

Artificial Intelligence and Algorithms in Tax Auditing by the Tax Administration Service in Mexico: Analysis of Potential Biases

Pedro David Nieto Olvera¹

¹Instituto Politécnico Nacional, México

Corresponding Author:

Pedro David Nieto Olvera

Instituto Politécnico Nacional, México

E-mail: dr.nietodavid@protonmail.com

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ABSTRACT:

This article analyses the increasing implementation of Artificial Intelligence and algorithms by Mexico's Tax Administration Service (SAT) to optimize its auditing processes. While these technologies, driven by the analysis of large data volumes such as Online Digital Invoices (CFDI), promise greater efficiency and capacity to detect tax evasion, they also introduce significant risks. The main challenge is the potential for algorithmic bias, which could lead to systematic discrimination against certain groups of taxpayers, exacerbated by the lack of transparency in the operation of these systems. This situation threatens fiscal equity and violates fundamental rights such as non-discrimination, due process, and privacy, enshrined in the Mexican legal framework.

KEYWORDS: SAT, Artificial Intelligence, Tax Auditing, Algorithmic Bias, Taxpayer Rights

1. INTRODUCTION

1.1 GLOBAL CONTEXT: THE DIGITAL TRANSFORMATION OF TAX ADMINISTRATIONS

Tax administrations (TAs) worldwide are undergoing a profound transformation driven by digitalization and the adoption of advanced technologies such as Artificial Intelligence (AI). This global trend responds to the need to improve operational efficiency, optimize the detection of tax fraud, and increase revenue in an increasingly digitalized economic environment. The Organization for Economic Co-operation and Development (OECD) has articulated this vision under the concept of "Tax Administration 3.0," a model where taxation is seamlessly integrated into everyday economic transactions, aspiring to a scenario where tax compliance "just happens" with minimal friction for the taxpayer. The adoption of AI goes beyond the simple digitalization of paper-based processes; it involves redesigning workflows, integrating advanced analytical capabilities to achieve almost default compliance. The drivers of this evolution include the general digitalization of the economy, continuous technological advancements, and disruptive events such as the COVID-19 pandemic, which forced TAs to adapt quickly and assume new roles.

The use of AI in TAs is diverse and growing. According to OECD data, a significant proportion of administrations already use AI, mainly for fiscal risk assessment (69.4%) and the detection of evasion and fraud (75.5%), although it is also used to assist officials in administrative decision-making (49.0%) and, to a lesser extent, for making final decisions (6.1%) or dispute resolution (6.1%). Virtual assistants and chatbots are also common tools (53.1%) to improve taxpayer service. The emergence of Generative AI (GenAI) opens new frontiers, allowing more natural

interactions with taxpayers, assistance in interpreting complex regulations, and analysis of unstructured information, potentially redefining the relationship between the state and its citizens.

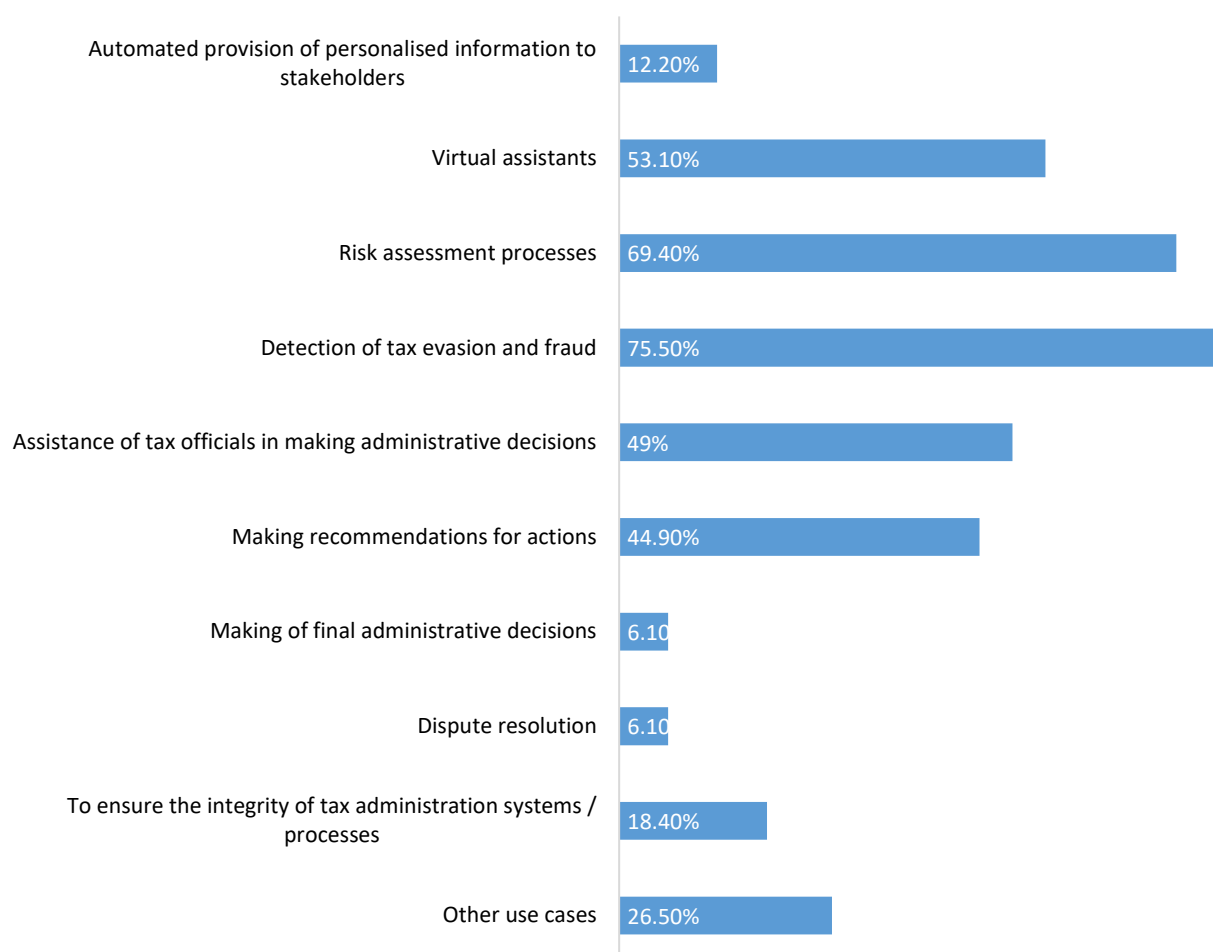


Figure 1. Use of AI by tax administrations

The expected benefits of this digital transformation are considerable. The aim is to significantly reduce administrative burdens and compliance costs for taxpayers, increase fiscal certainty, decrease errors in declarations, and more effectively combat tax evasion. The OECD has even estimated that digital transformation has the potential to generate substantial additional revenue for governments. International organizations such as the OECD itself, the International Monetary Fund (IMF), and the Inter-American Development Bank (IDB) in conjunction with the Inter-American Centre of Tax Administrations (CIAT) play a crucial role, investigating these trends, promoting good practices, facilitating international collaboration, and providing comparative data and reference frameworks such as the Inventory of Tax Technology Initiatives (ITTI) or digital maturity models.

