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Research Article

AI-Powered Tax Compliance: Enhancing Accuracy and Efficiency Through Predictive Modeling

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ARTICLE INFO **ABSTRACT**

As compliance requirements are increasing internationally, organizations are under more scrutiny and pressure to ensure the accuracy and timeliness of their reporting obligations. Therefore, through a proposed solution, this white paper discusses how the compliance process can be made more efficient and cost-effective for commercial organizations amidst a myriad of compliance complexities by employing artificial intelligence (AI) as part of the solution. With the increasing use of AI and emerging techniques like machine learning, many avenues arise for further development due to the vast potential of effective predictive modeling. The growing sophistication of compliance obligations and business processes around the world has increased the expectations of tax authorities, promoting increased scrutiny over reported tax and assurance processes. This has led to a rapid and dramatic rise in the volume of compliance across the world, with pressures increasing drastically to ensure accuracy prima facie but also that sufficient interpretations are made in time and deemed defendable. As a consequence, organizations are increasingly facing the challenge of compliance in order to mitigate excessive liability, reputational risk, or unnecessary cash outflows.

In the game of compliance, those with the most limited resources are usually dealt the worst cards. Medium organizations are caught between an increasing complexity of tax compliance across jurisdictions and business processes, and revenue authorities leverage technological advances to increase scrutiny of compliance defenses. This white paper discusses how the further use of AI has the potential to dramatically reduce the cost of preparing compliance, despite the limitations of robustness and interpretability. In particular, the usage of an ML algorithm for both ingestion of compliance inputs from various unstandardized data pools and outputs and extracting predictions on them by means of textual pattern-recognition is discussed in detail. This paper is concluded by outlining how further development on this technique could make a significant dent in costlier, more burdensome compliance obligations while increasing robustness and expelling trivialistic outputs. AI has the potential to extract coherent and legally defensible implicit data from massive tax compliance checks across jurisdictions, although the output often requires extensive human verification.

Keywords: AI, Artificial Intelligence; Machine Learning; Taxation; Tax Compliance; Classification Model; Predictive Modeling; Decision Tree Broadcasting Internet News Systems; Internet News Indexing and Retrieval.

1. Introduction

Tax compliance is one of the most complex and multifaceted phenomena faced by policymakers worldwide. The tax system of a country generates predominantly cash inflows which subsequently affect a government's economic capabilities. However, tax evasion undermines this mechanism, leading to high tax gaps in many countries and consequently impacting other aspects of the economy. This article attempts to gain better insight into tax evasion behavior by building an agent-based model of firms in a stochastic tax system which successfully replicates important stylized facts observed in many countries. The contributions of the model are twofold: theoretically, it unifies explanations for both the emergence of tax gaps and taxpayer heterogeneity; empirically, it offers tractable numerical algorithms to estimate tax compliance models or predict the impact of policy changes. Policy implications are discussed based on the suggested model and numerical estimations.

Tax compliance is potentially the most complex, nuanced, and multifaceted phenomenon faced by policymakers in various forms, worldwide. The level of tax compliance in a country is arguably the biggest variable that determines the willingness and the ability of a government to influence, direct, and lead the economy, and the society as a whole. Tax payments provide the cash inflows which subsequently are turned over into roads, schools, health care, daily security, or whatever else that affects the welfare of the population. However, tax evasion directly undermines this mechanism, leading to high tax gaps, and consequently to high levels of disappointment of the government regarding its own ability to affect those factors. In turn, the absence of those necessary aspects of life increases the incentives to evade taxes. This vicious cycle is witness to a failing system and a deteriorated economy.
Prior work related to optimal taxation and tax-evasion modeling can be grouped into two main categories: analytic and computational. The seminal work introduced a model of optimal taxation posed as a portfolio allocation problem, which was analytically solved and used to obtain tax-minimizing time-consistent policies. Several scholars built on this model by also introducing labor supply and public goods. The complexity of the phenomenon was highlighted early on by researchers who challenged the monotonic relationship between tax rates and tax evasion. One of the drawbacks of the analytical approaches was that they often implied less behavioral heterogeneity on behalf of taxpayers than what was suggested by empirical evidence. The great insight behind this critique was that –whatever the tax and auditing system– taxpayers do not likely behave the same way. An additional and often just as critical issue is that analytical approaches could not fully capture the dynamics of tax evasion. Beyond the issue of accounting for heterogeneity, there exists much interesting structure in taxpayers' behavior if one considers fine-grained models of their evolution through the tax system. Such considerations have led to computational-based approaches in the form of agent-based models. Computational approaches may allow for more realism by having a large number of agents interact with each other, based on a predetermined and heterogeneous distribution of characteristics related to the taxation parameters and the intrinsic utility functions.

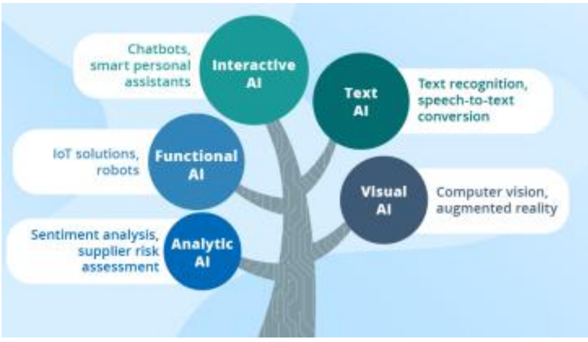

Fig 1: AI-Powered Tax Compliance

1.1. Background And Significance

The Internal Revenue Authority (IRA) of Cameroon's mission is to levy taxes in a fair, reliable, and efficient manner in accordance with tax laws. In recent years, taxpayers' compliance rates have improved, but there is still a significant proportion of tax evasion and tax avoidance, particularly in corporate income tax compliance. Study is done to investigate the implementation of a predictive classification model for evaluating the compliance status of taxpayers. The knowledge discovery in databases (KDD) methodology is used. For the first stage, data pre-processing, and quality processes are applied. Exploratory data analysis is used in the second stage, and for evaluation purposes machine learning methods such as Random Forest, Decision Tree, and Logistic Regression are applied in the last stage.
The method is implemented in a prototype case-selection application and is designed to improve the compliance analysis process. The extracted knowledge (model) can also be used to analyze other tax types as well as other case-selection areas not limited to tax authorities. The components of the KDD process are represented in a methodical way, allowing a flexible approach to be used. The prototype system is capable of assessing the compliance status of a sampled taxpayer by classifying it into either the compliant or the non-compliant class. This approach can be used in the early detection of non-compliant taxpayers and other tax compliance improvement strategies. The model is robust, valid, and fit for case-selection using continuously changing and evolving data.
The application of a predictive classification model in understanding the compliance status of large numbers of taxpayers is highly recommended. The knowledge discovery process produces many benefits in terms of costs and time. Such a system can be of great help to the administration of tax authorities in improving tax compliance analysis and detection. The knowledge of the model can be used to identify compliance problems and formulate respective compliance improving strategies. This study has broad perspectives, with regard to the tax compliance of the government; tax research and enforcement; economics; and obtaining knowledge in general.

