development of tax analytics and compliance systems.

These principles are increasingly being addressed in tax administration compliance and regulatory processes, supporting the development and implementation of tax analytics—including data integration, stewardship, methods, standards, and specific technologies—and the deployment of predictive and explanatory models and systems that detect anomalies in taxpayer behaviour and compliance. The responsible use of AI in the national tax administration of country is centred on five elements: a governance structure, an ethical framework, tax analytics and practical considerations, compliance systems, and national tax authorities. Potential avenues for future research include quantitative modelling of compliance interventions, examining the impact of COVID-19 relief measures on tax compliance and risk, and undertaking qualitative studies on compliance coping behaviours.

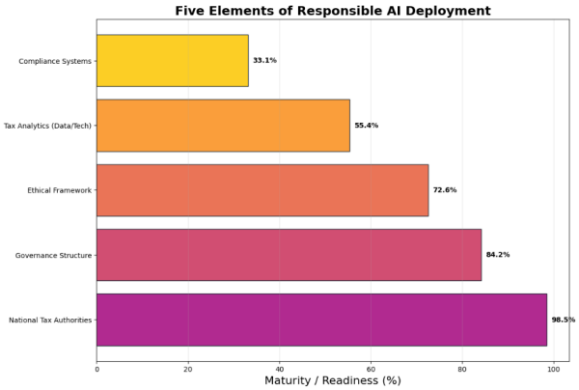

Fig 4: Five Elements of Responsible AI Deployment

7.1. Final Thoughts and Future Directions for Responsible AI in Tax Administration

Responsible AI is a societal necessity and vital to building a trustworthy and ethical relationship between authorities and the public. Since tax authorities already use technologies that fall under the umbrella of artificial intelligence (AI)—in particular, analytics supporting the investigation and prevention of non-compliance and evasion—responsible AI needs to be clearly defined and incorporated into these systems. Doing so requires the elaboration of methodologically agnostic, technical and non-technical principles that embody responsible AI. These principles are informed by evidence found in the literature and in the domains of AI ethics, risk management and audit. Finally, using information from national tax administrations that pursue responsible digitalisation strategies, roles and responsibilities for directing responsible AI in tax analytics and compliance systems are mapped out.

The elements of technical and non-technical responsible AI for tax administration constitute the foundation for a broad governance model that addresses risk management, audit and oversight, institutional roles and responsibilities, and stakeholder engagement and public transparency. Stakeholder engagement and public transparency increase public trust and ensure that data-driven decisions are made with integrity. The eight technical and non-technical principles can aid national tax administrations in addressing AI-related risks while enabling the development and use of accountable, transparent and explainable data-driven technologies. They span all of the life-cycle phases associated with creating, implementing and overseeing models for tax analytics supporting tax-compliance risk assessment, selection of non-compliant cases for audit or investigation, and detection of anomalous tax-reporting behaviour.

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