1.2 LATIN AMERICAN AND MEXICAN CONTEXT

Latin America has not been immune to this wave of modernization. Countries such as Chile, Brazil, and Mexico have been pioneers in the region in implementing advanced digital tools for tax management. A central and enabling element of this transformation in Mexico has been the early and massive adoption of the Digital Tax Receipt via Internet (CFDI). The CFDI, whose most recent version is 4.0, seeks to incorporate more detailed data to strengthen fiscal control, generating a large volume of transactional information in real time. This accumulation of structured

data has become the cornerstone upon which the Tax Administration Service (SAT) has built its Big Data analysis capabilities and, more recently, Artificial Intelligence (AI).

The SAT has made significant investments in technological infrastructure and is considered one of the institutions with the largest volume of information in the country. Its commitment to technological modernization included in its 2025 Master Plan confirms the incorporation of AI as a strategic tool. Specifically, the use of graph analytics and machine learning models is mentioned "in order to optimize auditing processes, improve collection, and strengthen taxpayer service." These actions are part of the SAT's institutional "ABCD" strategy: Augment collection efficiency, bring down tax evasion and avoidance, Combat corruption, and deliver the best taxpayer service.

1.3 CENTRAL APPROACH: EFFICIENCY VS. EQUITY AND RIGHTS

The adoption of AI by the SAT, while aligning with global trends and promising benefits in efficiency and collection capacity, introduces a series of ethical and legal risks. The central promise of AI in auditing is optimization: processing massive volumes of data to identify complex evasion patterns, selecting high-risk taxpayers with greater precision, and ultimately, increasing collection without the need to create new taxes or raise existing rates. However, algorithms are not intrinsically neutral. They can reflect, perpetuate, and even amplify biases present in the data with which they are trained or in the design decisions made by their creators. This inherent risk of algorithmic bias generates deep concerns about equity, justice, and potential discrimination in the SAT's actions. Could algorithms disproportionately select certain groups of taxpayers for audit based on irrelevant or biased factors? Could automated risk assessments systematically harm certain sectors or regions?

The problem is exacerbated by the opacity that often characterizes these algorithmic systems, especially those based on complex machine learning. The difficulty in understanding how an algorithm reaches a certain conclusion (the phenomenon known as the "black box") hinders the ability to detect and correct possible biases, limits the possibility for taxpayers to exercise an effective defence, and complicates the supervision and accountability of the authority. Although the SAT has stated that AI is mainly used in the planning phase and that human review exists, the lack of detailed transparency about the specific models and their operation prevents an independent and rigorous evaluation of these risks.

The relevance of this article lies in exploring this fundamental tension between the pursuit of administrative efficiency through AI and the safeguarding of human rights. The implications of uncontrolled or biased use of AI in auditing directly affect rights such as privacy, due process, legality, and non-discrimination, as well as general trust in the tax system. The technological modernization of the SAT, although necessary and inevitable, must be carried out ensuring that these new tools are implemented in a responsible, ethical, and equitable manner.

1.4 RESEARCH QUESTIONS AND OBJECTIVES

This document seeks to answer the central question: How does (or could) the SAT use artificial intelligence and algorithms in its auditing processes, and what are the potential biases inherent in these systems and their possible consequences for taxpayers in Mexico? To this end, the general objective is to analyse the use of AI and algorithms in SAT's auditing, identifying the risks of algorithmic bias and evaluating its ethical, legal, and social implications. Specific objectives include: mapping the areas of AI application in the SAT; identifying the data sources and probable types of algorithms, analysing their potential biases; evaluating the differential impact of such biases on different taxpayer segments and on fiscal equity; examining the capacity of the Mexican regulatory framework to address these challenges; analysing the necessary transparency and accountability mechanisms; and proposing considerations for ethical and equitable implementation.

2. THE ALGORITHMIC LANDSCAPE IN SAT'S AUDITING

2.1 KEY AREAS OF POTENTIAL/ACTUAL AI APPLICATION IN AUDITING

The implementation of AI and algorithmic tools by the SAT covers, or has the potential to cover, various critical areas of the auditing function. Based on official statements, observed practices, and international trends, the following key applications can be identified:

1. **Taxpayer Selection for Audits and Reviews:** The SAT uses, or plans to use, AI-based predictive models to identify taxpayers who present a higher probability of non-compliance, evasion, or tax avoidance. These

models analyse historical data, behavioural patterns, CFDI information, and other sources to generate risk profiles and prioritize auditing actions. The Master Plan explicitly confirms the "classification of taxpayers by risk" using these technologies.

2. **Fiscal Risk Assessment:** Closely linked to the previous point, AI allows for the development of more sophisticated risk scoring systems. These systems can assign a risk level to individual taxpayers, economic sectors, types of operations, or even specific transactions, based on the multidimensional data analysis performed by algorithms.
3. **Detection of Inconsistencies and Fraud:** The ability of AI to process and analyse massive volumes of data (Big Data) is fundamental for detecting anomalies, discrepancies, and indications of fraud. This includes the automated cross-referencing of information between issued and received CFDIs, tax declarations (ISR, IVA, DIOT), third-party information, and potentially bank data. A particular focus is on identifying networks of Companies that Invoice Simulated Operations (EFOS) and complex evasion schemes, where graph analytics is especially useful, as well as detecting inconsistencies associated with crimes such as smuggling.
4. **Deep Surveillance:** This term refers to a specific type of procedure implemented by the SAT, which, although not formally initiating verification powers (such as an audit), uses technological tools and Big Data analysis to conduct automated reviews. These surveillances compare information from various sources (CFDI, declarations, bank data, third-party information, even GPS location of the tax domicile) to detect possible omissions or inconsistencies. Subsequently, an invitation letter is issued through the Tax Mailbox, urging the taxpayer to clarify their situation or self-correct. This process, described as systematic and scalable, relies heavily on algorithmic capacity to process and cross-reference massive information.
5. **Pre-filled Declarations:** With the aim of facilitating compliance and reducing errors, the SAT uses algorithms to pre-fill certain fields in tax declarations, for example, the annual declaration for individuals. This functionality is based on information previously available to the authority, primarily CFDIs and historical taxpayer data.
6. **Taxpayer Service:** Following international trends, the SAT could implement or improve the use of AI-based virtual assistants (chatbots) to answer frequent queries, guide taxpayers through procedures, and offer basic assistance, freeing up human resources for more complex tasks.