Equ : 1 Predictive Risk Scoring Model

$$\text{Risk Score} = \sigma(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)$$

- X_i: Features such as income variability, past compliance history, industry type
- β_i: Learned model weights
- σ: Sigmoid function to constrain score between 0 and 1

2. The Role of AI in Tax Compliance

Tax compliance involves a wide variety of different activities that aim to ensure tax conformity within business organizations. These activities consist of outreach and communication, policy and process design, data collection, adjustment preparation, and reporting, among others [2]. New responsibilities, such as moving from a historical to a forward-looking perspective with the implementation of new tax laws across the globe, constantly shift the environment in which tax compliance operates. Organizations can incur tax penalties or suffer reputational damage if tax compliance is incorrect. Furthermore, the consequences of incorrect tax compliance can be multi-fold, affecting not only businesses involved but also country budgets and global environments. Efforts to overhaul systems and introduce new legislation have fallen short of curbing such concerns across various jurisdictions, impacting multiple companies globally. Owing to the complexity of tax laws, lack of reporting standardization, and discrepancies in the understanding of facts across tax authorities, taxpayers, and tax governance bodies, compliance is mostly manual-intensive and consists of elaborate processes. These processes involve multiple functions grappling for knowledge clusters, lengthy and varied correspondence among involved parties across several jurisdictions, disparate formats of data collection, translation efforts in order to present adjustments in a basic common way for different jurisdictions, variabilities in countries' budget years and legislations, and incomplete numerical data and always changing facts . Deterrents are not only considerable, but penalties can also have a multiplicative effect, if not circumvented successfully. However, tax authorities have large datasets containing all transactions between organizations and jurisdictions and likely possess data on peer players. Tax regulations also contain better defined responsibilities on action and inaction, in addition to deterministic penalties for fines and reputational damages. Thus, prediction of compliance likelihood and recommendation on key actions is likely feasible and beneficial.

2.1. Overview of AI Technologies

Artificial intelligence (AI) has been a hot topic for years, with models quickly becoming integral to businesses. The incredible computational power and aggregated data created an onslaught of AI solutions. In theory, AI-based solutions could crack any complex problem more intelligently. However, in practice, there are still many limitations. With many models falling short of expectations, organizations face the challenge of increasing unsuitability and explanation. The AI-powered search is the current perspective on computational power and the amount and significance of aggregated data. Therefore, the AI-offering platform quickly learns from the data available and provides the most exact and relevant search results automatically. The algorithm controls the documentation, and special calculations are run automatically on the traversed data, thus keeping every query strictly below 1 second and maintaining users' patience.
AI in the financial services domain covers a broad range of applications, such as credit risk modeling, algorithmic trading, fraud detection, and chatbots for customer service. However, providing oversight over such AI systems is challenging. One of the major challenges faced by financial institutions is the modeling of AI systems. AI models are based on probabilistic assumptions, and describe a system approximated by a probability distribution rather than a deterministic value. With no explicit mathematics or language to describe the model, it becomes impossible to unearth the assumptions and behaviors beyond input values. Self-regulating AI is a spend, which automates extensive model interpretations and enables ongoing monitoring of AI systems while proactively managing out-of-spec behavior. This approach combines the use of model interpreters identified through a factor analysis of explainability techniques with a knowledge graph to oversee and adapt the interplay of modeling factors. It can detect changes in the AI model's environment capturing the need for a model returning. It also predicts model performance according to a range of retrospected actions. Implementing either scenario automatically contextualizes the AI model explaining its inputs and outputs.

2.2. Current Trends in Tax Compliance

Tax compliance is likely to become more significant with developments such as self-assessment and electronic commerce. This paper re-examines the meaning of tax compliance. The paper describes the purpose of tax compliance and the factors that affect the willingness of taxpayers to comply with a tax system. It discusses two different approaches to tax compliance: behavioural/fiscal and economic/administrative. It is suggested that caution should be shown in the use of penalties and that the emphasis should be on assisting self-employed taxpayers to meet their tax obligations. The increasing importance of tax compliance prompted a review of the relevant literature outside taxation and academic research that could assist in developing an improved understanding of the behavioural aspects of tax compliance processes. In the area of tax compliance and self-assessment, there seems to have been little interest in either the concept or its relevance to tax administration exserial tax accounts. A pressing task is the development of an approach that incorporates both the economic and behavioural approaches to tax compliance under the general heading of the reasons for tax compliance. There have been various definitions of tax compliance. It is widely accepted that among the various obligations of citizenship there is the obligation to comply with the laws of the land, including tax laws. Tax compliance may thus be regarded as a special case of law compliance. Tax compliance is likely to become a more significant aspect of tax policy as most of the old problems remain and new considerations are raised by developments such as self-assessment, the emergence of the global economy and electronic commerce. A broad definition of tax compliance is the willingness of taxpayers to pay the proper amount of tax and to meet their other responsibilities under the tax obligation. In the same line of research, types of tax compliance are also mentioned; these are assumed to be "active compliance", "passive compliance" and "non-compliance". Tax compliance is a part of the tax system; it is not an end in itself. Tax compliance has an importance that cannot be overestimated; in fact, it underpins any tax system, it ensures revenue for the government, and ultimately, it affects the quality of life for all. In turn it is anticipated that tax compliance will be affected by factors such as the willingness of taxpayers to obtain and report income, the fairness of the tax system and tax audit rates. In addition, non-compliance with tax law presents challenges in both society and policy.

Fig 2: Compliance Trends in 2024

3. Predictive Modeling in Tax Compliance

Tax compliance is the act of reporting and paying taxes owed to the government. Compliance can be measured objectively as the difference between taxes owed and taxes paid. Taxpayers can be broadly classified as compliant or non-compliant; the latter category consists of taxpayers who do not accurately report yet still voluntarily file, and taxpayers who do not file at all. Tax compliance is critical to the government, making tax compliance a classic problem in research, education, and practical applications. As taxpayers have different characteristics such as industry or ownership forms, taxpayer classification is usually necessary for tax compliance analysis. In practice, classifying taxpayers into compliant and non-compliant classes is known as taxpayer risk assessment. Research works analyze the features of non-compliance cases of auditing tax databases and build a classification model to determine auditees for case-selection. These models are used to examine taxpayer characteristics because researchers can analyze trends in compliance expectations by tax class. Decision tree models are widely used in risk assessment for the tax compliance problem. Data mining techniques such as building models to classify compliant and non-compliant cases on a small scale are vital to the tax authority. Data engineering techniques such as ETL processes for large datasets, processing workloads of a petabyte of tax records are critical to being able to apply data mining to the big datasets. In the tax compliance domain, research efforts have utilized classification models built using historical taxpayer audit data by the revenue authority. These models are used to predict the compliance status of taxpayers in a case-selection application prototype. Experimental results indicate that the model is effective modeling and fit for case-selection with an accuracy rate of 65% for the 3-class classification model and prediction efficiency of 65% for non-compliant case identification. Compliant case identification is also useful for profiling, but expected to be lower in performance by nature of datasets and not for current focus. With more sources of taxpayer information and increased quantity of taxpayer data, the accuracy and prediction efficiency of the models applied to case-selection is expected to improve significantly.

3.1. Definition and Importance

A Tax Compliance Model is defined as a science or discipline of collecting or gathering knowledge on tax compliance. Also, this growth of information (knowledge) is such a manner that one evaluates or judges incoming tax compliance data and determines what should be accepted (compliance) or rejected (non-compliance). In essence, a Tax Compliance Model involves keeping records, growth of information, selection of documented data, and evaluation or judgment of the selected data on whether the tax compliance is a mistake (non-compliance) or a judgment error (compliance). It is designed to monitor incoming Tax Compliance data and extract tax compliance knowledge that can evaluate the Tax Compliance data and classify it correctly. A good Tax Compliance Model is able to maintain accuracy in conjunction with a consistent and well-chosen confidence threshold. A Tax Compliance model can also be referred to as a Tax Compliance or tax compliance mechanism. Such a mechanism could be in terms of a Tax Compliance rule, Tax Compliance formula, statistical model, computer software, etc. Tax Compliance involves the selection of a set of treatment objects from a set of possible treatment objects and the ensuing treatment of the treatment objects so selected. Also, typically, the treatment is assumed to affect only the treatment objects and not the remaining objects which are referred to as the control objects.

