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Leveraging Artificial Intelligence for Strategic Decision-Making in Tax Administration and Policy Design

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Abstract: Leveraging Artificial Intelligence for Strategic Decision-Making in Tax Administration and Policy Design presents Artificial Intelligence (AI) – both its opportunities and uncertain consequences – within the sphere of public tax administration. We show how tax administration, as a strategic operator of AI, can draw from its traditional managerial methods and management sciences to augment the ability of AI to decide strategically in the design of tax policy and the creation and manipulation of incentives and payoffs that motivate taxpayer decisions. AI has arrived at the doorstep of a techno-economic moment that has knock-on effects affecting the very pillars of society. We argue that it is the task of decision-makers to leverage AI but also to ask themselves – are there questions with uncertain answers that AI cannot help us with? As new models of machines and services become available to help us navigate our environment, AI capable of doing strenuous and difficult work without pause becomes a partner for innovation and decision-making. Exploring the explication of large recognitive models, we highlight the implications of AI for tax administration business processes, and for key areas of operations. The joint distribution of discrete data policies implicitly suffices to reflect the multi-routing of communications and identifying agent principals, including transactions and interactions in a digital landscape where digital profiling predicts and infers possible agent actions – buying, selling, manipulating, cheating. Lessons from current AI models serving image processing or vector classification become incredible platforms for new risk management workflows. However, supplementing AI Risk Assessment models, management must prepare and maintain an intuitive feel for reality and collective unpredictability, the very characteristics that distinguish human strategic thinking and decision-making from machines – that model all the inductive and deductive relationships and their distribution through a holdout remainder set.

Keywords :Artificial Intelligence, Strategic Decision-Making, Tax Administration, Policy Design, Data Analytics, Machine Learning, Predictive Modeling, Automation, Risk Assessment, Tax Compliance, Revenue Forecasting, Fraud Detection, Natural Language Processing, Data-Driven Insights, Real-Time Monitoring, Taxpayer Behavior, Decision Support Systems, Algorithmic Optimization, Policy Simulation, Digital Transformation, Tax System Efficiency, AI Governance, Intelligent Systems, Behavioral Analytics, Public Sector Innovation, Regulatory Compliance.

I. INTRODUCTION

Shortly before a multitude of tasks and jobs will be executed by AI models, the least we can say is that a new era is starting. Not only are they a brand new technology that is causing disruptions across industries, but these models are now some generalist technology that can be trained or fine-tuned for many tasks that require intelligence. Policy and Strategic Decision makers should thus understand how these models could serve the actions and responsibilities of State Institutions, in many fields of activities: Health, Defense, Real Estate, Fiscal Policy, Cybersecurity, Public Finances, Employment Policy, Development Policy, Crisis Management, Foreign Affairs… The usability of AI tasks be they generative, insightful, predictive, prescriptive, supportive for decision, innovative, optimization oriented is so high that there is almost no limit to the way these models can help public agencies. Serious Fiscal Institutions are working on such models, and many of them are public and accessible.

Tax administrations are reaching a maturity level which pushes them to largely increase efficiency in the achievement of their missions. The baseline is a digital transformation process more than 20 years old in most countries where investment has been substantial. At the same time, tax administrations are not cubic meters of economic rationality, not cost centers nor service providers more than facilitators of taxpayer compliance obligations.

The way they interact with taxpayers and how they design their policy parameters is not solely subordinated to formal and rational economic rules. The reward system is very particular with the adherence of taxpayers to domestic policy lines and with the aid of International Financial Organizations. State legitimacy is an essential solidarity linkage with the taxpayers that in return demand quality, clarity and precaution.

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II. THE ROLE OF ARTIFICIAL INTELLIGENCE IN TAX ADMINISTRATION

The term "artificial intelligence" (AI) broadly encompasses techniques and technologies with the capacity to perform tasks commonly requiring cognitive functions associated with human intelligence. Such techniques and technologies combine vast amounts of information with advanced algorithms to achieve an analytical capability for tasks including natural language processing, facial recognition, and voice recognition and analysis, as well as making predictions and automating routine tasks. Automation in the context of AI therefore refers to the execution of cognitive tasks traditionally carried out by humans, employing machine learning and other approaches.

Fig 1: AI in Finance – How AI is Transforming the Industry

AI capabilities are already contributing to a range of applications across several key functions within tax authorities. However, the use of these technologies for tax administration and policy design is still nascent; there is much potential to leverage AI technologies to optimize operational processes and improve decision-making, service delivery, and compliance outcomes. By integrating AI-enabled tools into various functions within tax authorities, governments are already beginning to harness the potential efficiencies associated with automating process-heavy backend functions, improving the front desk service experience, detecting and preventing compliance risk, and dynamically modeling taxpayer behaviors.

The speed at which these AI technologies are entering the market and being adopted by organizations in many sectors including tax, highlights the growing importance of such technologies and tools not only for the optimization of functions associated with large data volumes, but also for automating routine activities, improving customers' interactions with organizations, and enhancing predictive capabilities. Developed in response to vast amounts of data, powerful algorithms, and large, increasingly low-cost data processing capabilities, several AI technologies are finally productized and available at a low cost. Associated with the rapidly growing availability of data, including unstructured data, these diverse capabilities are entering the mainstream.

2.1. Overview of AI Technologies

Artificial Intelligence (AI) is a set of computer programs that emulate human cognitive abilities such as perceiving, recognizing, remembering, reasoning, learning, planning, communicating, and decision-making. AI technologies automate functions such as language translation, image identification, drawing inferences from ambiguous patterns and optimum path finding, which previously required human intelligence. More often than not, however, AI applications are specialized to solving specific problems and accomplishing specific tasks. AI has become a new general-purpose technology due to the confluence of the progress made in computing power, large amounts of data and economic incentives to apply data to production processes.

Machine learning (ML), a method of learning from data has been the key enabler of many recent successes. These ML algorithms forecast and analyze data better than their predecessors. In ML, algorithm performance improves by adjusting its parameters, as it is exposed to more data. Very much like humans can learn, refine and achieve better results given more experience, in supervised learning, the optimal parameters of the prediction model are learned from labelled training data, while in unsupervised learning, the algorithm tries to find patterns in the unlabelled data.
While ML methods have been used for solving such pattern recognition problems for a long time, certain methods have enabled a considerable increase in the accuracy with which such problems are tackled. These advances are combining pattern recognition with deep learning and neural networks with graphics processing units and large amounts of labelled data.

