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Challenges of Artificial Intelligence Adoption in Tax Administration

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Abstract

This study aims to analyze the main challenges associated with the adoption of artificial intelligence (AI) in tax administration. The research is based on a systematic review of more than 86 relevant scholarly studies. The findings indicate that tax administrations face multiple challenges in adopting AI, including a shortage of qualified human resources and specialized skills, difficulties in effectively leveraging big data, and ethical concerns related to the privacy of individuals and businesses. Furthermore, political and legal challenges associated with data regulation, organizational culture, technological innovation constraints, environmental, economic, and social factors, difficulties in interpreting AI-generated results, and institutional challenges also influence the adoption process. This study contributes to a clearer understanding of these challenges and emphasizes the importance of addressing them to ensure the successful adoption of artificial intelligence, enhance administrative efficiency, and improve the quality of services provided to taxpayers.

Keywords: *Tax Administration, Artificial Intelligence, AI Adoption Challenges.*

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Introduction

The world is rapidly undergoing a digital transformation driven by artificial intelligence (AI) and enabled by big data. Data is no longer merely a vast accumulation of information; rather, it has become a strategic asset for nations. As described by Clive Humby, data represents "**the oil of the 21st century**." It plays a critical role in shaping public policymaking and decision-making processes, while also enhancing government transparency and accountability through the monitoring of public budget execution and the detection of financial corruption, embezzlement, and tax evasion by firms and individuals, particularly through anomalous spending behaviors and suspicious financial transactions.

This transformation is commonly referred to as the Fourth Paradigm, in which data analysis has shifted from sample-based inference to the examination of entire datasets. Within this paradigm, (Mayer-Schönberger & Cukier, 2013) argue that "**we no longer need to understand the causal mechanisms of a phenomenon; instead, we allow the data to speak for itself**." In this context, big data analytics has emerged as a powerful instrument for enhancing the efficiency and effectiveness of tax administration policies, enabling real-time adjustments based on highly granular and timely quantitative evidence. The unprecedented volume, velocity, and variability of data have rendered traditional database systems insufficient for combating tax evasion, thereby necessitating the adoption of artificial intelligence techniques and advanced analytical methods to extract actionable insights and generate added value (De Mauro, Greco, & Grimaldi, 2016).

Despite the growing academic interest in the application of technological tools for fraud detection and financial analysis within the big data environment (Sanad & Al-Sartawi, 2021) , empirical research on data analytics in auditing remains at an early stage (Earley, 2015). This limitation is partly attributable to the lack of transparency by public accounting firms particularly the Big Four regarding their data analytics practices, despite their pioneering role in the adoption of advanced analytical techniques in audit processes. A similar situation applies to the use of artificial intelligence by tax administration in developed countries for tax evasion detection, as highlighted by (Gepp, Linnenluecke, O'Neill, & Smith, 2018).

Unlike to the auditing domain, several fields have made substantial progress through the adoption of big data and AI techniques, notably financial distress prediction, financial fraud detection, stock market

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forecasting, and quantitative modeling. Nevertheless, A growing body of literature indicates that the implications of integrating advanced technologies into fraud detection processes remain inconclusive (Sanad & Al-Sartawi, 2021).

With respect to the adoption of big data analytics in tax auditing, government agencies and tax administrations in particular continue to face a significant mismatch between data generation capabilities and data utilization capacity. This imbalance stems from several structural, technical, and organizational challenges identified in both the academic literature and applied studies, which are examined and discussed in the present study.

Skills Challenges

The McKinsey Global Institute (2011) reported a significant shortage of professionals possessing big data skills and technical competencies in auditing, taxation, risk management, and consulting. The report projected a shortfall of approximately 140,000 to 190,000 specialists with advanced analytical expertise in the United States by 2018. In addition, the U.S. was expected to face a deficit of nearly 1.5 million managers and analysts capable of effectively interpreting and making decisions based on big data analytics.

Similarly, (Gupta K. , 2019) identified a substantial gap in artificial intelligence related skills, which could significantly hinder the implementation of AI-driven governance. These findings underscore the critical need for a sufficiently trained and skilled workforce to support the deployment of advanced analytics and AI-based solutions.