Tax Compliance Models usually result in estimates of the average treatment effect. However, in general, these estimates can suffer from selection bias. Because tax compliance is by nature with self-selection, healthy treatment of selection bias in Tax Compliance Models require an explicit behavioral model of tax compliance. It is shown that this need not be a limitation. Thus, by introducing a parametric model for the willingness to comply with tax compliance, estimates with outcome models without selection bias are obtained. Other potential evaluation strategies, namely inclusion of observables, matching strategies and hidden covariates, are discussed, and their limitations demonstrated. Developing policies to encourage tax compliance is of interest to both governments and researchers in both developed and developing countries. A class of tax compliance policies, tax compliance mechanism, is studied, under which agents choose whether to comply or evade, and policymakers select a tax compliance level to implement.

3.2. Types of Predictive Models Used

The choice of which predictive models to implement for automatically assessing tax evasion risk should be primarily based on the nature of the input data (tabular or graph). When the input data is in graph (or relational) format, existing methods primarily use a local node classification model with domain knowledge provided as an additional set of node features to enhance prediction accuracy and validity. On the other hand, when the input is in tabular format, two general prediction strategies could be used: the methods with enacted domain knowledge launched from representative machine learning techniques; and the methods without any special domain knowledge based on graph embedding or autoencoder techniques. In the scenarios where acted domain knowledge is preferred, multiple machine learning models, mainly tree-based ensemble models, outperformed other types of models in terms of accuracy and interpretability. Ensembling and some simple feature engineering techniques derived from domain knowledge complement the merits of the models and further improve the prediction accuracy. Nevertheless, ensembling techniques complicate the interpretability of the models since they induce many weak models to make the final prediction. The methods without any special domain knowledge also obtained satisfactory prediction performance in terms of accuracy and interpretability, but with much less interpretability than those taking domain knowledge as inputs.

Equ : 2 Anomaly Detection (Reconstruction Error from Autoencoder)

$$\text{Anomaly Score} = \|X - \hat{X}\|_2$$

- X: Original input tax data
- $\hat{X}$: Reconstructed data by the autoencoder
- Large values imply higher likelihood of anomalies

4. Data Sources for Predictive Modeling

To fully exploit the opportunities of big data environments, tax administrations need to develop knowledge-driven approaches to data exploitation. In general, big data-driven decision support systems possess four basic functions: data preparation and mining, discovery, evaluation, and analysis. In general, the whole process of designing, developing, and implementing predictive models encompasses several iterative phases. In the first two phases, the understanding of the business problem and the dataset are addressed. Information about tax evasions and compliance risks is extracted and collected from various data sources, including collected data from public registers, banks, and public companies. The third phase is data preparation, including data cleaning, data transformation, and data summarization. Due to the importance of the quality of data in big data analytics, investigations on its quality, including currency and completeness, are conducted. The fourth phase is modeling, where various modeling methods are evaluated on a specialized big data analytics machine and the best-performing method is selected.

In the fifth phase, the understanding of the modeling result is assessed, providing key insights into tax evasions. The final phase is deployment, where the knowledge-based model is implemented at tax administrations. Several recent big data-driven approaches proposed for collecting value from public data sources for smart cities are presented. An empirical summary-based analysis of the approaches on their potential of addressing the evaluative dimensions of real software engineering in practice is also provided. Public statistical data are of great potential for assessing the quality of predictive customer data analytics, but also for a better understanding of customer behavior that might be expected from their usage.

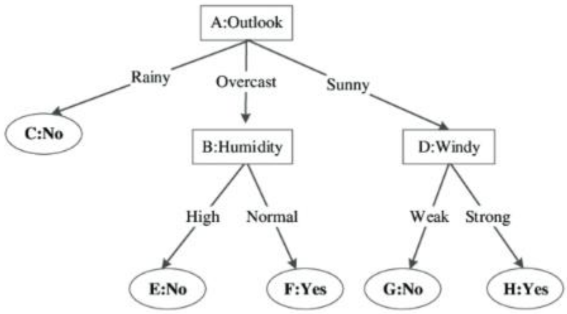

Fig 3: Predictive Modeling

4.1. Internal Data Utilization

The positive impact of the digital transformation of businesses on tax authorities' ability to obtain information on taxes due, potential tax evasion, and potential non-compliance is acknowledged and being actively exploited in many advanced regional tax jurisdictions. However, this impact is regarded as insufficient in the developing country context, particularly where there are large sectors of informality. Organizational design, audit strategies and practices, and reliance on the use of models are recognized by tax authorities as practices that influence and shape the effectiveness of compliance risk management investigations into suspected tax evasion and non-compliance. The individual building blocks are regarded as important to collectively addressing jurisdiction challenges. In cases where there is an acceptance of a growing maturity of compliance risk management, efforts to design successful models will be greatly assisted by research on and guidance in this area.

Tax authorities have introduced a capability to evaluate and predict the likelihood of non-compliance. Subsequent, successful, experience with such models has led tax authorities to want to build on these experiences and introduce similar, more advanced modelling capabilities into their own tax authorities. These other models have been adapted from social and machine learning disciplines and are designed for predicting compliance behaviour based on external characteristics and behaviours, such as return anomalies or pre-existing compliance risk. The latter class of predictive models has been deployed globally by tax jurisdictions with materiality, though active, tax bases.

Machine learning models for recommending audit case selections are relatively more novel and have been limitedly implemented and reported in practice by developing economies. A non-generalized and generalizable ticket size estimation model for the project assessments of a tax compliance feasibility study is built and tested. The implemented machine learning models for recommending the case selection of tax compliance assessments and audits are configurable for training and deploying recommended case selections according to domain and data differences. Additionally, the developed tax compliance audit and assessment training and testing data generators for written mathematical descriptions are machine readable and can be easily parameterized, configured, and scaled to produce input datasets for training and testing different machine learning models, making it useful for the machine learning developer experts, but not limitedly, and tax jurisdiction public servants.

4.2. External Data Integration

Integration of data from external sources in predictive models should be viewed in two dimensions. The first dimension is how to select the sources. Different experts want to build different models based on different data and they have different needs. So, data providers need to talk to modelers to understand their objectives in a good manner. Next, on the basis of better understanding of the task and what it intends to achieve, suitable external data sources shall be sought. In such scenarios, ideal external data sources will be the ones which not only have the same meaning as the internal data used by statistical models, but also provide a higher information level. The knowledge of domain experts is also part of external data sources. Despite it is hard to quantify the knowledge of domain experts, there are still some ways which could make use of external data sources to take advantage of the knowledge of domain experts. The effort may include clustering or mapping of customers by domain experts' rule of thumb, or concatenating some variables serving as indicators to some significant group. The second dimension focuses on how various external data sources can be integrated. Integration of different types of outside sources originates from very different data formats and information meanings as shown. They are likely to require different types of processing and treatment. For example, some models may have to recode the format before using the external data, while some other models may need normalization or transformation to make units consistent across the datasets. In terms of forecasting tasks, hypotheses of models in different integration scenarios may differ as well, because some sources may be available at the real-time or only once per time unit. This works as a major constraint in evaluation of modeling results. Several major technological challenges on external sources integration in question are also addressed. It includes comparison of prediction performances in different modeling scenarios in terms of practical index measures, and reproduction of pre-processed and treatment of external data.

4.3. Data Quality and Accuracy

As significant portions of data are captured and stored by organizations, data quality (DQ) has emerged as a major issue in assuring that the data provided for downstream tasks, such as predictive modeling, is of sufficient quality. DQ issues occur prior to, during, and after data integration. The aim of the study was to gain insight into various features of DQ, especially in regard to the AI pipeline, and to answer the following questions: (1) How do various properties of DQ affect the performance of supervised learning tasks? (2) How do the results differ depending on the target feature's type (categorical or continuous)? The research also examined what recommendation engineering and decision-makers could take away to assure sufficient DQ.