2.2 PROBABLE ALGORITHMIC TOOLS: BEYOND OFFICIAL ANNOUNCEMENTS

While the SAT has confirmed the use of certain technologies, an analysis of its capabilities and international practices suggests a broader range of algorithmic tools potentially in use:

1. **Machine Learning (ML):** Explicitly confirmed in the Master Plan. This is the underlying technology for many of the applications mentioned: risk classification, CFDI anomaly detection, evasion pattern identification. Presumably, both supervised learning techniques (trained with historical examples of compliance and non-compliance) and unsupervised learning techniques (to discover hidden or atypical patterns in the data) are used.
2. **Graph Analytics:** Also officially confirmed and highlighted by experts. This technique is essential for visualizing and analysing complex relationships between entities, such as transaction networks between taxpayers (CFDI issuers and receivers). It is particularly relevant for identifying suspicious structures, such as EFOS networks, or for tracking complex financial flows.
3. **Predictive and Classification Models:** These are the mathematical basis for risk assessment and audit selection. These models, likely built using Machine Learning techniques, assign probabilities, e.g., probability of tax avoidance, or classify taxpayers into discrete categories, e.g., low, medium, high risk.
4. **Data Mining:** Although sometimes used as a generic term, it refers to specific techniques for extracting knowledge and patterns from large databases. The SAT already employed these techniques before the formal adoption of the AI label and they likely continue to be part of its analytical toolkit.
5. **Natural Language Processing (NLP):** Although less confirmed, it is a relevant AI technology for analysing unstructured text. It could be used in the development of virtual assistants or, potentially, to analyse the content of descriptive fields in CFDIs in search of inconsistencies or red flags, e.g., the codes used for products or services.

6. **Internal Development:** A relevant aspect is the SAT's affirmation that its AI models (graphs and ML) have been developed by internal teams, without resorting to external providers. This could have implications in terms of control, internal knowledge, and, potentially, in the transparency policy regarding such systems.

2.3 PRIMARY DATA SOURCES AND THEIR POTENTIAL FOR BIAS

The effectiveness and fairness of the SAT's algorithms critically depend on the quality and nature of the data that feeds them. The main identified sources, along with their potential biases, are:

1. **CFDI (Digital Tax Receipt via Internet):** This is the most voluminous and central data source for the SAT's digital auditing. It provides specific data on practically all transactions.
Potential for Bias: The quality of CFDI data is not perfect; errors in issuance by taxpayers are common and can introduce false data or alerts. Regulatory changes (such as the transition to CFDI 4.0) can generate temporary inconsistencies or affect historical comparability. More structurally, the CFDI universe primarily represents the formal economy; its intensive use could lead to an underrepresentation or inadequate modelling of sectors with high informality or with economic operations not easily capturable in this format.
2. **Tax Declarations (Annual, Provisional, Informative - DIOT):** These constitute the basis for verifying compliance and are a key source for cross-referencing information with CFDIs.
Potential for Bias: As self-declared information, its veracity and accuracy can vary. Taxpayers with less fiscal literacy or access to advice may make more involuntary errors. Historical declaration data may reflect past compliance (or non-compliance) patterns that do not necessarily predict the future equitably.
3. **Bank Information:** Used for cross-referencing information in audits, it allows comparing cash flows with declared and invoiced income.
Potential for Bias: Its use raises important privacy dilemmas and requires a solid legal basis. Patterns of banking service use vary among individuals, business types (SMEs vs. large corporations), and sectors (formal vs. informal). An algorithm that does not adequately weigh these differences could generate biased conclusions about fiscal risk based solely on bank movements.
4. **Third-Party Data:** Information from clients, suppliers, social security institutions (IMSS, INFONAVIT), public registries, customs authorities, etc.
Potential for Bias: The quality, timeliness, and completeness of this data can be heterogeneous. Errors or delays in information provided by third parties can generate apparent discrepancies that harm the audited taxpayer. Dependence on external data introduces uncertainty into algorithmic analysis.
5. **Other Potential Sources:** Although not explicitly confirmed for the SAT, international practices suggest the possible future or current use of social media data (to verify lifestyles), data from technology platforms, and e-commerce.
Potential for Bias: These sources are particularly sensitive in terms of privacy. Their use can overrepresent certain demographic or consumption profiles, introducing significant biases if not handled with extreme care.

2.4 CONSIDERATIONS ON THE SAT'S ALGORITHMIC ECOSYSTEM

The analysis of the SAT's algorithmic landscape reveals complex dynamics. On the one hand, there is official communication that, while confirming the use of advanced technologies such as machine learning and graph analytics applied to CFDIs, could be simplifying the operational reality. Procedures such as "deep surveillances," as described by specialists, suggest the integration and cross-referencing of a much broader spectrum of data, including bank information, third-party data, and even geolocation. This possible discrepancy between official discourse and inferred practice creates a zone of opacity. If the SAT effectively cross-references data sources beyond CFDI routinely and automatically, the evaluation of associated risks, especially in terms of privacy and potential bias introduced by these additional sources, is hindered by the lack of detailed and transparent information from the authority. The assertion that models are developed internally could, paradoxically, serve to justify a lesser need for external scrutiny, deepening this opacity.