In response to these challenges, the American Accounting Association (AAA), with the objective of advancing the integration of big data and analytics within the accounting profession, organized a series of conferences on big data. These initiatives led to the development of online educational seminars and promoted collaboration between academic researchers and professional practitioners. As (Sledgianowski , Gomaa, & Tan, 2017) acknowledged, there are limited educational resources for big data and business analytics in accounting, including the field of taxation. Existing resources are largely confined to activities such as online tax research using software platforms (e.g., Checkpoint RIA, Westlaw, LexisNexis), querying digital tax law databases, and employing tax return preparation software. Meanwhile, the rapidly increasing volume of tax-related data generated by organizations, along with the emergence of new data standards such as XBRL, necessitates that students acquire tax analytics methodologies to extract deeper and more meaningful insights from such data. However, the same study indicates that while some of these educational materials may exist within individual academic curricula, they are not consistently disseminated or made accessible to the public.

Several researchers have proposed recommendations for the development of accounting programs and curricula in response to the growing influence of big data and analytics. (Appelbaum, Kogan, & Vasarhelyi, 2017) emphasized the need to place greater focus on the competencies required by auditors in this evolving environment, highlighting the importance of preparing auditors beginning at the undergraduate level to serve as key partners in the effective use of audit data analytics.

Similarly, (McKinney Jr, Yoos II, & Snead, 2017) argued that accountants should approach big data analytics as informed skeptics. This perspective underscores the necessity for strong critical thinking skills and the ability to challenge analytical outcomes by posing well-formulated questions within relevant domain areas.

Building on these recommendations, (Fay & Negangard b, 2017) conducted a simulation-based experiment employing real, modified data in the form of a case study. Participants assumed the role of external auditors tasked with analyzing journal entries in a high fraud-risk context. The analysis was carried out using IDEA, one of the most widely adopted Generalized Audit Software (GAS) tools and a recognized form of Computer-Assisted Audit Techniques (CAATs), and was implemented in two distinct phases. The first phase addressed a fundamental challenge associated with big data by evaluating the accuracy of written audit documentation and testing client-submitted files for completeness. The second phase further

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developed analytical competencies through a series of tests designed to identify journal entries that could potentially elevate fraud risk.

At the conclusion of the experiment, student feedback strongly supported the adoption of this case study in other academic institutions, with 100% of master's students and 90% of bachelor's students recommending its use. Consistent with these findings, (Sledgianowski , Gomaa, & Tan, 2017) suggested that, in the absence of comprehensive educational resources, instructors can introduce students to big data and business analytics through descriptive studies that incorporate real-world examples and illustrative experiments demonstrating how these tools are applied in professional practice.

Within the context of fraud detection, prior research has demonstrated that the use of big data analytics and forensic auditing has a positive and significant impact on fraud detection outcomes. Specifically, (Syahputra & Afnan, 2020) ،found that forensic accounting audits partially mediate the relationship between big data analytics and fraud detection effectiveness. These findings are consistent with the results reported by (Mittal, Kaur, & Gupta, 2021) as well as (Mehta, Mittal, Gupta, & Tandon, 2022) , who emphasized the critical role of applying big data techniques and enhancing awareness of forensic accounting tools in strengthening fraud prevention mechanisms.

Accordingly, these studies recommend the integration of big data analytics and forensic accounting into business education curricula. At the undergraduate and master's levels, coursework should emphasize foundational knowledge and conceptual understanding of business intelligence (BI) tools, while postgraduate programs should focus on advanced applications of business intelligence and analytics (Rezaee & Wang, 2019). Collectively, this body of literature highlights the strong interconnection between forensic accounting practices and the detection of tax evasion through the use of artificial intelligence and the identification of creative accounting behaviors.

At the professional level, core accounting competencies remain essential when adopting advanced analytics, including the ability to plan audits, review accounting and tax data, and report findings. However, the demand for new competencies such as statistical analysis and computer skills, which are often lacking among public sector employees is increasing. Accordingly, (Pencheva, Esteve, & Mikhaylov, 2020) recommend investing in big data capabilities while simultaneously strengthening institutional capacity (ISE) or integrating these skills into existing standard operating procedures. (Malaszczyk & Purcell, 2017) further elaborate on strategies for developing these competencies, which include hiring new personnel with backgrounds in statistics and computer science, enrolling accounting students in courses that provide the necessary analytical and computational skills, and, more broadly, recruiting qualified individuals such as AI specialists with limited or no accounting background to complement audit teams. Additionally, existing employees can be trained to achieve proficiency in digital analytics applications.