To investigate these questions, an extensive, large-scale empirical study was conducted. Fifteen supervised learning algorithms from five different families were used to predict categorical and continuous target features for thirty-one datasets. DQ was polluted in a configurable manner via six machine-learning-independent data preprocessing operators simulating DQ issues typically occurring in practice. The results of the combinatorial treatment of the two experimental dimensions revealed a dataset's properties (e.g., the imbalanced class distribution) as one property significantly negating a model's performance. Moreover, while a training dataset's renaming and format inconsistencies strongly affected the trained model's performance, biases in training data were not restrictive for deriving a valid model.

5. AI Algorithms for Tax Compliance

Artificial Intelligence (AI), one of the most innovative approaches to tax compliance, is predicted to bring improvements in efficiency, accuracy, and speed by taking over repetitive and mundane tasks. So far, evidence shows the success of AI in a few select areas of tax compliance. For example, in an online survey conducted among senior state and local government tax officials in the US, 46% reported the use of AI-based models to automate assessment processes; 64% indicated AI-based prioritizing of audit leads; and 64% reported the use of AI-based resources to assist staff in examining audits. The technology is considered to help make more accurate predictions on taxpayer business processes, thus increasing return on investment by helping to uncover a greater number of high-risk returns. AI is expected to reduce the time and effort spent on enabling staff to understand new analytics models.

Data science (DS), whose core is predictive modeling, within which the intent to predict and action for automated decisioning is crucial. The strategy is often based on metadata, such as taxpayer demographics (location, industry, type), tax return statistics, tax compliance record/history, external tax data about businesses in the respective industry, and taxpayer industry characteristics. Representative DS methods include predictive modeling (PM), clustering (CLST), and automated fait assessment/decisioning and zonal analysis (Z-ANL). For tax compliance within OECD economies and the EU. ML is viewed as a statistical technique for predictive modeling that takes advantage of large amounts of detected regularities in data. As a result, the transparency of espoused business processes and their implications are often compromised, and risks of biased or discriminatory treatment of di-affluent taxpayers or entities are raised.

In domestic tax authorities, empirical research on AI applications is limited mainly to screening of tax returns for tax evasion, tax avoidance, and transfer pricing. Additionally, descriptive research on the transfer of knowledge from commercial sectors to public sectors has focused on technocracy, professionalism, and the politics of AI. Empirical investigations of the effectiveness of the technology and the impact of corporate tax accountability based on AI/ML remain sparse. Researchers are encouraged to explore if it is possible to inform model risk governance and controls with metrics from within AI/ML models or its embedding, e.g. cognitive ability & decision style, calibration, interpretability, stability, robustness, and so on. Other avenues for predicting achievement of compliance objectives from metadata, including taxpayer/market characteristics, and the further automation of audit detection and selection through natural language processing/filtering and decision/interpretation, are also recommended.

5.1. Machine Learning Techniques

As it is explained in the previous chapter, tax compliance could be improved if tax authorities can allocate their resources for reviewing tax declarations of taxpayers who are more likely to have incorrect or suspicious tax declarations. In turden to allocate resources effectively, tax authorities need to determine the degree of correctness of submitted tax declarations and assess tax declaration risk. For that purpose, they essentially need to know the expected outputs of tax declarations. This can usually be modeled through either a rule-based or a data-driven approach. Models based on heuristic business rules are common in practice but can hardly be constructed and maintained in a timely manner in today’s dynamic economy. Nevertheless, thanks to the explosive growth of Historical taxpayer records, tax authorities around the globe can increasingly benefit from machine learning methods to assist their predictive modeling and tax compliance enhancement processes.

A guided review on predictive data mining techniques applied to tax compliance assessment is conducted. Tax compliance assessment is first introduced as recording and measuring the tax declaration accuracy and the risk

level of a tax declaration. Within that context, six tasks of predictive data mining are outlined. The application of the six tasks in tax compliance assessment is elaborately reviewed together with the methodologies used, performance evaluation indices, contributions, limitations, and future research opportunities. It is hoped that this work can inspire both tax authorities and researchers to conduct more relevant research and studies. At the same time, it is also hoped that future work can be conducted to further enhance tax compliance and tax authorities' performance based on the relevant insights.
In tax compliance enhancement, tax authorities aim to minimize compliance costs through gentle persuasion, that is, reducing the chance of errors in future tax declarations. However, tax authorities may not know the effective, domain-specific persuasiveness of campaigns or nudges, nor can they afford multi-month, real-time randomized field experiments with millions of taxpayers. Thus, in providing data-driven decision support for compliance enhancement, substantial information asymmetry exists. The tax authority needs to predict the risk of taxpayers responding positively to campaigns, while the advising accountant has to score the wrongful accounting behaviors based on tax declarations.

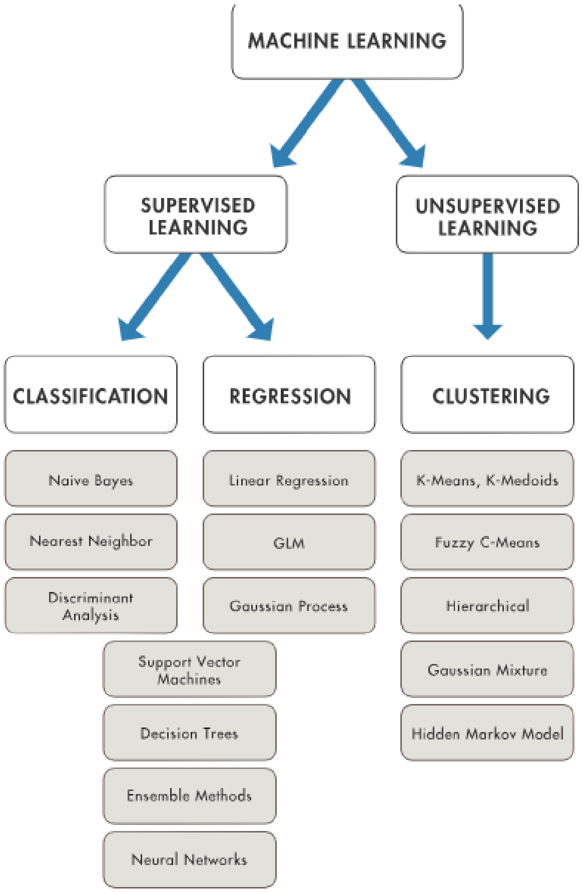

Fig 4: Machine Learning Techniques

5.2. Natural Language Processing Applications

Recent advancements in machine learning have begun to reach a point where they can no longer be ignored in the tax controversy space. Rapid advancements in natural language processing have made it possible to communicate with non-technical users in a natural language format. The launch of ChatGPT has marked a watershed moment, showing how new technology can impact knowledge-based industries and knowledge transmission, as well as unprecedented opportunities for good or evil similar to the advent of spreadsheets, Wi-Fi, and the internet. Tax law, which is simple in structure but complex in interpretation, can benefit from the same technology. Where taxpayers meet with agents to design solutions to complex situations that involve competing rules and policies, generative AI could be the interface. Technology could drive intense competition among firms for the first viable, trusted generative AI-powered tax compliance tool because tax rules constantly evolve. The validity of predictions and recommendations, their accompanying confidence measures, and whether users can revise predictions and recommendations are also critical heuristics for assessing AI's suitability for tax compliance use. GPT is an autoregressive LLM that uses deep learning to produce human-like text. It was developed by OpenAI and launched in November 2022. As an autoregressive model, it predicts the next word in a sentence, given all the prior words within the text (as specified by a text prompt). GPT is trained on pairs of text prompts and corresponding completions. It has 175 billion parameters in its latest version, GPT3.5, as of 2023. By feeding it a text prompt, users can generate or complete messages written in natural language. While the original applications of GPT are social media, chatbot, and conversational text generation, it can also be used in other fields, including knowledge-based industries like programming, journalism, and legal services. Beyond its text-generating function, GPT effectively captures tax systems, a subcategory of legal systems, which have heavy text burdens and design-system incentives. The manner in which it structures text and maintains text length with brevity while comprising completeness and approach to compliance risk is directly applicable in tax discourse.