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Supervised learning has offered enormous value by substantially reducing error rates in speech and image recognition. There have also been significant improvements in machine translation, video analysis, and optical character recognition, as the alphabet of languages becomes the main limiting factor. Other AI applications such as using unsupervised learning to discover information hidden in vast stores of unstructured data have become more common without extensive curriculum design that has characterized it.

2.2. Current Applications in Tax Systems

Despite the broad range of AI applications available to the public, exploratory research into the actual application of AI in tax administration, reported tax policy design, or tax policy-related projects is limited to a handful of countries, notably in the Global North. It is already being used by tax administrations in several areas, with tax compliance (both fraud detection and tax avoidance circumvention) getting the largest share of reported projects. Starting in tax compliance, especially fraud detection, AI has been used to analyze vast datasets, automatically sorting through the noise in order to identify the small number of accounts where suspicious activity can be flagged up for human review. Other reported tax compliance-related applications include scraping and analyzing social media datasets to detect noncompliance; advanced forecasting models to predict the yield of tax policies or tax compliance, particularly around major events; chatbots for frequently asked questions; and the use of data analytics to detect corruption in tax audit procedures.

Eqn 1: Taxable Income Formula

$$TI = GI - D$$

- TI: Taxable Income
- GI: Gross Income (total earnings before deductions)
- D: Deductions (standard or itemized)

The remainder of AI applications fall into the more general but extremely important category of operational and knowledge management, with the goal of increasing internal efficiency and/or securely managing valuable internal data. Examples include automation of annotations of existing datasets to facilitate machine learning-driven projects in the agency; a tool that uses AI to find patterns in complex internal datasets without requiring advanced data science skills; tax policy impact modeling to gain a better understanding of the effect that policies have, before they are implemented; and semantic search engines. Automating the data management and internal annotation process frees up time for expert humans, allowing them to focus on more delicate, sensitive tasks.

III. STRATEGIC DECISION-MAKING FRAMEWORK

Strategic decisions concern the overall plans and actions an organization adopts to achieve its long-term objectives. Several different concepts are used to refer to strategic decisions—strategic management, strategic planning, strategic choice, and strategy formulation—but most of the academic literature on strategic decision-making tends to focus on either (i) the processes that lead to strategic decisions, or (ii) the decisions themselves, and the behavioral aspects surrounding those decisions. The first stream of literature emphasizes that strategic decisions are not made in isolation, or in a short period; indeed, the process involved in making a strategic decision is usually much longer than for other types of decisions. Moreover, such decisions typically involve a great number of players both within and outside of the organization, operate at the extremes of an organization's risk/uncertainty spectrum, and often entail decision-making in high-stakes situations. On the other hand, the second group of researchers emphasize the characteristics of the strategic decisions most organizations take. These studies show that, in contrast to non-strategic decisions, strategic decisions have a major impact on an organization's success and ultimate survival. Furthermore, they involve the highest level of uncertainty and potential risk, are more complex, and are closely related to the further development of key resources of the organization.

Decision support systems have been used for decades to describe systems designed to support managers in the decision-making process. Following this unusual understanding of the word "support" used in the context of decision support systems in decision-making processes, it is claimed that only very few systems developed in the context of artificial intelligence may actually be described as decision support systems.

Most AI systems are designed to independently take action, rather than support the human decision maker in the decision-making process in a more or less automated way. They call these systems "decision actuation systems" or "decision and control systems." However, we follow the interpretation of the decision support concept in a more general sense to include both "decision support systems" and "decision actuation systems."

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3.1. Defining Strategic Decision-Making

Within the fields of strategic management and decision support systems, there is a long-standing interest in understanding the nature of strategic decision-making. Given that the term "strategic" can have multiple meanings and connotations, it is important to clarify its role in strategic decision-making. A relatively basic definition proposes that strategic decision-making is about addressing the most important issues of an organization. Such decisions are typically concerned with issues that influence the organization direction, with a long-term outlook, and with considerable risk and uncertainty. The decisions are usually made by a limited number of participants, who often come from the upper echelons of the organizational hierarchy, as they usually have more experience and expertise. The decisions have a considerable impact on the success or failure of the organization and have significant resource allocations.

In a more flexible definition, specific dimensions and attributes can characterize strategic decisions, as compared to operational or tactical decisions. For example, it can be proposed that strategic decisions change the organization. More ambitiously, the argument is made that strategic decisions create or change the identity of the organization. The traditional focus on the particular decisions is recently complemented by an interest in the underlying processes through which strategic decisions are made, and in a dynamic approach that considers the temporal dimension of strategic decision-making or the sequence of strategic decisions over time. What this variety of definitions ultimately suggest is that there must be a willingness to explore different perspectives and aspects on strategic decision-making.

Fig 2: Strategic Goals Examples, Importance & Definition

3.2. Integrating AI into Decision-Making Processes

While AI is expected to increasingly augment human capacity to analyze data and help devise plans, it also needs to be integrated into established decision-making frameworks. For decision support, AI-based tools must assist administrators in making the final decisions. In the context of the proposed SAM, AI can be used for collecting and synthesizing data and producing and evaluating the options. At the same time, expert knowledge is particularly needed to assess values and priorities among objectives and criterion weights, shaped by political considerations, and to provide moral legitimacy to the final policy decision. The integration of AI-based tools into these decision support functions could look as follows. Problem definition and data collection: AI could identify the problem based on the data and report it in the decision frame, highlighted against historical patterns and/or linked to its policy effects. Generally, its role could consist in extracting from various data sources the relevant variables, on a timely basis, to identify changes in individual and social behavior potentially linked to policy design or political change and to estimate their significance. Its monitoring function could also help to identify new problems. Synthesis of the functions assessed by tax policies: AI could help to define the focuses under different perspectives by synthesizing complementary functions based on available data. Generate policy option scenarios. Once the problems to be fixed and the perspectives envisioned have been defined, AI could produce scenario options. Functional AI tools are available to take advantage of the extensive knowledge accumulated along the years on tax policy design and quasi-experimentations. They could suggest policy options for the initial scenario selected and indicate their effects on the functions' quantile estimates.