On the other hand, the undeniable strength of the system lies in the massive nature and granularity of CFDI data. This information source is the pillar upon which much of the SAT's digital auditing and AI capability is built. However, this strong dependence turns CFDI into a kind of "double-edged sword". Any inherent limitation of the CFDI system itself, whether frequent errors in issuance by taxpayers, the difficulty in capturing the complexity of certain operations, or its limited representativeness of the informal economy, becomes a critical factor. AI algorithms that predominantly feed on this data will inevitably inherit and potentially magnify any bias, error, or structural limitation present in them, directly affecting the equity and accuracy of algorithmic auditing results. The quality and representativeness of CFDI are not just technical issues, but central elements that condition the fairness of the SAT's tax AI system.

3. ALGORITHMIC BIAS IN TAX AUDITING

Algorithmic bias is defined as the tendency of Artificial Intelligence systems to produce results that systematically and unfairly discriminate against certain individuals or groups. In the field of tax administration, this phenomenon translates into the risk that algorithmic tools employed by authorities such as the SAT generate differential and unjustified treatment towards certain taxpayers. This differentiation would not be based on an objective and verifiable fiscal risk, but on protected characteristics (such as gender, ethnic origin, etc.) or correlated variables (proxies) that the algorithm uses inappropriately or disproportionately. The causes of this bias are multifactorial and can originate at different stages of the AI system's lifecycle. Applied to the SAT context, the main sources of bias include:

1. **Data Bias:** This is perhaps the most common and critical source. The data used to train the SAT's algorithms—such as previous audit histories, CFDI information, tax declarations—may not be representative of the entire universe of taxpayers. They may reflect pre-existing social inequalities or biases inherent in past auditing practices. For example, if historically certain sectors or types of taxpayers were audited more frequently (perhaps due to operational ease or auditor prejudices), algorithms trained with that data could learn to associate those groups with higher risk, perpetuating the cycle. Incomplete, inaccurate, or erroneous data (such as those possible in CFDI issuance) also introduce significant biases that affect the quality of predictions.
2. **Model/Algorithmic Bias (Algorithmic Bias/Technical Bias):** The algorithm's design itself can be a source of bias. This can occur due to programming errors, the selection of inadequate predictive variables, the assignment of incorrect weights to certain factors, or an excessive simplification of the complex fiscal reality that the model attempts to capture. A particular risk is that the algorithm identifies statistical correlations in the data and misinterprets them as causal relationships, leading to biased conclusions. The technical decision on how to formulate the problem (for example, treating the risk of underreporting as a binary classification or regression problem) can have important consequences for the fairness of the results.
3. **Historical/Pre-existing Bias (Pre-existing Bias):** Algorithms, by learning from historical data, can encode and reproduce social, economic, or structural inequalities that already exist in society. If certain socioeconomic groups have historically had less access to quality tax advice, their declaration patterns might differ from those of more privileged groups. An algorithm could interpret these differences (derived from structural inequality) as an indicator of higher fiscal risk, indirectly penalizing already disadvantaged groups.
4. **Interaction/Feedback Loop Bias (Interaction / Feedback Loop Bias):** This type of bias arises when the algorithmic system's own actions influence the future data that will be used to retrain it. If an algorithm selects a specific group for a more intensive audit, the results of those audits (whether finding evasion or not) will feed back into the system in the future, potentially reinforcing the algorithm's initial decision, whether correct or biased. This can create feedback loops that amplify initial biases over time.
5. **Evaluation/Interpretation Bias (Evaluation Bias):** Even if the algorithm itself is technically neutral, the way its results or recommendations are interpreted and used by SAT officials can introduce biases. The conscious or unconscious prejudices of officials can influence how they value the information provided by the system. There is a risk of "automation bias," where humans tend to over-rely on machine recommendations, even if they are erroneous or biased, especially if the algorithm's internal workings are not understood.

Latent biases in SAT data and algorithms could manifest in various concrete ways, negatively affecting taxpayers:

1. **Discriminatory Selection for Audits/Reviews:** The most obvious risk is that algorithms disproportionately direct auditing actions (home visits, desk reviews, electronic reviews) towards certain groups. This could affect SMEs, independent workers, specific economic sectors, or residents of certain geographical regions, not necessarily because they have a higher actual risk of evasion, but because the algorithms have learned biased patterns from historical data or use inadequate proxies.
2. **Unfair Risk Assessments:** Taxpayers could receive a high fiscal risk rating (with the consequences that this entails, such as increased scrutiny or difficulty in obtaining refunds) due to factors that are correlated with their demographic or socioeconomic profile, but which are not direct indicators of non-compliance.
3. **Systematic Errors in Pre-filled Declarations:** If the algorithms that generate pre-filled declarations do not adequately capture the complexity of certain tax regimes or types of deductions (perhaps by excessively relying on simplified CFDI information), they could systematically mislead certain groups of taxpayers, who would then have to invest more time and effort in correcting the information proposed by the authority. For example: accumulated gain from the sale of fixed assets.
4. **False Positives in Fraud/EFOS Detection:** The erroneous identification of legitimate taxpayers or transactions as fraudulent or linked to EFOS networks is an inherent risk in network analysis and anomaly detection. If graph analytics algorithms are based on superficial patterns or spurious correlations, they could incorrectly flag companies, severely affecting their reputation, operations (e.g., restricting invoicing, cancelling their digital seal certificate), and generating legal and administrative costs to refute the accusation.
5. **Differential Treatment in Deep Surveillances:** The automated and massive sending of "invitation letters" based on algorithmic criteria could concentrate on certain groups if these algorithms are biased. This would generate a burden of anxiety, time, and compliance costs (to respond and potentially correct) unevenly distributed among the taxpayer population.

The introduction of algorithms in SAT's auditing does not occur in a vacuum. These systems operate on data that reflect the complex socioeconomic reality of Mexico, marked by significant structural inequalities, such as high labour informality, deep regional gaps in development and access to services, and unequal access to financial, technological, and tax advisory services. There is a considerable risk that algorithmic bias will not simply be an isolated technical failure, but will act as a mirror and, worse still, as an amplifier of these pre-existing inequalities. Algorithms, by processing data that inevitably capture these disparities, could learn to correlate indicators of structural disadvantage (such as operating in certain sectors, having atypical banking patterns due to lack of access to formal credit, or committing formal errors due to lack of advice) with a supposed higher fiscal risk. If auditing is directed based on these algorithmic predictions, it could disproportionately concentrate on already vulnerable groups, not necessarily because they evade, but because their "digital footprints" differ from the norm modelled from more privileged or standardized segments. In this way, AI, under a cloak of objectivity and technological efficiency, would run the risk of solidifying and legitimizing differentiated tax treatment, perpetuating and even deepening socioeconomic gaps through the tax system itself.