5.3. Neural Networks in Tax Analysis

If Neural Networks effectively estimate potential tax revenue, then they may act as valuable benchmarking tools. When comparable revenue streams from different countries' tax systems are examined, Neural Networks may yield more accurate estimates than simpler models such as Linear Regression. It may therefore be worthwhile to benchmark the expected impact of new policies on One-Tier Taxes and other potential revenue streams for countries considering implementing them. The ability of Neural Networks to make more accurate estimates of potential tax revenue than simpler models is a preliminary indicator of their efficacy in many tax compliance analyses. Future work should investigate whether Neural Networks are better than competing modeling approaches at estimating the effectiveness of different policies at decreasing tax avoidance. Presently, Neural Networks could receive additional model training for any analysis relying heavily on One-Tier Taxes, as this variable's values are not well represented in the encoder.

Analytical procedures aim to enhance understanding of financial information by integrating results and income or expense measurements to employ alternative analyses. On the other hand, financial data from general-purpose financial reporting is slightly adjusted to enhance decision usefulness. Thus, the adjusted financial information should be comparable across firms. However, with such comparability, choices about fundamental value would be relatively easier to convey, while quantitative modelling on unadjusted data would be more efficient. Reasoning all such issues would be efficient, contrary to beliefs. This inconsistency is generally noted but infrequently highlighted. This has implications for modelling realism in tasks of Valuation, Fair Value Measurement, Earnings Management Prediction and Credit Risk Analysis. A contradiction is noted in modelling realism and its implications for understanding real financial events. The debate is ongoing.

Neural Networks is one of several Machine Learning tools that may improve analyses with superior predictive and explanatory power. Future work should compare Neural Networks with various models to elaborate on their advantages. It is critical to ensure representation of the most important variables for modelling to avoid such issues. Benchmarks for predictive performance and validation methods should also be explored. General methodology design principles have strong support in the literature, but fine-tuning of both is challenging and never-ending. Experiences from banking studies may guide understanding of model design and selection. Similarities across uses may empower sequential model application, as a preferable architecture in one area likely benefits APT, TFT and CVA applications.

6. Case Studies of AI in Tax Compliance

Machine learning (ML) has infiltrated multiple creative and technical domains in the last quarter of the century, reinforcing tasks that require implementing a project. GMAT/GRE, exams, plagiarism detection, fake news detection, disputable image detection, etc., are some of the real-world applications of ML. In today's world, AI based technologies address the question of tax evasion to minimize their revenue losses. Tax evasion is an act of deliberately avoiding paying tax that is owed to the government. Therefore, in order to increase compliance, a set of probabilistically chosen firms can be audited with the aim of increasing the probability of uncovering a tax evading firm. We provide insight as to how the parameters of the above model can be chosen optimally in order to effectively cut tax evasion while maximally utilizing the auditing resources. This is done by proposing a custom metric named the Expectation Value of Tax Revenue Loss that quantifies the average expected loss of tax revenue over time. A combination of reinforcement learning and Q-Learning are then used to derive optimal parameters within this metric. It is shown that when the government pursues these parameters, it maximizes the expected tax revenue it receives. The question of how to effectively audit firms in a tax system that allows for tax evasion is addressed. Depending on the auditing strategy adopted, the overall tax revenue of the nation can change considerably over time. Those most profitable firms can fall prey to evasion, making them the auditors' focus. For firms that realistically resist total evasion as it equally incurs costs, a balancing mechanism that forces firms to alternative strategies between the two extremes was proposed. From this Q-learning model, a set of parameters was extracted and these parameters formed a lucrative and computationally simple auditing strategy. A commercially available paper folding model is trained on quarter-folded original documents. An encoder-decoder styled network is proposed to estimate the folded creases. The trained model is then deployed on ten unseen folded paper pieces where detailed analysis shows that this model can unravel the hidden crease information successfully and achieves a better crease recovery visual representation.

6.1. Successful Implementations

A model that would assist tax compliance officers in evaluating cases for audit was implemented. The following considerations guided the design and development of the model: considerations for the model, considerations for the application prototype, database and tools used. Recommended hardware and software were also

presented. To protect internal tax data used in the course of research, the model was implemented in the form of an application prototype which the users were unable to reverse engineer. The application prototype generated a prediction based on the data entered by the users then exported to an external file containing predictions made by the model.
The interface was designed to enable the user to interact with the model efficiently. User data could be added into the database by clicking the “Add” button or in the “dummy data” dropdown. The model then performed pre-processing of the user data. Given the large amounts of submitted data the model was configured to perform cross validation by running through the model multiple times given different data each cycle while monitoring performance. Performance was recorded per cycle and mean and standard deviation were calculated. Performance measures, accuracy, precision, recall ratio were derived from confusion matrices generated during each cycle. Users were then able to select audit cases via the application prototype. The model was validated for accuracy, precision, recall ratio using the confusion matrix. 725 out of 1116 instances presented to the network were correctly classified. The confusion matrix contains information on the actual and predicted classifications. Basing the evaluation on the above metrics of accuracy, precision, recall ratio and F-measure, the model is effective in identifying cases for audit.

6.2. Lessons Learned from Failures

Our current tax systems impose three steps on individuals: declare income, pay tax, or face penalties. Risk-averse firms face a non-zero probability of being audited and declared tax evaders if they report a profit suspiciously lower than the average. The firm can avoid detection by understating income, incurring a direct loss of the tax amount. By modeling a lone firm’s decisions, we will generate maps of the (auditing, tax) space based on its predictions. This tax authority may introduce a tax amnesty once a firm's dissatisfactions become greater than a certain threshold. To quantify tax amnesty’s effect and identify any potentially alarming parameters for macroeconomic policy makers, we developed a computational tax amnesty modeling process, whose main novelty lies on its prediction-driven nature and ability to map audits and revenues over a wide design space for time-varying auditing rates/tax rates. Given the exponentially large state space of the tax evasions problem, the supervisory/monitoring procedure will treat entry exams and tests independently, aggregating information only after the exam results are revealed.
An optimization process will treat exam-writing procedures from a game-theoretic aspect, whereby the upholder’s written exams can influence the test-takers’ writing strategy as well as their expected utility. Given known exam-writing distributions, a numerical optimization algorithm will compute the optimal scheme for an upholder. The box-constrained second-order trust-region algorithm is proposed to efficiently conduct optimization in applications. Uniqueness of the predicted scores on the test-takers’ behavior is guaranteed, which further supports the stability in equilibrium. To conduct numerical experiments, tax authorities may entitle a tax amnesty. This process incorporates finite-horizon projections of firms’ decisions over a macro-political timescale. It is noteworthy that under-perfect-correction policy research may not be implemented with the methodology in above jargon.