IV. DATA MANAGEMENT AND ANALYTICS

The last decade has been characterised by the advent of rapid technological developments in data collection, processing, storage, annotation, merging and analysis capabilities. Such technological advancements have led to the emergence of

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various new data-related business models powered by big data across multiple sectors of the economy. With the rise of the digital economy, tax administrations around the world have access to ample data – both traditional and new – which can shed light on tax-related problems on a real-time basis and can address and answer the challenges of strategic decision-making in tax administration and policy design in a more informed and timely manner than was the case of conventional data sources. However, to be able to harness these substantial opportunities requires careful considerations on the methods for the collection, analysis and management of data.

Tax administrations possess both traditional sets of data, such as tax returns, financial statements and other taxpayer reports, and new sources of data, including third-party reporting, tax compliance data, big data, and data from stakeholders. In addition to these traditional and new data sources, tax administrations could also be considering the use of predictive polling so as to combine these sources by using polling mechanisms, to generate new data that could augment their ability to address questions they face. New and novel tax-related policy questions are increasingly emerging in tax policy design and tax administration. Such innovation in tax reporting mechanisms has implications in the types of data sources accessed from traditional and new data sources, and how these could be best optimally combined. Machine learning algorithms, by improving predictive accuracy on unstructured datasets, are also allowing research questions in various social domains, such as politics, economics and other social questions, to be addressed using traditional data sources combined with new data.

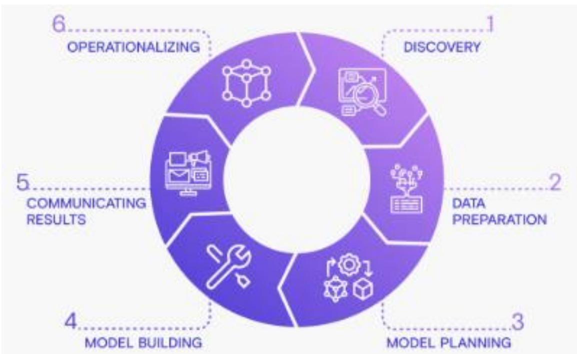

Fig 3: Data Analytics Lifecycle

4.1. Data Collection Techniques

Data is essential for any decision-making process, especially in the case of tax policy, which should be well-informed and evidence-based. Data deficits should be resolved by formulating a data strategy. Data has become increasingly available due to the rapid development of information technology. Both the breadth and depth of data have developed, and data from various sources with different levels of quality and integrity can be utilized for analysis. The tradition of relying on administrative data alone to understand the behavioral response from taxpayers and in the generation of predictions no longer applies. New tools of data capturing should supplement tax data and policy practice in order to account for new societal dynamics and the short-term responses of taxpayers to policies. A range of exercises can be conducted to either capture or supplement administrative tax data, resulting in the development of new or modified data sources. Of special interest to tax policy, as opposed to other forms of computation and prediction, is the use of data sources that can access or predict information at the individual level and at the level of taxpayers and taxpayers' agents. These individual-level data sources can be merged with administrative and other forms of data. The power of these various data exercises lies in the development of structural tax models that can explain taxpayer behavior and tax interactions or that can compute the causal implications of tax changes. The type of data available imposes restrictions on the modeling approach.

4.2. Data Analysis Methods

In order to answer our research questions, we selected a set of qualitative and quantitative data analysis methods. Building on an initial content analysis of relevant secondary data, including reports and documents from international organizations, academic literature, and from the set of primary data gathered through semi-structured interviews, we developed an analytical framework that combines the process tracing approach with a Bayesian Decision Theory to analyze and explain the uses of AI in tax administrations, in different countries.

Our analytical framework focuses on two critical elements: (i) the priority decisions to be made by tax administrations concerning different sectors of activities and how AI could assist them in the decision-making process; and (ii) the impact of different types of factors, involved in the design and execution of AI policies, on the operations to be carried out in each of these economic activities.

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Using this analytical framework, we defined the general typology of AI use specific to each of these tax administrations, with respect to the priority areas identified in the literature or mentioned by the interviewees, and to the factors that could affect the design and implementation of AI programs in the selected jurisdictions. We then indicated the common features of the typologies, linked to the factors specific to the jurisdictions and the administrations studied. To conclude, we present the major implications of our study on these two areas and how tax administrations could better use AI to improve their decision-making process. The objective of this study is to identify the factors that could encourage tax administrations to pursue the use of AI technologies and better correlate them with the economic realities in the various jurisdictions, to better assess each country's resources and competences, with a view to supporting revenue-generating institutions in less developed or developing economies.

4.3. Ensuring Data Quality and Integrity

The quality of any data analytics process is determined by the quality of the underlying data decision. Despite the tediousness, quality and integrity of data should not be sacrificed at the altar of speed. Machines or algorithms make decisions at speed without human supervision – many of these decisions are based on technical parameters gleaned from the data. Any poor decision due to bad quality data leads to mistakes, errors and waste. At the outset, effort put into improving the quality of the underlying data reaps future dividends. Good data quality improves overall consumption of resources and makes implementation of AI successful. Data quality has been important even before the advent of AI. When AI is leveraged for strategic decision making at the Tax Administration, it further emphasizes the importance of decision quality. Tax Decisions involve making choices or selecting one or more alternatives for implementation. Most Tax Administration decisions are made by Public Administrators upon input of data which is dependent on Taxpayer Behavior. In decision science, decision quality is measured by how well the decision appraises and prioritizes the known objectives, addresses the known causal factors, has a realistic chance of successful implementation and testing, and anticipates likely unintended consequences. These decision quality measures depend on the underlying data. Tax decisions made by algorithms, for implementation or advice, need quality data to ensure optimum allocation of resources. Informed decisions made by Public Administrators benefit from quality data for input into the decision making process.

Eqn 2: Data Accuracy

$$DA = \frac{N_{correct}}{N_{total}} \times 100$$

- DA: Data Accuracy (%)
- $N_{correct}$: Number of correct or verified data entries
- N_{total}: Total number of data entries

One of the most well-known definitions of Data Quality confines it to the conformance, accuracy and completeness of the data. Data integrity defines a broader concept than data quality: Data Integrity refers to the accuracy and consistency of the data, whereas Data Quality encompasses the enhanced perception of the data by the people managing it. Data Quality denotes the degree to which an overall data is logically consistent, conforms to specific data formats, maps to real-world entities, and above all satisfies the information needs of users. Hence, Data Quality is a measure of Data Integrity. Data quality and integrity are considered vital attributes of any data management initiative. Both the decisions on how to improve data quality and the business case for it are often founded on opinion rather than reality; balancing the improved data quality against the cost of achieving it.