Additionally, the very technical nature of the AI tools employed (particularly machine learning and graph analytics mentioned by the SAT) introduces a significant barrier to accountability. The inherent complexity and frequent opacity of these models (black boxes) make it extremely difficult, both for affected taxpayers and for non-specialized officials and auditors themselves, to understand the specific logic that led to a particular tax decision. This lack of clarity severely hinders the ability to detect whether a decision was the product of a legitimate risk analysis or an algorithmic bias. As a consequence, the taxpayer's right to defence is weakened, as it becomes almost impossible to effectively challenge a decision whose real basis remains hidden within the algorithm. Likewise, internal supervision and external auditing of these systems become much more arduous tasks. In essence, the technical complexity of AI can function, intentionally or not, as a shield against transparency, creating an informational imbalance that favours the authority and hinders the effective protection of taxpayer rights against possible arbitrary or discriminatory algorithmic actions.

4. DIFFERENTIAL IMPACTS ON TAXPAYERS AND FISCAL EQUITY

The implementation of AI-based auditing systems by the SAT does not affect all taxpayers equally. Certain groups, due to their structural characteristics, resources, or behavioural patterns, could be disproportionately affected by algorithmic biases or by the very logic of digital auditing:

1. **Small and Medium-sized Enterprises (SMEs) vs. Large Taxpayers:** SMEs often operate with narrower margins and have fewer resources to invest in cutting-edge technology, sophisticated accounting software, or specialized tax advice. This makes them potentially more prone to committing involuntary errors in CFDI issuance or in complying with other complex formal obligations. SAT algorithms, designed to detect inconsistencies, could flag these formal errors as risk indicators, leading to increased scrutiny of SMEs. While historically the SAT has maintained a significant focus on large taxpayers, the scalability and automation that AI allows could facilitate much more intensive and systematic surveillance of the universe of SMEs, whose data patterns might differ significantly from those of large corporations, being misinterpreted by models trained with aggregated data.
2. **Informal Sector vs. Formal Sector:** The informal economy in Mexico is extensive and largely operates outside formal tax registration systems such as CFDI. SAT algorithms, predominantly trained with data from the formal economy, would have intrinsic difficulties in modelling and evaluating fiscal risk in the informal sector. On the other hand, the intensification of digital auditing on the formal sector, perceived as more complex and riskier due to AI, could act as a disincentive for the formalization of economic units. Within the formal sector, salaried employees with simple income structures easily verifiable through electronic payroll could be consistently classified as low risk, concentrating algorithmic attention on other groups considered more "opaque" or complex.
3. **Independent Workers (Freelancers) vs. Salaried Employees:** Independent professionals, self-employed individuals, or freelancers often have more irregular and variable income and expense structures than salaried employees. Their invoicing (CFDI) and declaration patterns may be less standardized and more complex to analyse. Algorithms, especially if trained with data where more homogeneous patterns predominate (such as those of salaried employees or large companies), could interpret this variability or complexity as an indicator of greater fiscal risk, subjecting this group to potentially greater scrutiny.
4. **Specific Economic Sectors:** The SAT's 2025 Master Plan explicitly identifies a list of economic sectors that will be subject to priority attention in AI-supported auditing. These include automotive, alcoholic beverages and cigarettes, construction, pharmaceutical, hydrocarbons, logistics, technology platforms, real estate services, insurance and financial services, and transportation. While this focus may be justified by previous sectoral risk analyses, there is also the possibility that it reflects historical biases in auditing or simply the greater availability of structured and digital data in these sectors. This could lead to algorithmically concentrated tax pressure in these areas, regardless of whether the actual risk of evasion is uniformly higher in them compared to other non-prioritized sectors.
5. **Geographical Regions:** The economic and development disparities between different regions of Mexico are well known. These differences translate into variations in digitalization levels, internet access, banking penetration, productive structure, and tax culture. If SAT algorithms are not designed and calibrated to account for these regional heterogeneities, they could misinterpret local data patterns as anomalies or risks, resulting in geographically biased auditing that disproportionately affects taxpayers in certain areas of the country.

The potential differential impact of algorithmic auditing has profound implications for the fundamental principles of equity and justice that should govern the tax system:

1. **Horizontal Equity:** This principle demands that taxpayers in similar economic situations be treated the same way by the tax system. Algorithmic bias directly threatens this principle if it leads to individuals or businesses with a comparable level of actual tax risk receiving different treatment (for example, being selected for audit or not) because the algorithm relies on irrelevant characteristics or biased proxies.
2. **Vertical Equity:** This principle refers to the idea that those with greater economic capacity should contribute proportionally more to public spending. Algorithmic auditing could negatively affect vertical equity if, for example, it proves more effective at detecting non-compliance or formal errors in lower-

income taxpayers or SMEs (whose operations are perhaps more visible through CFDI and easier to process algorithmically), while more sophisticated tax avoidance strategies employed by large taxpayers or corporate groups are more difficult for current algorithms to model and detect. This could lead to a disproportionately higher effective tax burden on lower-income strata.

3. **Justice and Non-Discrimination:** The use of algorithms that incorporate biases can result in practices of indirect discrimination, even without an explicit intention to discriminate on the part of the tax authority. If the results of algorithmic auditing systematically harm groups defined as vulnerable by characteristics protected by the Constitution, the fundamental principle of non-discrimination and the justice inherent in the tax system would be violated.
4. **Trust in the Tax Authority:** The public perception that the algorithms used by the SAT are incomprehensible "black boxes," prone to errors, or that they operate unfairly or discriminatorily, can seriously undermine taxpayers' trust in the tax authority. Low trust in the impartiality and equity of tax administration can, in turn, erode tax morale and negatively affect voluntary compliance in the long term, creating a vicious circle.