Equ : 3 Time-Series Forecasting for Tax Revenue

$$\hat{y}_{t+1} = \alpha y_t + \beta y_{t-1} + \gamma y_{t-2} + \cdots + \epsilon$$

- y_t: Tax revenue at time t
- α, β, γ: Coefficients from AR model
- $\hat{y}_{t+1}$: Forecasted value

7. Challenges and Limitations

AI model governance refers to practices designed to support compliance for AI systems or the models underlying them. It includes model control standards and processes that are intended to ensure compliance either within or beyond one organization. As investment in machine learning increases rapidly, its governance becomes much more important and difficult. This paper focuses on the challenges of AI model governance that the financial services industry is facing. Interviews with in-depth feedback from quantitative analysts and model validators are first used to obtain a better understanding of the processes and challenges. Then, an AI-compound control model governance framework is proposed, capturing the main components of effective AI model governance. Next, model control needs related to the issues discovered in the interviews are discussed. After that, existing model governance practices and their limitations are presented. Finally, practical suggestions are made to help organizations better cope with the challenges of AI model governance in financial services.
AI-powered modeling is a newly emerged common approach and has found varied applications in numerous areas including news generation and social attribution prediction. Such applications based on AI-powered

modeling may not be simple building blocks but complicated black box systems trained using enormous amounts of data. Despite the fact that data governance with respect to data source, quality and bias is required for AI systems, as AI systems evolve rapidly, there arises an urgent need for such governance practices to keep up with the pace of growth in complexity of AI models and to establish a conducive environment for the use of AI. Increasingly stricter regulatory frameworks and new requirements from authorities add to the challenges. Recently, there have been calls from regulators across the globe for AI model governance. A close-up look at the financial services sector reveals the following challenges in its AI model governance.

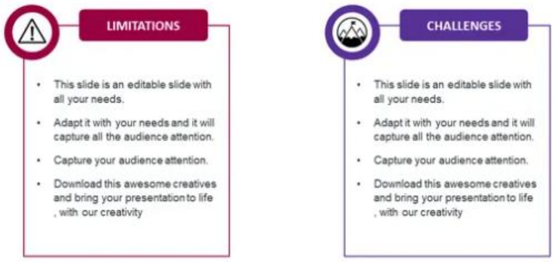

Fig 5: Challenges and Limitations

7.1. Data Privacy Concerns

The emergence of AI-driven tools to optimize existing tax compliance workflows is changing the marketplace and associated regulation. Although they bring substantial transformative benefits, data privacy is a major concern, especially when dealing with sensitive financial information. A central question in data protection regulations is whether organizations' systems or models correctly handle the users' data. Ensuring compliance is particularly challenging for complex AI-driven systems. Various organizations, due to their novelty or size, may be unaware of their obligations or may not have the technical expertise for multi-model assessment. This motivates the need for a quantitative data privacy checkup as a service, operating in a black-box manner without requiring expertise, while producing useful reports to users and organizations. Several design philosophies are presented in this regard based on the client's profile.

The tax compliance exam in the U.S. is generally a bureaucratic process that can last for years. Tax returns can be selected for an exam for a myriad of reasons, such as the existence of a suspicious form or input from whistleblowers, but the majority is picked based on a taxpayer's risk score. Tech-savvy tax clients can learn about their exemptions through automated filing systems or crowd-sourced intelligence. This change has triggered discussions regarding fairness and transparency of the AI used by the IRS to manage the selection process. Importantly, since the model itself is not designed for general availability, there are serious concerns regarding how this models' output could be audited for algorithmic bias on any sub-protective classes.

On the one hand, it is requested to assess whether the model sufficiently processes features that are proxies for race, gender, or other protected classes and on which reasonable unbiased group predictions are returned instead. In this case, the model would be able to massively scale compliance checks on individuals and corporate agents. Understandably, a feature by an attorney addresses earlier statements assuming that the attributes manipulated by the model were not based on any information on the underlying features. On the other hand, the audited may willingly choose to provide their features along with tax deductions, expenditure categories, complaints, or other details. These subtler vulnerabilities exist for traditional underwriting models trained on similar features.

7.2. Algorithmic Bias

Even as machine learning becomes more prevalent in tax audits, auditing systems have a significant impact on tax compliance and equality. Many questions remain unanswered: What influence do algorithms have over who is audited? Do more accurate algorithms predict audits equitably? Should government auditing algorithms seek social justice? Additionally, an algorithm can exacerbate income bias. Individuals with high incomes and legitimate revenue take more calories to audit. When uncertainty about income is decreased for low-income individuals, they become more predictable. The IRS may budget-constrained audits select the target who expects to report errors rather than considering the subjective evaluation of tax compliance. Among tax filers, only some randomly selected individuals would be audited. Tax filers with expected high reporting errors given the model are targeted. For example, high-income individuals who report revenues known for business foundations should be audited at very high expense. Others, such as low-income itemizers, may be audited at a lower price. This complicated logic confounds the intuitive notion of randomness. It cannot sample without heuristics that consider expected utility, and cannot capture the subjective choice of what deserves to be targeted.

Most tax return data and model access are severely limited and carefully guarded. Firms rely on this data and commercialization to develop business lines as alternative sources. The IRS is underfunded through political pressure and limited actorship. These resources and usage are heavily influenced by historical context. The audit target model is unavailable without additional solicitation. The IRS is more like a black box with very precise inputs and outputs but unknown algorithms. Public knowledge only exists on the form and distributions. Indirect estimation of a semi-parameter estimation is the method for model comparison; no access to implementation prevents attempting more complicated approaches. Given these limitations, the return on investment (ROI) auditing target model prediction models is examined. It explores multiple potentially fair models and some deterministic tests on auditing fairness and compliance inequality in the extreme information-diversion limit. Redefining the outcome and probability of being audited in a semi-parametric fashion, the effect of auditing on equity and fairness depends on two-sided errors. Fairness audits measure statistical measures of distributions and reveal uncovered inequity, parameters of real-world distributions, group split facts, a priori information treatment, and semi-parametric treatments of group membership.

7.3. Regulatory Compliance Issues

The tax compliance industry is under unprecedented scrutiny. Laws designed to combat money laundering, terrorism financing and illicit dealing have resulted in a vast and complex regulatory compliance landscape. These regulations demand enormous increases in compliance scrutiny. The data necessary for compliance is often poorly structured, spanning multiple databases across document repositories, spreadsheets, emails, and other media types. Furthermore, there is an acute lack of compliance professionals in both industry and regulators to implement the required scrutiny on the data side effectively. These factors lead to a cyclical crisis of compliance inefficiency, prompting discussions at the highest levels on whether compliance can be performed at all. Progressively stricter regulations have led compliance departments to require an assortment of individual compliance professionals (standards, records, risk, operations, etc.) in an ever-tighter race against deadlines, with tolerances for missing deadlines being cut as non-compliance risk grows. As a result, compliance professionals spend most of their time on repetitive, remedial work, with current productivity methods failing to keep pace. The job is rapidly becoming deskilling — and contextual knowledge-dependent. Consequently, the “near-100% compliance” target is increasingly threatened.

In response to increasing data and deadline pressure, compliance departments have begun using data mining, machine learning and AI. Compliance professionals are now scrambling to achieve higher levels of compliance performance in areas other than surveillance. However, when these tools are applied, the data-mining phase of the compliance pipeline is bypassed. In addition, transparency on final decisions made by humans acting on the model is often impossible, creating unappealing governance scenarios. Even organizations considering renewable governance techniques remain skeptical, slowing down their pipeline and hampering their overall compliance performance.

In addition, hiding complex underlying structures under simpler industrial/commercial interfaces frequently results in progress-deadlocks following model misoperation. Deep-learned risk models were trained in a way that only very small adjustments in feature representation occurred during application, as influenced by compliance professionals in open-loop execution. Once this proximity was lost, the models misfired catastrophically. Model stability equations dictated modest boundary changes to prevent model misfires, ensuring that it remained safe to use for prediction. However, this left the final model output unpredicted beyond the found boundary, imposing unexplained penalty rates for triggers beyond the boundary.