V. AI-DRIVEN POLICY DESIGN

The second type of decision-support problem is designing laws and policies. While tax policy design involves a plethora of choices, there are two principal and conjoined aspects to the type of decision we want to affect: what policies are needed and how policies will affect society. The first question involves determining the policy issues that the government should address. The second aspect of policy design addresses the economics – how policies will affect individual and corporate behavior and the costs and benefits of different policies. Answering the second question usually comes after designing the new policy.

Governments need to decide the issues they want to design policy for, and AI can both free up limited government capacities when identifying policy issues and improve the quality of decisions. The government currently spends a significant amount on policymaking broader than tax. Cutting the time that experts spend on diagnostics would free up time for more decisionmaking, elaborating, and scaling of best practices. It would also provide higher-quality, more accurate advice derived from masses of data.

For tax policy, AI could help identify needs on two levels: diagnosis both within and outside the IRS. From within the IRS, AI could optimize requests for information to avoid overburdening power users. Outside the IRS, AI can process external data for missing needs asking more directed and specific questions.

Once the tax policy issues are identified, tax policy experts need to determine how taxpayer behavior will react to changes in the tax code. The main tool that tax policy experts use is tax simulation models, which apply estimated behavioral elasticity multipliers to predict tax liability. Macro models use information on elasticities from the observed response of a population as a whole to policy changes and apply these estimates to the entire economy. Smaller simulations use elasticities estimated from specific income groups to model individual reactions to changes in the code, such as further increases in the standard deduction or attempts to eliminate the cap on state and local tax deductions.

5.1. Identifying Policy Needs

Artificial Intelligence can contribute to tax administration by helping identify the needs it should address through policy reform or new tool development. But policy design in tax administration typically emphasizes the selection of parameters for established policies. Modern governments are adept entities that already possess normative frameworks and actionable plans for action to secure particular policy objectives. In this traditional conceptualization of policy, the "what" is relatively fixed and the "how" is modified in response to evidence of effectiveness. It is only when particular problems are identified, or a late-stage vision becomes apparent, that the process resembles what many associate with the "design" of new tax policies. The reasons for the sanitization of the design phase can be synthetized into five categories: The nature of technology and policies; The role of tax administrators; The nature of taxpaying behavior; The institutional structure; and The technological components of tax governance. However, fiscal policy is rarely today preferred to be ill-specified and allows for some experimentation, inviting periodic mandates from political leaders. Budgeting largely fixates on production plans detailing how existing policies will deliver expected cash flows.

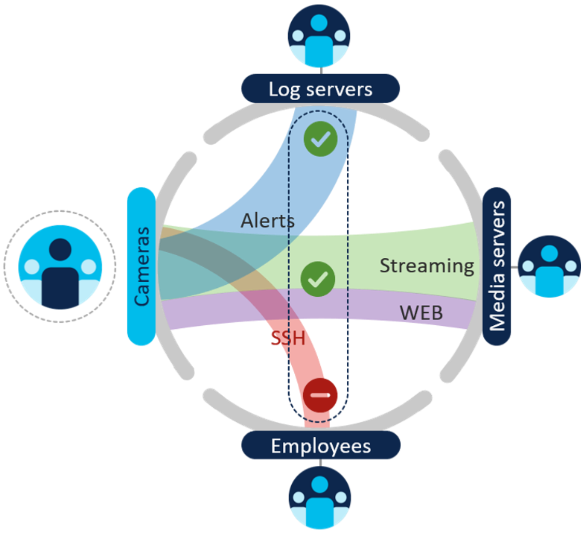

Fig 4: Write policies for right segmentation

AI can merely enrich the volume of inputs. With some caveats, it allows striking amplitude through big data and machine learning. When confronted with large varied sets of behavior-generating data, human expert storytelling becomes of less value in tax administration than automated generalizations. In this data-centric fiscal world, identifying system jaws will yield important insights into observable macro- and microeconomic policies on which expert judgment can be applied. However, the econometric task now undertaken by humans in tax administration is highly technical and largely unenviable; an applicant will have to satisfy an increasing set of mathematical prerequisites. In the near future, ethical use of AI will dictate clear demarcations of what will remain purely technical versus complex and qualitative inputs dependent on traditional human skills.

5.2. Simulating Policy Outcomes

Automation has expanded the capabilities of tax administrations. From collecting compliance data to managing taxpayer care and pre-filled returns, technology has generated efficiencies in all aspects of tax administration.

However, the predictive abilities of AI can also be leveraged to simulate policy outcomes, providing a basis for analysis that allows data to sit at the core of strategy development. Technology has changed our understanding of the relationship between the economy and tax policy. Macroeconomic simulation models allow major taxes to be subjected to some degree of simulation; models exist for corporation tax, value-added tax, and income tax.

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However, expanding policy impacts into areas beyond revenue collection has taken us into the world of general equilibrium modeling. The misspecification of the relationships between the economy and tax policy that leads to the sometimes chaotic short-term forecasting errors may be offset when tax policy changes are so large that they engage the behavioral transition equations of the models. When changes are so large that they engage the behavioral transition equations of the models, however, the medium-term forecasting errors are so large that they are not an effective basis for policy evaluation.

AI and its capacity for machine learning offer the potential to expand the policy analysis toolkit further. Instead of estimating the complex behavioral relationships that underpin simulation, data are simply allowed to speak for themselves. Using much faster computers, which allow for parallel processing, complex algorithms that compare a huge number of policy and economic factors can be employed to identify tax policy regimes that best fit the data. Data analyses combined with existing behavioral structure provide our best hope for solving the many tax debates that we will face in the future. Advances in automation are set to cause unprecedented change to the operational capabilities of tax administrations; there is a compelling case for seizing the opportunity afforded by the current technological revolution to also consider its potential implications for tax policy development.