The interaction between the SAT's advanced digital auditing capacity and Mexico's socioeconomic realities could generate worrying dynamics. On the one hand, there is the risk of "auditing the digitally vulnerable". The SAT's strong reliance on digital data such as CFDI, combined with the persistent digital divide in the country (in terms of access to technology, connectivity, digital skills, and availability of specialized advice), could lead to algorithms concentrating their scrutiny on taxpayers who, although part of the formal system, face greater difficulties in flawlessly complying with the growing complexities of the digital environment. SMEs, independent workers, or businesses in less developed regions could be flagged more frequently for formal errors or inconsistencies easily detected by algorithms, while more sophisticated forms of evasion (which perhaps do not leave such an obvious digital trace) or total informality (characterized by the absence of digital data) could remain relatively outside the reach of these same algorithms. This could result in disproportionate tax pressure on those who are within the system but lack the resources to navigate it impeccably, affecting the distributive equity of the tax burden.

On the other hand, the very effectiveness and rigor of AI-powered auditing, if not accompanied by adequate support mechanisms, simplification, and guarantees against errors or perceptions of arbitrariness, could generate a counterproductive effect on efforts to broaden the tax base. If the experience of interacting with digital auditing is perceived as excessively burdensome, complex, unpredictable, or punitive, the perceived cost of operating formally could increase significantly. This could deter informal economic units from moving towards formalization, or even lead small formal businesses to consider informality as a less risky alternative to avoid intense algorithmic scrutiny. In this way, algorithmic auditing perceived as inflexible or unfair could, paradoxically, hinder the objective of strengthening economic formality in Mexico.

5. MEXICAN LEGAL FRAMEWORK FOR ALGORITHMIC AUDITING

The SAT's actions, including the use of AI and algorithms in auditing, must strictly adhere to the Mexican legal framework. The main relevant regulations are:

5.1 POLITICAL CONSTITUTION OF THE UNITED MEXICAN STATES (CPEUM)

1. **Article 1:** Establishes the principle of non-discrimination for any reason (ethnic origin, gender, social status, etc.) and the obligation of all authorities to promote, respect, protect, and guarantee human rights. This article is the main foundation for questioning algorithmic biases that result in discriminatory treatment.
2. **Article 16:** Enshrines key fundamental rights in the tax-taxpayer relationship: the right to legality (no one can be disturbed except by written order of a competent authority), the right to legal certainty (the act of disturbance must be founded and motivated), the inviolability of the domicile (applicable to home visits), and the right to the protection of personal data. The requirement of foundation and motivation becomes particularly complex to satisfy when decisions are based on opaque algorithms.

5.2 FEDERAL TAX CODE (CFF)

Governs the federal tax relationship. It contains crucial provisions such as:

1. **Verification Powers (Art. 42):** Lists the powers of the tax authority to verify compliance, including desk reviews, home visits, and, relevant to this analysis, "electronic review" (fraction IX), based on the analysis of information held by the authority.
2. **Electronic Review Procedure (Art. 53-B):** Details the stages of this specific procedure, including notification via the Tax Mailbox, provisional resolution, the period for the taxpayer to provide evidence or correct their situation, and the issuance of the final resolution.

5.3 DIGITAL FORMAL OBLIGATIONS

Establishes key obligations that generate data for algorithmic auditing, such as keeping electronic accounting (Art. 28) and issuing CFDIs (Art. 29, 29-A).

1. **Tax Mailbox (Art. 17-K):** Establishes it as a mandatory electronic communication medium between the authority and the taxpayer.
2. **Legal Presumptions:** Contains presumptions that the authority can apply, such as the non-existence of operations covered by CFDIs issued by EFOS (Art. 69-B).

5.4 FEDERAL LAW OF TAXPAYER RIGHTS (LFDGP)

This law seeks to balance the tax-taxpayer relationship, presenting specific rights:

1. **General Rights (Art. 2):** Include the right to be informed and assisted, to obtain refunds, to know the status of their procedures, to know the identity of the responsible authority, not to provide documents already held by the acting authority, to be treated with respect, to self-correction, to choose a domicile for notifications (although relativized by the Tax Mailbox), and to the confidentiality of their tax data.
2. **Right to the Least Burdensome Action (Art. 2. IX):** Establishes that tax actions must be carried out in the least burdensome way for the taxpayer. These right gains relevance in the face of the burden that digital compliance and responding to automated requirements can represent.
3. **Rights in Verification Procedures (Arts. 12-17):** Details specific guarantees during audits, such as being informed at the outset, the right to correct the tax situation, the right to have the visit concluded if copies of accounting are provided, and the right to formulate pleas and present evidence. The Charter of Taxpayer Rights Under Audit, issued by the SAT, seeks to materialize these rights in practice.

The application of AI and algorithms in SAT's auditing, especially if carried out with biases or a lack of transparency, can violate various fundamental taxpayer rights:

1. **Due Process and Right to Be Heard:** While the Supreme Court of Justice of the Nation (SCJN) has considered the 15-day period for responding in electronic reviews (Art. 53-B CFF) to be constitutionally reasonable, the effectiveness of this right can be compromised if the basis of the tax imputation is an opaque algorithm. An adequate defence requires not only presenting documents but also understanding the logic of the accusation to be able to refute it. If the "how" an algorithm reached a conclusion is not transparent, the taxpayer is at a disadvantage to fully exercise their right to be heard and to offer relevant evidence. Notification via the Tax Mailbox, although validated by the SCJN, also presupposes constant access and monitoring by the taxpayer, which may not be universal.
2. **Legality and Legal Certainty (Foundation and Motivation):** Constitutional Article 16 requires that every act of disturbance be duly found (legal basis) and motivated (specific reasons for the case). Satisfying this requirement becomes a major challenge when the decision originates from a complex algorithmic model whose internal logic is not easily translatable into traditional legal argumentation. Is it enough to cite the algorithm's result as motivation? Or must the authority explain how the algorithm works and why it applied to the specific case? The lack of clear regulations on how AI-based acts should be founded and motivation generates legal uncertainty.
3. **Non-Discrimination:** This is the central risk associated with algorithmic bias. If SAT systems treat taxpayers in similar situations unequally based on illegitimate criteria (biased proxies, non-representative historical data), the prohibition of discrimination under Constitutional Article 1 would be directly violated.