8. Future of AI in Tax Compliance

As firms have begun to adopt AI for tax compliance, a wide range of practices have emerged. However, all these practices share common challenges. AI models can be complex and difficult to comprehend. A broad range of AI techniques can produce models with different levels of interpretability. This range limits a firm’s ability to either understand or contest decisions resulting from the adoption of AI and undermines trust in AI as a decision-making tool. Reviewing vast amounts of AI-generated output to identify and contextualize decisions that can be questioned is tremendously labor-intensive. The number of regulations affecting the use of AI has increased. Regulators have started asking firms whether decisions made by AI technologies have been validated. New regulations exist surrounding the use of AI, and noncompliance can expose firms to significant fines and liability. As regulatory scrutiny of AI adoption has increased, tax compliance firms face a host of challenges related to interpretability, governance and controls, and regulatory compliance. Machine learning has exploded in the last decade, fueled by advances in algorithmic techniques, GPU processing power, and the availability of large amounts of observational data. Examples include self-driving cars, facial recognition, and automatic translation. Finance is also being transformed by the development and adoption of machine learning techniques. Not only are machine learning techniques being applied to innovative financial products, but machine learning is also being used to alter how financial services are offered. However, the increasing sophistication of machine learning applications has led to unexpected failures. Such failures can have substantial reputational, legal, and monetary consequences. Hence, financial services regulators worldwide have published speeches, research reports, opinions, and more formal regulations. These efforts have addressed questions of efficacy, transparency, fairness, and risk.

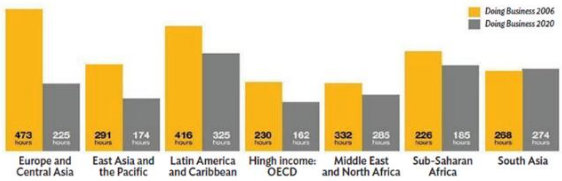

Fig 6: Digital Tax Administration Transformation

8.1. Emerging Technologies

Technologies that increase productivity have a long history in the tax compliance ecosystem. The evolution of more efficient structures for filing tax returns and making payments to governments was made possible by the invention of standard forms and tax return software decades ago. Comparatively recent technologies change the centuries-old function of interpreting and applying the law. This occurred first in the form of online databases of legal citation and analysis, which have exponentially expanded and become more sophisticated over the past 20–30 years. More recently, generative text models that create human-like text from prompts have been trained with content from the Internet, identifying patterns in the complex sequences of words Australians rely on for communication. Similar to humans, this technology can be prompted to respond to queries with relevant text or explanations. As the technology improves, it is expected to be more widely applied and more accurately produce the desired types of outputs. Models of this type are known as large language models (LLMs).

As this technology is acquired and further developed by tax agencies, possibly resulting in consolidation of infrastructure or structures for compliance, triaging of inquiries and tax returns, and more extensive digitization of tax filings and compliance processes is expected. Text conversion of tax returns is also likely to occur. The tax agency may also make alterations to the structure of the law, including the modelling of administrative discretion or legislative intent. This text generation capability is an important technological development that can be tempered by the public debate and reaction it generates. Understandably, concerns have been raised. Such use may risk abuses of discretion, making failures of mandated processes less apparent which in turn may deteriorate public confidence. Alternatively, LLMs may assist in the technology-enabled and governmental task of forming a more accurate position on whether or not laws are adhered to, with adherence to be interpreted by the policies and practices of the tax agency.

8.2. Predicted Trends and Developments

Tax compliance has the primary responsibility to determine tax liability, collect taxes, account for them, remit them to the government and file periodic reports with various tax authorities. At the same time, taxpayers have the right to expect that taxes will be collected fairly. In recent years, the responsibility for tax compliance has shifted more to the taxpayer and less to the tax authority. Tax authorities around the world have been moving from a pre-filing to a post-filing assessment environment since the Late 1980s. With this change, taxpayers face tremendous compliance pressures, especially large corporations that typically have homes in various tax regimes. The compliance costs are enormous. Tax compliance is verbosely documented in thousands of pages of income tax rules, tax circulars and previous tax authority rulings. The rules must then be interpreted, massively sifted through and applied in order to prepare filing forms and supporting materials. This is a Herculean task and an opportunity for advanced AI-assisted systems to step in. This focuses on predicting trends affecting the tax compliance ecosystem. From a Revenue Administration perspective, consumer prices around the world have continued to rise steeply and the global economy has essentially been decoupled from inflation. This has prompted monetary authorities to raise interest rates sky-high and maintain them at high levels. Such policies lower demand for money, increase default probabilities for borrowers, force market players to rethink pricing models, and widen arbitrage opportunities which for some involve tax avoidance. These disruptors may hinder the efficiency of tax compliance by either forcing corporate tax departments to staff down or, on the contrary countercyclical efforts to scale up hiring while trying and still being unable to compete with Google, Microsoft, or other tech behemoths, thereby straining the human resources devoted to compliance work.

9. Best Practices for Implementation

The implementation of AI-powered tax compliance solutions requires careful planning and consideration. Five main practices can enhance the successful deployment and long-term effectiveness of a predictive modeling approach: Engage stakeholders, mount interest by creating internal champions and emphasizing operational requisite benefits, align techniques with stakeholder expectations, begin with infrastructure and reporting readiness, and avoid one-shot solutions and transient projects.

The engagement and sponsorship of disparate tax, operations, and IT teams is critical for the successful alignment of predictive modeling outputs with business operations. As a first step in implementation, firm leaders should conduct a current-state assessment of tax and company-wide data infrastructure. Understanding how capacity and maturity vary across teams can create champions who internalize AI-enabled data science solutions. Such ambassadors can also help curb skepticism and ensure that stakeholders understand the difference between statistical modeling and decision support systems. The latter are often required for tax optimization but are not foundational for internal compliance.

At the outset of the planning phase, firms should identify implementing partners who can build tax compliance systems or, at a minimum, deliver predictive AI modeling results that can be ingested by existing systems. During implementation, firms should understand that in-house candidates may not be available until analysts are trained and operationalized. Key operational outcome benefits should not be emphasized. AI, particularly predictive modeling, is highly usable; deploying refined outputs often requires little integration. Stakeholder expectation management is contingent upon understanding each party's level of familiarity with predictive modeling techniques. This knowledge can inform how much technical jargon vendors should employ, which outputs they should prioritize, and the need (or not) for operational adherence.

Firms may undertake model building without system integration and by combining already compartmentalized outputs in spreadsheets. However, expected bottlenecks may arise during a project's transfer-of-systems phase. As previously noted, devoted infrastructure and systems for various AI applications may be naïve. Computational capacities are often overloaded when new predictive modeling approaches are ingested. This can lead to friction. Alongside rollover readiness, firms must scrutinize how predictive modeling results are consumed by tax analysts and converted into tax compliance reports.

9.1. Strategic Planning

In this stage, discussions among the business process owners are needed. The manager and process owner of tax return and audit business processes in the SKB need to provide, together with the up-to-date state-data of these business processes, which groups of organizations would be of interest for predicting their behavior or outcome. The external observer function has to be implemented in the ZOCO System by transaction design in a way that the created groups are close to the groups the owners of these business processes had in mind. The external observer function also has to be implemented in order to develop the knowledge models required for predictive modeling. According to the executives of the SKB, the high-level users of the ZOCO System that would generate the prediction request are also the ones that would most likely prepare the knowledge models in the model building activity. Therefore, executive functionalities for these activities have to be designed in the ZOCO System.

As the last step in the initial configuration, the mapping also has to be prepared in a way that all anticipated anomalies would be detected by the ZOCO System. Moreover, variables of the ZOCO System that would facilitate the elimination of false alarms have to be created. The analytical data mart that can be queried by the OLAP client is anticipated to be implemented on a database. After this initial setup of the ZOCO System is completed, the practices of the SKBs concerning the other five elements of predictive modeling have to be accommodated as needed.