To ensure the success of such training initiatives, it is critical to align workforce development with the global evolution of digital tax management. (Bentley, 2020) highlights this radical transformation in administrative personnel, outlining the characteristics of effective training systems and identifying suitable delivery methods to support the implementation of a comprehensive digital transformation strategy.

Data Challenges

Numerous studies have investigated the reasons behind the mismatch between the rapid generation of massive amounts of data and the capacity for data consumption within governmental organizations. (Mittal, 2020) provided a comprehensive overview of the "Big Data Application Framework" in public administration through data-driven e-governance (DDeG), expanding the scope of e-governance by examining technological components such as the Internet of Things (IoT) and artificial intelligence (AI). E-government is frequently linked to AI applications, as it provides a reliable infrastructure for the collection, integration, and delivery of big data, thereby enhancing the potential for AI systems to analyze this data and improve public administration services.

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Accordingly, (Duan & Xiong, 2015) recommend that organizations adopting big data analytics invest in robust data infrastructure to capture and store valuable information, integrate business analytics into strategic and operational processes, keep pace with evolving big data technologies, and implement effective employee training programs. (Malaszczyk & Purcell, 2017) further emphasize that infrastructure decisions should consider the choice of analytics platform, which often involves cloud-based solutions provided by vendors. Decision-makers must therefore understand relevant terminology and available options; active engagement with professional associations and a thorough evaluation of these options can facilitate the selection of the most effective approach for analyzing corporate and governmental tax fraud.

(Sadasivam, Subrahmanyam , Himachalam , Pinnamaneni , & Lakshme, 2016)) presented a method for detecting administrative fraud using information contained in annual reports. Given the volume and heterogeneity of these reports, data analysis was conducted on Hadoop, a big data platform, resulting in a tenfold reduction in feature extraction time compared to traditional methods. Similarly, (Adamov, 2019) proposed a conceptual framework for applying data analytics in taxation, highlighting how tax authorities can leverage operational data and defining key initial success indicators for the effective deployment of advanced analytics. These include electronic invoicing, electronic filing, and electronic accounting, which collectively support promising initiatives in electronic auditing. Furthermore, (Sharma, Pandey, & Kumar, 2016) demonstrated the utility of unstructured data in mitigating financial fraud. They developed a practical framework that utilizes unstructured online data, such as content from Twitter and Facebook, to illustrate the implementation of the framework and analyze the results obtained.

Innovation Challenges

Feature selection is a critical step preceding the development of financial fraud detection models (Yue, Chu, Wu, Wang, & Li, 2007) ،Currently, there is no consensus on the most effective indicators for fraud detection, highlighting the urgent need to integrate financial data with additional information such as auditor size, financial ratios, and governance style for comprehensive analysis. This aligns with the findings of (Kaminski, Wetzel, & Guan, 2004) who provided empirical evidence of the limited ability of financial ratios alone to detect or predict fraudulent financial reporting. Moreover, (Yeh, Chi, Lin, & Chiu, 2016) demonstrated that non-financial ratios provide valuable information for detecting fraudulent financial statements, yet they are frequently excluded from early detection models. Their study also showed that a hybrid approach combining Rough Set Theory (RST) and Support Vector Machines (SVM) achieved the highest classification rates with the lowest incidence of Type I and Type II errors. These results are consistent with those reported by (SADGALI, SAEL, & BENABBOU, 2019). Overall, hybrid fraud detection techniques are increasingly preferred because they leverage the strengths of multiple traditional detection methods.

Earlier, (Dong, Liao, Fang, Cheng, & Chen, 2014) developed an integrated language model for detecting fraud in financial data, combining a statistical language model (SLM) with latent semantic analysis (LSA). This integrated model addressed the limitations of SLM in capturing long-term dependencies and extracted semantic patterns that distinguish fraudulent from non-fraudulent financial data, demonstrating high accuracy in fraud detection. Similarly, (Chen S. , 2016) implemented a CHAID-CART hybrid model, which proved more effective in detecting financial anomalies. The first stage employed decision tree algorithms, including Classification and Regression Trees (CART) and Chi-CHAID, to select key variables. The second stage combined CART, CHAID, Bayesian belief networks, SVMs, and artificial neural networks. (Chen & Wu , 2017) further compared these approaches, showing that the SVM-QGA clustering model achieved higher clustering accuracy on generated datasets compared to six other models, including decision tree, logistic regression, neural network, KNN, SVM-GA, and SVM-POS.