VI. ETHICAL CONSIDERATIONS IN AI IMPLEMENTATION

AI is a powerful tool that can help implement tax policy and enhance compliance, but there are ethical considerations that warrant discussion when implemented in its more powerful practical forms. Bias and fairness, as private companies using AI for credit assessment, pre-crime, and insurance purposes must wrestle with, are critical when considering using AI to audit and/or penalize taxpayers, assess penalties, and place taxpayers into risk categories. Algorithms behind AI are trained to both replicate human behavior and suggest action based on that behavior. If the behavior exhibited by humans has shown bias toward particular outcomes, the algorithm will inadvertently reflect that bias. Whether that bias be matched to race, nationality, religion, financial means, social status, or other factor, resulting negative repercussions can be extensive and devastating for individuals and families affected, as well as all of society. In a public forum where taxpayer outcomes and penalties are wrought with agency and privacy concerns, leveraging AI without examining the subtleties involved could lead to substantial harm to both citizens and the tax authority. Care in tax forms and data input as well as training within the tax authority of the output, including item explanations, will help minimize risk.

Eqn 3: Explainability / Interpretability (SHAP Sum Check)

$$\sum_{i=1}^{n} \phi_i = f(x) - E[f(x)]$$

- ϕ_i: SHAP value for feature i
- $f(x)$: Model output for instance x
- $E[f(x)]$: Expected output (baseline)
- Used to explain predictions in transparent, additive ways

Transparency is a key ethical consideration. Fairness requires accountability, and the taxpayers being analyzed by AI expect a degree of transparency. While all algorithms effectively solve for the Bayesian model and thereby appropriately model joint probabilities, the choice of algorithm determines the components of the Bayes theorem used in estimation. Taxpayers behind the data used to train and assess risk from the algorithm ought to be able to understand the features that lead it to policy outcomes that directly impact them; otherwise, we are functioning in a dark realm where taxing individuals and companies are opaque to those affected by the policy determinants.

6.1. Bias and Fairness

Social justice advocates and computer scientists have identified bias and fairness as the most important ethical considerations for AI implementation. Bias can stem from people's choices and structural limitations or from technical systems. In the case of tax AI applications, algorithms implemented in systems which are processed by tax officers or private tax systems are likely to produce biased decisions, output and predictions if no fairness standards are applied during the modeling process. While the technical analysis aims to minimize direct biases or to balance accuracy by adding costs for different groups within the algorithm, the democratic influence empowers stakeholders to take part in the decision-making about designing the choice parameters, predicting outcomes and setting the thresholds.

If established and used wisely, fairness standards can ensure tax AI applications assist tax administration and policy design without causing economic or social exclusion. Algorithms can even test for indirect bias revealing discrimination against people with specific characteristics which might be prohibited in a specific country: AI models for the classification of communities, analyzing the probability of being socially and economically disadvantaged, can assist in

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determining the funding need of a community or its residents for the justification of tax exemption for the establishment, development or sustainability of specific services. AI models can also locate problem areas regarding tax violence, especially when recommending a pattern analysis approach. A different implication addresses algorithmic assurance regarding classified features. Knowledge of discrimination-free borderlines reduces the danger of overgeneralizing misclassifications by technical systems because they determine the very attributes by which they are prohibited to act. It allows tax administrations to assist excluded or discriminated groups particularly through targeted service offers when needed.

6.2. Transparency and Accountability

The lack of transparency in many AI systems poses challenges for tax administrators, taxpayers, and, more broadly, society. Transparency is important because it allows users and third parties to understand the rationale for AI predictions and outcomes. This understanding is crucial for tax administrators, who need to explain their policy decisions to relevant stakeholders, such as the taxpaying public, courts, and legislators. Moreover, taxpayers and other stakeholders need to be able to assess and understand the integrity of the private or public entities making and acting on determinations based on AI system outputs in order to retain trust and confidence. In addition, transparency is necessary to address biased outcomes and to hold sufficiently accountable decision-makers whose decisions were guided by an AI system. However, many off-the-shelf AI systems are opaque, such as deep learning systems that do not provide answer explanations to accompany predictions. For these systems, the lack of transparency can carry important legal implications in sectors like tax administration that already have well-established rights to explanation, especially when questions of fundamental rights and discrimination are at play.

To compound the issue, tax administrators may fear that the transparency of their prediction systems may undermine the effectiveness and efficacy of tax enforcement. Tax systems are riddled with asymmetries of information. This is especially true in tax compliance and enforcement activities with high risks of noncompliance. While AI can help detect instances of fraud or illicit evasion, potential tax criminals may exploit the bureaucratic disclosure obligations to distort taxpayer behavior. One solution would be to make the algorithms and models available only to a limited number of people, civil servants who are highly trained and obliged not to share the information with the public. Even though this may seem promising, it does not address the issue of accountability. Ultimately, what is at stake is who has the last word on the decision proposed by the AI solution? What is the recourse process undertaken by the taxpayer in case of a biased, discriminating decision?

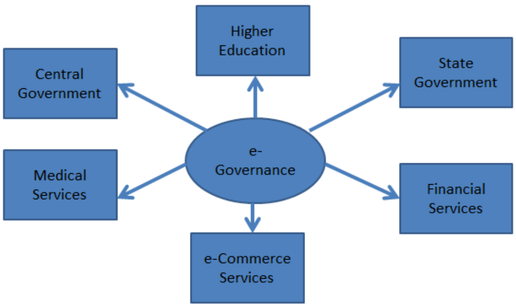

Fig 5: Architecture of e-Governance

VII. CHALLENGES IN IMPLEMENTING AI IN TAX ADMINISTRATION

Implementing Artificial Intelligence (AI) in tax administration is challenging but vital for improving the efficiency and effectiveness of the tax system. However, there are challenges in the implementation process. For instance, technology can fail, especially if there is a short fall in the development and investment needed to create a technically and academically advanced environment for the system's development. Failure may be mainly due to over-expectation or under-delivery or inadequate planning. Governments have higher expectations from the use of AI due to which more than a few AI-related projects fail every year. Warnings have been issued that tax authorities may rely on AI solutions that are merely cheaper or cater to higher ambitions but fail to deliver the desired operational efficiency and long-term project viability. Another concern is over-workload.

At least two issues concern the generation of workforce overload in AI implementation. One is the higher priority that tax administration usually puts on the delivery of outcome through testing, approving, monitoring and sanctioning.