4. **Privacy and Personal Data Protection:** Algorithmic auditing involves the massive and automated processing of large volumes of personal and fiscal data (CFDI, declarations, bank information, third-party data). This intensifies privacy risks, protected by Constitutional Article 16. Strict compliance with data protection principles is required: legitimate purpose, proportionality, limitation of retention period, information security, and transparency regarding processing. The National Institute for Transparency, Access to Information and Personal Data Protection (INAI) issued general recommendations on data processing in AI environments, but its specific application to the fiscal sphere requires attention.
5. **Inviolability of Domicile:** The SCJN has determined that electronic review, by not involving physical intrusion, does not violate this right. However, if the selection of taxpayers for a traditional home visit is based on algorithmic criteria, the corresponding visit order must continue to rigorously comply with the foundation and motivation requirements of Constitutional Article 16.
6. **Right to Information and Assistance (LFDCP):** The taxpayer's right to be informed about the content and scope of their obligations and fiscal procedures (Art. 2.I LFDCP) is undermined if the authority's action is based on algorithmic logic that neither the taxpayer nor, potentially, the official assisting them can fully understand.
7. **Right Not to Provide Already Existing Documents (LFDCP):** In theory, AI and massive data access should facilitate the fulfilment of this right (Art. 2.VI LFDCP). However, if systems are not perfectly integrated or algorithms generate automated requests without previously verifying all available information, redundant documents could still be requested, contradicting this right and the principle of least burdensome action.

5.5 CONSIDERATIONS ON THE LEGAL FRAMEWORK AND FISCAL AI

The analysis of the Mexican legal framework regarding SAT's algorithmic auditing suggests two main considerations. First, there is a significant regulatory gap. Current tax laws, although containing formal guarantees designed for a traditional or early digital auditing environment, do not explicitly address the unique challenges posed by advanced Artificial Intelligence. Concepts such as algorithmic opacity, the potential for automated discriminatory bias, and decision-making based on complex probabilistic analyses do not find specific regulation in the current framework. Existing jurisprudence, while validating the legality of electronic procedures in form, has not yet penetrated the "algorithmic black box" to evaluate whether the substance of AI-based decisions complies with constitutional requirements of foundation, motivation, and non-discrimination. This regulatory void regarding algorithmic transparency requirements, bias auditing, or specific explanation mechanisms for tax AI creates a grey area that can leave taxpayers unprotected.

Second, there is a perceived tension between the pursuit of administrative efficiency and the safeguarding of taxpayer guarantees. The SCJN's decisions on electronic reviews, by validating short response deadlines and electronic notification as the main means, seem to prioritize the agility and collection capacity of the State in the digital era. However, this prioritization could be weakening, in practice, the effectiveness of fundamental procedural guarantees such as the right to a hearing and adequate defence. When the act of disturbance originates from a complex and opaque algorithmic analysis, the taxpayer requires time and resources not only to gather documentation but potentially to understand the underlying logic and build a substantive defence, something that a short deadline could prevent. The balance seems to lean towards fiscal efficiency, which, in the face of algorithmic opacity, could be implicitly eroding the taxpayer's real capacity to defend themselves against the authority.

6. TOWARDS TRANSPARENT, EXPLAINABLE, AND RESPONSIBLE AUDITING

Despite the growing relevance of AI in its processes, the SAT maintains a considerable level of opacity regarding the technical and operational details of its algorithmic systems. While the Master Plan mentions the use of graph analytics and machine learning, this information is generic and does not allow for understanding how these systems actually function. To public knowledge, there is no detailed information on:

- The specific algorithms implemented.
- The exact variables considered by the risk models.
- The precise data sources used for training and operating each algorithm.
- The performance, accuracy, and, crucially, fairness metrics of these systems.

- The internal procedures for validating, auditing, and updating the algorithms.

The SAT's official communication tends to focus on macro-objectives (increasing collection, combating evasion) and the expected benefits of technology, without delving into the internal mechanisms. The assertion that development is internal could even be used as an argument to limit the disclosure of technical details considered strategic or confidential. Furthermore, no specific public or internal guidelines issued by the SAT are known that establish clear rules on ethical development, responsible implementation, periodic auditing, and the transparency required of its own tax AI systems.

In this context, the role of Transparency for the People as the guaranteeing body for transparency and personal data protection is fundamental. INAI showed interest in the issue, promoting the need for "algorithmic transparency" and the "right to explanation" and issuing general recommendations on the processing of personal data in the context of AI and on the use of biometric data.

6.1 EXPLAINABLE ARTIFICIAL INTELLIGENCE (XAI) IN THE TAX CONTEXT

Given the inherent opacity of many complex AI models (such as deep neural networks or ensembles of decision trees, which could be behind the SAT's "machine learning") and the high impact of tax decisions on taxpayer rights, the adoption of principles and techniques of Explainable Artificial Intelligence (XAI) becomes indispensable. The fundamental objective of XAI in the tax field is to overcome the algorithmic "black box," allowing different stakeholders (taxpayers, their legal representatives, SAT officials, internal and external auditors, administrative review bodies such as PRODECON, and judges) to understand, at least at a functional level, why an AI system made a particular decision. This understanding is crucial for:

1. **Verifying legality:** Evaluating whether the algorithmic decision conforms to applicable tax regulations and respects legal principles.
2. **Justifying reliability:** Demonstrating that the algorithm's result is not arbitrary or erroneous.
3. **Detecting and refining biases:** Identifying whether illegitimate factors or biases in the data influenced the decision, allowing the model to be corrected.
4. **Guaranteeing the right to defence:** Providing the taxpayer with the necessary information to effectively challenge a decision they consider unfair.
5. **Complying with the right to an explanation:** Satisfying the legal requirement (implicit in due process and the right to information) for the authority to explain the reasons for its actions (the authority's duty to motivate).

Various XAI techniques can be applied, depending on the type of model and the level of explanation required. Some of the best known include SHAP (Shapley Additive explanations) and LIME (Local Interpretable Model-agnostic Explanations), which seek to determine the contribution of each input variable to a specific prediction for a particular case. Other techniques analyse the global importance of variables or the partial dependence of the result on certain factors. Even the use of Large Language Models (LLMs) is being explored to translate the technical outputs of AI models into more understandable narrative explanations for non-experts.

However, the implementation of XAI is not without its challenges. There can be a trade-off between a model's explanatory capacity and its maximum predictive accuracy. Additionally, the generated explanations must be adapted to the audience: an explanation useful for a data scientist may be incomprehensible to a taxpayer or a judge. The key is to design XAI solutions that provide the legally relevant information to evaluate the conformity of the decision with the regulatory framework and taxpayer rights.