In contrast, (Spathis C. , 2002) demonstrated that models based on univariate and multivariate statistical methods, such as logistic regression, can effectively identify factors associated with fraudulent financial statements, assisting both internal and external auditors as well as tax authorities, other government agencies, and the banking sector. This finding is supported by (West, Bhattacharya, & Islam, 2015), who showed that intelligent statistical and computational approaches, despite varying performance levels, can

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reliably detect multiple forms of financial fraud. Computational intelligence (CI) methods, including neural networks and support vector machines, are particularly effective due to their ability to learn and adapt to evolving fraudulent strategies (Table 1 **presents selected accuracy rates for various intelligent models**). Similarly, (Temponeras, Alexandropoulos, Kotsiantis, & Vrahatis, 2019) emphasized that the primary goal of these studies is the reliable identification of fraud features a task that is challenging and often impractical without the application of machine learning techniques.

Table 1: Comparison of the Efficiency of Financial Fraud Detection Models

Accuracy ratio	The model	Sample	the study
98.09% 95%	PNN Genetic algorithm	Numerous ,companies but most do not exceed .202	**(SADGALI, SAEL, & BENABBOU, 2019)**
42.92% 60.11% 66.43% 80.18% 88.00%	Logistic KNN DT SVM RF	103 fraudulent companies non- 160 fraudulent companies	**(Liu, Chan, Hasnain, Kazmi, & Fu, 2015)**
63% for the target group 95% for the counterpart category	Genetic algorithm	fraudulent 51 companies non- 339 fraudulent companies	**(HOOGS, KIEHL, LACOMB, & SENTURK, 2007)**
90.3% 80% 73.6%	Bayesian belief network Decision tree NN	fraudulent 38 companies non- 38 fraudulent companies	**(Kirkos, Spathis, & Manolopoulos, 2007)**
_____	different models were 32 compared on the same .data The best model is AV5_NoNN	All publicly .traded U.S companies subject to) specific (conditions	**(Geppa, Kumara, & Bhattacharya, 2020)**
86.84% 60.53%	Bayesian Naïve Classifier Beneish traditional auditing	companies 53	**(Dbouk & Zaarour, 2017)**
94.88% 87.18%	LSTM RNN	fraudulent 51 companies non- 102 fraudulent companies	**(Jan, 2021)**

Source: Prepared by the authors based on the literature review

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Similarly, a study by (Handoko, Mulyawan, Tanuwijaya, & Tanciady, January 2020) confirms that big data analytics will add significant value to audit firms by uncovering hidden patterns that would not be visible in limited datasets (such as limited audit samples). This will provide decision-making support, enabling firms to compete and grow, and will lead to more accurate, faster, and more organized processes, increasing productivity and reducing costs. It will also improve customer service in e-commerce. One application of big data analytics is fraud detection, which commonly occurs in the financial sector. In the same vein, numerous studies have utilized artificial intelligence techniques.

For example, the study by (Fanning & Cogger, 1996) employed an AutoNet (automatic self-organizing artificial neural network) alongside standard statistical tools. This study enhanced the validity and efficiency of AutoNet as a search tool and provided further empirical evidence regarding the benefits of the proposed red flags for fraudulent financial statements. Furthermore, the results of the study by (Ravisankar , Ravi, Raghava Rao, & Bose, 2011) surpassed those of a previous study using the same method. The data showed that GP and PNN outperformed all other techniques by selecting features with equal accuracy. The framework of the study by (Gupta & Singh Gill, 2012) recommended using correlation rules, a descriptive data mining technique, to prevent fraudulent financial reporting, along with predictive data mining techniques such as classification, for successful identification and detection of financial data fraud. This was also applied in the study by (Shukla, Sidhu, Jain, Patil, & Sawant-Patil, 2018) to characterize and detect potential tax evaders using information related to tax payments through big data analytics techniques. They applied the K-means clustering algorithm to form groups of taxpayers with similar behaviors and then used decision trees to classify each group into taxpayers with and without fraud. The associated behavioral patterns were then identified, and an artificial neural network was trained using these patterns to detect potential tax evaders based on the available information.