With regard to issues of implementation in tax authorities given our assumptions, we can identify a lack of actual utilization or delivery issues. There are dependency issues that could generate serious delays in the delivery. We may

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find risks on organizational or legal subjects. Many tax administrations are poorly organized to be digitally ready. Digital implementation thus raises the concern of organizational resistance because of higher levels of anxiety associated with computerized technology. It implies that the possible displacements and change could generate higher resistance within the various stakeholder groups involved in the digital transformation of tax models. Public authorities are especially exposed because of poorer quality of dialogue on the associated risks or uneconomically higher costs of AI implementation, notably those related to major relocation of personnel likely to be affected by the change, particularly in certain functions of strategic importance for the organization.

7.1. Technological Barriers

In addition to vulnerabilities to cyberattacks, unidentified cases of algorithmic biases, and violations of citizens' rights, tax officials worry about the impact of the growing use of AI in taxation. Governments collect and store large amounts of tax-related data that can be hacked, even in countries with sophisticated cyber infrastructures. Security requires a multi-pronged approach, including regular updating of software systems, costly security audits, and regular check-ups. Companies developing AI tools must implement strong security measures to protect their algorithms, as well as tax officials' testing of the systems to minimize security weaknesses.

Another worry is algorithmic bias. Algorithms learn from historical data that may present factually based inequalities against specific communities and groups. If the data is a model of society's past behavior – that is, where the citizens have kept complying with rules and the regulations – then applying these algorithms to predict future behavior raises ethical, predictive, and legal questions. These biases need to be identified, diagnosed, and prevented. It is precisely in areas such as tax administration that any undetected biases could raise ethical implications and be disastrous. The other side of this concern is AI neutrality, which consists of providing the same result in identical situations. Revenues from taxes funded continuous public programs to repair damaging effects of economic downturns on specific populations. If forecasting tools predict that a community is going to violate tax rules but such predictions are not nuanced about specific group's specific identities, then overworking from past violators would unjustly punish citizens' fiduciary responsibilities.

The technological barriers to AI use do not reside only in the algorithms and software. Large companies have treasury resources and large pools of talent to invest in cutting-edge digital transformation. Small and medium-sized enterprises lack both skilled employees and the economic capacity to outsource large-scale infrastructure investments to AI systems integrators. This means that developing AI solutions is more feasible for experts than the actual application. Large scale investments in skill building and outsourcing are needed to overcome this gap and use technology as an equalizer.

7.2. Organizational Resistance

There is new expectation on governance – fueled by data, analytics and AI – to make more of a difference in the lives of people, and to do so smarter, better and more efficiently than in the past. But frequently, these expectations do not match with the capabilities and incentives of the organizations actually providing the public goods and services, be they governments or companies in the private sector. Institutional inertia means that organizations often not only fail to address the new demands placed on them, but that they also resist them, either actively or passively. Another key point in shaping the process of AI adoption may be the organizational entrenchment that can occur over time. The tax administration is a highly specialized organization, and as such, may lack the capabilities to build and implement an AI-driven approach to regulatory tax compliance.

The revenue authority or tax office has expertise, processes, systems, and internal and external networks built over decades, even centuries, in meeting their established performance objectives. But in addition to being expert in specific functional areas, an entrenched public organization may also come to focus intently on how to achieve their mission-oriented goals, perhaps even to the exclusion of the mission itself. A good example of this is how some tax administrations can sometimes have Audit targets based more on the revenue bumps and input numbers than the actual impact on compliance behavior and tax policy outcomes. The alleged self-focus or mission drift might make us question whether tax administrations could build and action the innovation capabilities needed to respond to the significant changes AI brings into the marketplace and to the wider firmly laid foundations of tax policy.

7.3. Legal and Regulatory Issues

Using AI may also trigger complex regulatory questions. Participants focused on the need to ensure that the use of AI in tax administration complies with basic legal principles, including equality before the law, legality, proportionality, non-discrimination, data protection, privacy, and access to justice. Discussions provided some insights into how these principles may be reconciled with the goal of harnessing AI to improve tax administration and policies. Luckily, participants agreed that there is a need for a more coordinated approach to the regulation of AI across jurisdictions. The

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recommendations showed that AI creates more challenges in countries that have not yet achieved significant levels of digitalization, as the Digital Divide is often a reflection of inequitable access to data and technology assets, education, skills training, and capital.

Many participants shared the view that the use of AI by governments should be an application of the rule of law, designed to improve interactions with the state and access to services, and to help governments in their mission of serving citizens. Their discussions otherwise suggested that this ideal relationship should not be disrupted by potentially infringing choices made to make public-private partnerships more attractive to the private entity. A basic rule was therefore suggested: government should leverage such technologies to better serve society but refrain from using AI to surveil or collect taxes from citizens. This proposition can naturally be expanded into a negative externality clause, with the purpose of ensuring compliance with the legal principles indicated above.

VIII. CASE STUDIES OF AI IN TAX ADMINISTRATION

As the usage of artificial intelligence (AI) or machine learning (ML) algorithms gains pace, increased implementations and deployments in the field of tax administration are becoming visible. These instances provide an insight into the potential, the possibilities, the limitations, the failures, and the obstacles of AI techniques in tax systems. For instance, the Thailand Revenue Department developed a multilingual chatbot to provide taxpayers with helpful information and to promote tax compliance in low- and intermediate-income tax brackets.

In India, special taskforces consisting of IT specialists and tax officials are working on systems like the Goods and Services Tax Network and the Tax Administration Reform Commission. These systems rely on IT-enabled frameworks. One initiative assuaged the revenue potential by incorporating a data analytics and AI component within the GST regime—in particular, through artificial neural networks to classify taxpayers according to their chances of evading taxes. The VAT/GST models are all efforts at tax facilitation and, ultimately, greater voluntary compliance by the taxpayer.

As a cautionary tale, Brazil's Federal Revenue Office had earlier undertaken a project to introduce a chatbot for taxpayer assistance on tax queries and further reduce tax compliance costs, but it was aborted. Some AI ventures in entities of the Brazilian Federal Revenue Office performed poorly because agents are incentivized to collect information rather than to assist in the decision-making process for taxpayers. These examples highlight the paradox of hyperspecialization in tax administration as its apparent expertise in a narrow technical domain creates a proclivity for self-defeating aversion to adopting innovative solutions.