6.2 NECESSARY MECHANISMS FOR ACCOUNTABILITY AND SUPERVISION

To ensure that the SAT's use of AI is responsible and does not violate rights, it is essential to implement a robust system of accountability and supervision. This requires a combination of internal and external measures:

1. **Robust Internal Controls:** The SAT must develop and integrate specific internal controls for the lifecycle of its AI systems into its operational processes. This includes rigorous procedures for validating the quality and representativeness of input data, systematic testing to detect and mitigate biases before and during

deployment, continuous monitoring of the performance and fairness of algorithms in production, and controlled change management mechanisms.

2. **Algorithmic Auditing:** It is fundamental to establish periodic and independent audit programs (conducted by specialized internal units and/or by qualified external auditors) to comprehensively evaluate the SAT's AI systems. These audits must go beyond simple verification of technical accuracy and cover aspects such as security, regulatory compliance (privacy, non-discrimination), fairness of results, robustness against manipulation, and the adequacy of governance processes. Given the complexity of the issue, these audit teams must be multidisciplinary, including experts in technology, law, ethics, and the fiscal domain.
3. **AI Governance Frameworks:** The SAT should formally adopt an ethical and governance framework for AI, which could be based on internationally recognized principles (such as those of the OECD) or national guidelines. This framework must establish clear principles (justice, transparency, explainability, accountability, human oversight) and translate them into concrete and enforceable operational policies and procedures.
4. **Significant Human Oversight:** Although automation is a goal, decisions with a high impact on taxpayer rights or economic situations should not be completely automated. There must be a control point where a trained human official reviews and validates the algorithmic recommendation. This oversight must be significant, meaning informed, critical, and with real capacity to modify or reject the system's decision, not just a formal ratification.
5. **Effective Complaint and Appeal Mechanisms:** Existing mechanisms must be strengthened and adapted so that taxpayers can challenge decisions they suspect are based on erroneous or biased algorithms. This implies guaranteeing access to sufficient explanations (derived from XAI) to support their claim and ensuring that review bodies (administrative ones like PRODECON, or judicial ones) have the capacity and criteria to evaluate the legality and equity of algorithmic decisions.
6. **Reinforced Role of External Control Bodies:** It is necessary to clarify the powers of the new Transparency for the People body to supervise compliance with personal data protection in public sector AI systems, including the SAT.

6.3 INHERENT CHALLENGES TO ALGORITHMIC TRANSPARENCY AND ACCOUNTABILITY

Implementing transparent and responsible algorithmic auditing faces intrinsic challenges. One of the most relevant is the dilemma between transparency and anti-fraud effectiveness. On the one hand, transparency about how algorithms operate is essential to protect taxpayer rights, allow for bias detection, and ensure accountability. On the other hand, tax authorities have a legitimate concern that revealing too many details about their fraud detection models (the specific variables they use, risk thresholds, the logic of their algorithms) could be counterproductive. Finding a balance that satisfies the need for public scrutiny and rights protection without compromising the state's ability to effectively combat tax evasion is a central challenge. This suggests the need to explore mechanisms for differentiated or controlled transparency, such as providing detailed a posteriori explanation for specific decisions affecting a taxpayer, allowing access to more detailed information for auditing bodies under confidentiality agreements, or publishing aggregated information on system performance and fairness without revealing critical operational details.

Another fundamental challenge lies in the attribution of responsibility in complex algorithmic environments. Although the SAT indicates that human review exists in its processes, AI-based decision-making involves a chain of actors: those who define the objectives, those who collect and prepare the data, those who design and train the algorithms, those who implement and operate them, and those who ultimately use their results. If an AI system produces an erroneous or biased decision that causes harm to a taxpayer, determining who is responsible can be extremely complex. Was it a problem in the source data? An error in the algorithm's design? A misinterpretation by the end-user? A lack of adequate supervision? The inherent opacity of some AI models makes it even more difficult to trace the origin of the failure. This diffusion of responsibility can weaken accountability mechanisms and leave the affected taxpayer without a clear path to redress. Therefore, it is crucial that AI governance frameworks establish clear lines of responsibility and procedures for investigating and attributing failures in algorithmic systems.

7. CONCLUSION

The analysis confirms that Mexico's Tax Administration Service (SAT) is in an advanced phase of digital transformation, actively incorporating Artificial Intelligence (AI) tools, such as machine learning and graph analytics, and massively exploiting data generated by the CFDI ecosystem, as well as potentially other information sources. This modernization, aligned with global trends, offers significant opportunities to improve collection efficiency, optimize the allocation of auditing resources, streamline procedures for taxpayers, and, crucially, detect complex patterns of tax evasion and avoidance.

However, this transition to algorithmic auditing carries inherent and substantial risks that cannot be ignored. The main one is algorithmic bias, the possibility that AI systems produce systematically unfair or discriminatory results against certain groups of taxpayers, whether due to problems in training data, in model design, or due to the amplification of pre-existing inequalities. This risk is exacerbated by the opacity that frequently surrounds these systems, making it difficult to detect biases, for affected parties to understand decisions, and for control bodies to effectively supervise. The conjunction of bias and opacity threatens to violate fundamental taxpayer rights codified in the Mexican legal framework, including the right to non-discrimination, due process (especially the foundation and motivation of authority acts and the right to an adequate defence), privacy, and legal certainty. Furthermore, algorithmic auditing perceived as unfair or arbitrary can negatively impact fiscal equity, both horizontal and vertical, and potentially erode public trust in tax administration, affecting voluntary compliance.

Artificial Intelligence represents a tool with enormous transformative potential for tax administration in Mexico, capable of modernizing processes, improving efficiency, and strengthening the State's capacity to ensure tax compliance. However, like any powerful technology, its implementation is not neutral and entails significant risks that must be managed proactively and responsibly. The legitimate pursuit of collection efficiency cannot come at the expense of fiscal equity or taxpayers' fundamental rights. Opacity, algorithmic bias, and the lack of adequate accountability mechanisms can turn a promising tool into an instrument of injustice or discrimination. The path forward requires finding a delicate balance. It is necessary to embrace technological innovation, but channelling it through solid governance frameworks, clear ethical principles, and effective legal safeguards. The key lies in adopting a human-centred approach, where technology serves a tax administration that is more efficient, yes, but above all, fairer, more transparent, and trustworthy for all citizens. Building this future requires continuous dialogue and close collaboration among the SAT, legislators, control bodies, academia, technology and ethics experts, and society as a whole. Only then can it be ensured that artificial intelligence contributes positively to strengthening the fiscal pact in Mexico.

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