Instead of teaching the settings of the ZOCO System, a more general approach is applied in this proposal. Instead of teaching the use of the five elements of predictive modeling in detail, the steps and tasks which have to be performed in these stages to conduct predictive modeling within the ZOCO System are summarized. Each task is associated with the required function and metadata of the ZOCO System would help users perform this task. Also, the SKBs' practices concerning predictive modeling are detailed on a high level and mapped to the applicable functionalities of the ZOCO System and the metadata to be used. Therefore, this proposal can also guide developing a new set of predictive modeling in the ZOCO System, contrary to just helping prepare the original set of predictive modeling in the ZOCO System.

9.2. Stakeholder Engagement

The mapping of the model to stakeholders is among the most crucial issues with regards to performance of ground truth qualification. Indeed, a sophisticated DQ-learning model ideally requires freezing the salary and tax rates of all population sectors, while keeping the rule-based model plausible and convincing. Given their huge fuss in revenue, there are compelling reasons to be supportive of methods which enhance revenue by improving modeling accuracy. When engaging stakeholders prior to eliciting ground truth knowledge, it is typically useful to not only be able to characterize the underlying behaviour, but also visually depict or demonstrate some initial parts of the process. Indeed, rule-based models might be used to provide a visual analogy and lively cartoon rendering of a simulated scenario. In contrast, DQ-learning effectiveness could be conveyed via reporting statistics on variables and episode behaviour on simple 3-max-competitor environments, augmented with 2D renderings. The struggle would be of utmost criticality in dealing with portions of the population for which performance variances were on the order of June tax payment changes. Nevertheless, the resolution proposed in principle might be unwitting to stakeholders, either because they run simply on a server or due to the over-complexity of function approximators trained with sufficient data. A more engaging player-level illustration or animated simulation depiction showing DQ-mask discriminating between corporate and self-identified AA firms would help vividness, while intention-eliciting student competitions mimicking consideration in doubtful environments would facilitate ground knowledge on tax rate behaviours.

Taxation provides a critical means for raising revenue for governments, but there is a continuing battle between tax authorities and taxpayers because the latter typically have a motivation to hide their income or wealth and even to evade paying tax. Tax payers have extensive strategies for selecting how much income or wealth to hide and a corresponding strategy on how much tax to evade, given the taxation system. For example, they may select to cheat on tax deductions with marginal rates that are less than the effective rate for omitted or inflated income. Influential parameters affecting these strategies include the complex nature of the tax system, the level of taxation and taxpayers' relative risk aversion. On the other side of the coin, tax authorities also play a cat-and-mouse game by employing various strategies to reveal or punish tax payers' tax avoidance over the compliance and non-compliance spectrum, and vice versa. For example, they may hire more interpreters or detective inspectors to examine the intelligence of tax return submission. Tax agencies' strategies become important if they wish to employ either tax regimes or statuses to detect some kinds of tax avoidance. The authorities, therefore, are modeled as the chess player with the castling of roles to ensure the stability of taxpayer modelling, which may be achieved by simplifying the tax system.

9.3. Continuous Improvement Processes

Continuously improving the AI model is critical to the utility of the resulting service. AI services must be continuously monitored and updated in order to remain compliant with changing regulations and improve accuracy. There are three key reasons for improvement of manufactured AI services: improved model quality and accuracy, greater accuracy in outputs, and improved business practices and processes. Key dimensions of attention for improving models include using more or better data from more diverse sources, better cleansing and publication of data, and better error estimation and metrics. Processes regarding data and model development, deployment, and monitoring can affect the accuracy and utility of the model.

Continuous model monitoring is important to ensure the ongoing accuracy of predictions and outputs. The data used in models can drift over time and new data sources can become available. In addition, deployment details such as number of cores, timeout period, and storage can change over time. Similarly, AI models can drift, and processes such as encoding, variable selection, and hyper-parameter policies can provide new options for improving models. Because of fallibility, the results of models must be produced with an estimation of their accuracy.

In order to improve models, prediction must be made of the performance of different model architectures and they must be retrained at feasible intervals to ensure their accuracy. Performance improvements and the tracking of results during retraining can inform future model development. There are multiple metrics for model prediction accuracy, including mean absolute error for regression models and the area under the receiver operating characteristic curve for classification models.

10. Conclusion

AI technology offers tax compliance professionals increased efficiency, accuracy and productivity in a variety of ways, and through the adoption of predictive modeling techniques a model can be constructed which identifies taxpayers who are considered non-compliant with regards to their corporate tax Return or self-assessment returns, and thus should be audited. To illustrate the production of a case-selection model, which estimates the compliance status of taxpayer Time Based Income corporate tax Return, based on a dataset containing multiple attributes was illustrated. The model produced was demonstrated with a working prototype. Results demonstrate an effective model with 65% accuracy rate fit for the case-selection application prototype developed. In terms of future considerations from the case-selection perspective, given Kenya's current position, it would be feasible to consider developing a time-series model which predicts taxpayer compliance status for a future period or year. This would aid in the continued effort to maximize compliance of taxpayers by using resources on the taxpayers considered at the greatest risk of being non-compliant. With respect to revenue maximization in the context of a state consisting of lenient governance from an independent Revenue Authority to more strictly governing, stricter regimes in terms of the Revenue Authority's tax policies and procedures should be encouraged. This would encourage taxpayers to comply to a greater extent and in turn contribute a greater share of their earnings, dividends, shares and profits, to the state. As a result, this would lead to greater expenditure within a society, which is ultimately the motivation of a state. Fiscal institutions of tax authorities need to develop expenditure tracking capabilities to restore and keep trust in the fiscal system. For the Revenue Authority case-selection systems to function as intended, these additional tracking capabilities need to be developed. Without these systems, tax authorities are very limited in securing taxpayer interests. Further research on developing expenditure tracking systems for tax authorities is encouraged.

10.1. Future Trends

Looking forward, the growing cost of compliance will force tax departments to look for a renewed focus on efficiency-led tooling to partially solve their inefficiencies. Increased automation of compliance and workflow management tasks will start to be driven by advances in AI techniques. From a technology landscape perspective, robotic process automation and workflow tooling will become commoditized, whereas visual programming techniques will help democratize tooling creation. However, generative AI will be the game

changer. Natural language processing (NLP) techniques will change the way tax professionals interrogate data to gain insights proactively. Text to code will lead to an era of auto-creation of more than simple routines using formal programming languages. Eventually, interfaces with a completely different look and feel than today's spreadsheet-based UIs will emerge. Next, either defined firms or business line-centric clouds will become the large-scale data & analytics ecosystems, with fresh thinking around data privacy and control.
Given these predictions of great advances, the broad stroke statements about AI potentially removing up to 70 percent of compliance tasks and a huge hike in compliance efficiency hardly seem exaggerated. For mid-market firms and MNCs that lack the current, proven enabling technology for that 70 percent, these projections call for serious reconsideration of the game plan. The questions are whether this outlook is in line with expectations, how such a transition will unfold for current technology vendors and customers, and how this affects operational and competitive technology approaches during this transitory phase. For mid-market firms already using AI-based tooling today, uncertainty again centers on how much of the labor force can be reallocated from the time-consuming, tedious drivers of operational costs toward business development and customer relationships, and how to achieve such a shift in a well-governed way.
Technology vendors should themselves frame scenarios in order to steer existing customers and prospects through the transition. As technology alliances are increasingly a must-have for all mid-market firms, it is essential to focus alliances and go-to-market approaches forward. Finally, back-office functions should consider replacing some of the draft-style methodologies currently in use by more automated ones, so as to collect, evaluate and prioritize detailed visionary input from current users.

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