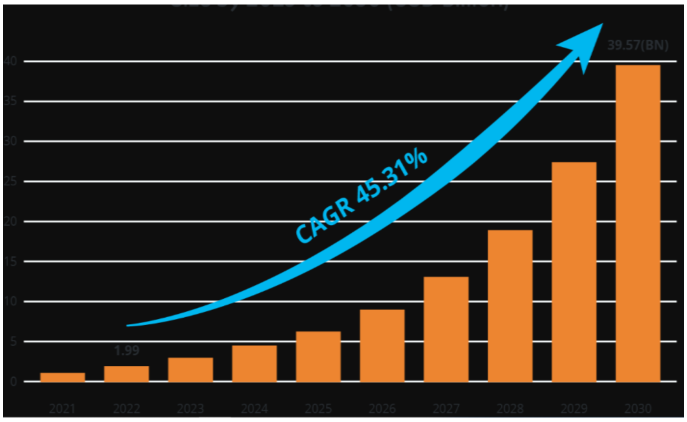

Fig: How AI is impacting the accounting and finance sector

The temptation to use AI, therefore, will have priority for tax systems with the least experience with taxpayer service. For those countries where taxpayer service has evolved over decades, the use of AI could make tax administrations contemporaneous with other serious service providers, private and public.

8.1. Successful Implementations

Some AI applications continue to grow, scale and generate value across various public and private organizations. As these solutions move into production mode, they deliver proven results that can illustrate both the feasibility and the potential impact of AI solutions addressing tax administration challenges.

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At the forefront of available examples is the Application Yoda, a powerful tax assistant app based on two widely known AI tools - a neural-based translation tool and large language model known for its writing and summarization capabilities - that was developed by the State Tax Administration. As an AI assistant deployed in multiple centers, Yoda has provided real-time answers to hundreds of thousands of requests for tax policy advice. This AI chatbot is able to rapidly answer a wide range of questions, including on the interpretation of highly complex and confusing tax and regulatory language.

Answering customer inquiries is a tight-fitting application for an AI model, and a potentially high-impact one. Tax administrations receive millions of inquiries relating to a range of tax and regulatory matters every year, from issues relating to how to file taxes or questions about tax law provisions to indecipherable requests for assistance in highly technical tax areas. Indeed, the sheer volume of calls and other inquiries can be overwhelming at times. In China alone, the State Tax Administration reportedly fielded over 30 million calls for assistance in 2019. Handling these calls is extremely expensive and mostly unproductive. AI chatbots can provide timely and accurate responses to large portions of these customer inquiries, freeing up live agents to respond to the more complex questions and provide fully satisfactory responses.

8.2. Lessons Learned from Failures

In exploring the lessons learned from the failures noted, it is useful to understand it through two lenses: the machine and the user. The machine must be able to sort, classify, predict, or infer successfully; everything else is softness. This is where tax administrations are largely failing.

On the user side, tax administrations are currently able to focus much of their current activity on the effectiveness and efficiency of data collection methods. They are also capable of using a variety of tax policy techniques to affect taxpayer behavior. Indeed, there is substantial research into the behavioral economics of taxpayer compliance. But these user techniques are not concentrating on their fundamental purpose of determining if the taxpayer reporting the amount of tax owed on their tax return is truly the taxpayer who owes the amount reported. Such an identification result is essential to the collection of the amount due.

We traditionally think of the computing technology of government as one that is increasingly capable of sorting, classifying, predicting, and inferring the quality of options associated with the taxpayer, but failing in the process of identification of the taxpayer and the amount due. Meanwhile, tax administrations are increasing the technology and procedures that push taxpayers toward self-identification of the amount of tax owed while failing to use their unique access and control over the very data that must be cleaned and processed to allow taxpayer identification. Thus, for taxpayers accustomed to the anonymity and avoidance of the physical process of interacting with the tax administration, the lens of the user gives us no confidence that the further development of computing technology will narrow or close the gap between machine and user.

IX. FUTURE TRENDS IN AI AND TAX POLICY

It is instructive to consider emerging Federal AI policy regarding the application of AI to address administrative ills, such as flimsy privacy, security, and civil rights protections, governmental authority development, review disorganization, unhelpfully hyperfocused, intertwined expenditure and grant management problems, insufficient seasoned expertise, typography, and inconsistent use of technology, and poor communication and workflow deficiencies. At the same time, the administration has issued an Executive Order promoting American Leadership on AI that policy and industry have found helpful.

Tax policy and administration are at the forefront of society's rapid move toward using technology-enhanced communications and data analytics to better organize the economy and society. Insofar as work from home has become a principal labor organizing feature of the economy, and work monitoring and time management through technology have become principal employer tools, attempting to disaggregate the cloud, moving from the cloud to transacting, operating, and adding value to local business needs and preferences have become important purposes of shopping or searching technology. Emerging capabilities in tax administration can be anticipated to smooth the rougher edges of this transaction-induced reorganization of American life.
How adjustments such as these affect equity and efficiency in the broader American economy are open questions to which the answer must be written in tax policy design choices and tax expenditure incentive choices.

9.1. Emerging Technologies

Over the past decade, a number of entirely new data processing and analytic tools about which decision makers have had little knowledge have emerged. These tools fall in the general category of 'Artificial Intelligence' (AI), the most common

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AI functions being natural language processing (NLP) and machine learning (ML). Each has diverse subcomponents, and other tools primarily involving advanced data processing capabilities also exist. Most decision makers are only familiar with some early examples of AI. Often mentioned are the large language models (LLM) that emerged recently, as well as image generation models. These examples are, however, almost entirely comprised of tools based on only one implementation of one of the many AI capabilities, LLMs. Thus, AI's capabilities and potential applications are far broader than is suggested by decision makers' familiarity with such LLM. In fact, LLM ChatGPT is the least customizable of all LLMs, and many other LLMs optimized for specialized purposes became available at the same time or even before it, as have a number of other categories of AI tools.

Furthermore, ML and deep learning functions have existed for decades but are included under the broad rubric of AI only in the past decade. Likewise have been specialized models for computational choice modeling, demand forecasting and demand estimating, text classification via supervised ML, sentiment analysis for text from public opinion, computer vision applications for a variety of tax policy purposes, and fraud detection and internal audit exploration and analysis.

9.2. Predicted Changes in Tax Administration

What are likely to be some of the most important near-term AI-related changes in tax policy, and especially within tax administration? These changes are likely to be both very significant and – in many circumstances – very easy to implement. The use of "tax modules" in tax administration software may very soon start to produce dramatic bottom-line increases in tax administration's effectiveness. By providing "the robotics" that use reams of existing taxpayer files both to identify the characteristics of taxpayers most likely to cheat and to compile the necessary inputs for the slow and tedious process of eventually attempting to audit these individuals, information and decision-support systems will help to bolster – and in the most compliance-challenged jurisdictions, to restore – the real power of tax audits to deter tax evasion. Audits will be far more efficient.

These tax modules will also greatly increase the effectiveness of automatic audits. The use of AI robots to scan incoming information returns for "clear" discrepancies with taxpayers' information and income tax returns may soon produce mighty increases both in tax revenues and in the speed and ease of their collection. The latter point is especially important, as the costs associated with the collection of tax revenues have an inverse, not a direct, relationship to the revenues being collected. Given the poor effectiveness of the "do-it-yourself automatic autofills" and their striking failures to either attract large numbers of taxpayers or to reduce errors, there is an urgency in the work of enhancing the automatic audit approach.

X. RECOMMENDATIONS FOR POLICYMAKERS

Adopting AI at its fullest extends beyond technology investment. Political leaders, stakeholders, and experts in the area need to strategize and execute a roadmap for digital transformation, creating a trustworthy AI governance model that encompasses the principles of inclusion, equity, and accountability, while respecting sensitivity. The establishment or consolidation of an internal planning and risk management capability could be a part of this roadmap, ensuring alignment with the institution's strategic objectives, tailored resource allocation, and oversight for self-management of technology-induced operational risks. Additionally, enhanced collaboration with academic institutions and the private sector, that stimulate research and innovation, together with the setting of a beneficiary-inclusive approach, participatory development method, and adaptive learning process to support decision-making at all stages of the project life-cycle, could provide a more effective and insightful implementation plan to maximize efficiency gains and other expected benefits.

Building stakeholder engagement is critical to successful AI adoption and entails information sharing and collaboration with both internal and external actors. Setting up an Internal Algorithmic Impact Evaluation Board within the institution could address and mitigate skepticism among internal stakeholders about algorithmic use cases for automated-decision making that affect them, and support transparency aspects by reviewing potentially biased algorithmic outputs before they are made public. Peer agencies and international organizations are obvious potential partners for setting up external committees to proactively conduct algorithmic impact assessments for automation of public-facing services with high public-impact.

10.1. Best Practices for AI Adoption

While consulting with best practice documents is usually the right step when adopting AI, pieces do not always address strategy and organizational design. Typically, these documents instead focus on engineering issues like algorithms, tools, computing platforms, data, and experimental methodologies, while leaving out the more subjective questions of stakeholder determination, culture, roles, team design, and processes. AI is a specific type of technology that usually falls

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outside the expertise of the majority of stakeholders. Unheeded, such stakeholders can ask for the wrong outputs, react negatively to non-optimal outputs, delay capability development, or even derail development efforts entirely. Hence, AI-specific best practice documents should list key organization roles with a short description of what the organization could ask each person performing the function, with a recommendation to ask them to read a short description of AI. Even with a short paragraph explaining what the specific technology can do for the organization, behavioral technology has an important additional filtering role: It prevents stakeholders from asking for unreasonable system objectives; it reduces the risk of negative property effects and delays; and it shortens initial capabilities.

Aside from this guidance on key roles, capabilities, and initial interactions, almost all of this "people" advice is also appropriate for adopting any advanced data-centric technology. There is basic agreement that it is ultimately business people who best understand organizational data and processes. They are the ones who best know where data is, how to clean it, what new data product or business process innovations would add the most value to the organization, and how to best implement them to achieve maximum return on investment.

10.2. Building Stakeholder Engagement

Stakeholder engagement is a key element of developing and implementing AI policies and developments more broadly. It not only ensures that the needs of AI system users are taken into account, but also that the outlined principles, norms, and standards are feasible in implementation. Given the complexities of AI applications and the potential for emergent harmful and unintended consequences that may arise, a collaborative, multilayered, and interdisciplinary approach between various stakeholders and communities will ensure that the potential synergies can be best captured while minimizing counterproductive dynamics.

Essentially, there exist two levels of stakeholder engagement. The first is a community-based engagement in which policymakers proactively utilize input from different communities with real-world experience of, or expertise in, these changing dynamics in particular use cases. Policymakers should have a structured framework to ensure this can be achieved. First, policymakers should conduct a thorough assessment of potential communities with key ecosystem knowledge that span a range of diverse characteristics and expertise applicable to the use case of interest. For example, should AI-enhanced data analytics be used by revenue bodies, community-based organizations representing immigrant workers could assist in understanding the potential challenges of using data heuristics that are risk-enhancing or that profile particular populations. The importance of this diverse representation in ensuring equity and diversity as a foundation of AI systems implemented should be substantiated with appropriate mechanisms if needed. A second activity would be to identify how this expertise would be best harnessed. Such mechanisms might include advisory panels, community consultations, or workshops that provide real value to stakeholders involved. Third, ensuring that stakeholder engagement is appropriate to the phase of policymaking is essential. If community input is requested too prematurely, it can result in disengagement and mistrust.

XI. CONCLUSION

Before concluding our work, we present three summary points related to the main aim of this paper, the need for decision-making support, and the analytical and methodological emphasis. First, we argue that the analyses here recommend that support from AI will probably become necessary for strategic decision-making in tax administration and policy design. This is not an original claim; multiple scholars have extended it to other areas of the public sector. However, in our case, it is particularly crucial, as tax administrations and public investments support the funding of the public policies that a country implements for decision-making and their financing aim is the allocation of resources in economy.

Second, we can affirm that the chances for success, in terms of positive impact, sustainability and desirability, of the 13 options for transforming and innovating the tax administrations and tax policy design in using AI as the main instrument are conditioned by the decision-making support models of the administrative agencies that design and implement them and that guide their actual decision-making.

Having stated this, we must clarify that we do not aim for an exhaustive analysis of AI as a tool for decision-making support, since this is not the scope of our work, nor do we follow a deterministic discourse regarding its usages and effects evaluate. Our main objective and idea in this work is to encourage inspiring discussions, evaluations and reflections among academia and the public sector, thereby contributing to further the understanding of a crucial element of public administration in the Fourth Industrial Revolution era. Third, regarding the tools and specific usage of models, we provide a general step-by-step path that could be followed in developing model-based AI recommendations for supporting strategic decision-making processes.

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