Building on the work of researcher Benish, the study (Kumar , Nandini , & Kumar, 2018) developed cluster models for detecting manipulation, They presented a new simulation-based sampling technique for efficiently handling unbalanced datasets. This technique confirmed the potential of the proposed approach to identify companies behaving outside their usual patterns. It further noted that, since the machine learns from the provided data, the likelihood of improved results is linked to increased information obtained about defaulters. This was also demonstrated by the success of a machine learning algorithm model for detecting anomalies in the financial data of listed Vietnamese companies, which was able to rank quarterly financial reports in terms of creditworthiness (Lokanan, Tran, & Vuong, 2019) In the study (Zhang, 2022), a random forest algorithm was introduced for detecting anomalies. Simulation experiments showed that, compared to two other distance-based anomaly detection methods, the random forest-based anomaly detection method offers greater advantages. The other two aspects, in terms of improving model accuracy and reducing computation time, were also discussed in a study by (ZEMÁNKOVÁ , 2019). This study examined the application of blockchain technology and its implications for auditing, including smart contracts and smart auditing procedures based on blockchain technology, and evaluated existing applications and auditing tools developed by leading Big Four accounting and tax consulting firms.

The study also addressed the advantages of improving model accuracy and reducing computation time. Similar to all previous studies, the study by (Chen & Wu , 2017) uniquely developed a big data-based approach to fraud detection for the financial data of business groups (rather than a single organization) to improve the accuracy and efficiency of fraud detection, thereby reducing investment losses and risks and enhancing the investment decision-making benefits for investors and creditors. The study by (Monge, Poza, & Borgia, 2022) also attempted to expand knowledge in the field of tax fraud indicators, as it applied factor analysis to create a composite index and used techniques focused on partial integration (ARFIMA) and partial co-integration VAR FCVAR to evaluate the behavior of the suspicious tax fraud indicator against tax collection and GDP. It confirmed that the indicator allows for tracking trends in fraud intent and consequently designing specific control policies. If the tool is applied effectively, it can be a complementary and important advance in this field

Challenges of Interpretation and Translation

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The adoption of artificial intelligence (AI) and machine learning techniques in auditing and accounting practices is almost invariably accompanied by challenges related to the interpretation and evaluation of big data analytics results. Numerous studies have addressed this issue. For instance, (Fawad , 2019) provided a systematic review of the literature examining the relationship between memory processes, auditors' judgment, and decision-making under the influence of perceptual and cognitive biases. Similar to the limitations imposed by constrained knowledge resources—which compel auditors to rely on sampling and inference when analyzing accounting information—the use of big data may expose auditors to information overload. This, in turn, can lead to cognitive errors and the misidentification or overemphasis of irrelevant information signals. These concerns are supported by the findings of (Gray & Debreceny, 2014), who argue that ineffective use of data mining techniques may generate false positives (i.e., misleading indicators of tax evasion or creative accounting practices) as well as spurious patterns. Such outcomes can significantly increase audit workload, as auditors are required to conduct extensive follow-up investigations to validate or refute these signals. Consequently, data mining cannot be considered a universal solution for detecting all types of fraud schemes and must be applied with caution and professional judgment.

In this context, (Brown-Liburd, Issa, & Lombardi, 2015) emphasize that big data should not be treated as the sole source of audit evidence. Instead, it should be used to corroborate audit findings and support risk identification. Given the growing availability of advanced data analytics tools, auditors are advised to carefully select the most appropriate analytical techniques and data sources for each audit engagement. The use of inappropriate tools may result in significant Type II errors, thereby reducing audit effectiveness, or Type I errors, which lead to unnecessary audit procedures and inefficiencies.

Furthermore, auditors must critically assess the quality and reliability of non-financial data incorporated into their analyses. In the absence of formal and generally accepted audit data standards governing the use of big data, Brown-Liburd et al. (2015) recommend that audit firms either develop robust internal quality control standards or adopt existing data standards promoted by professional bodies such as the American Institute of Certified Public Accountants (AICPA).

Environmental Challenges

Several studies most notably (Pencheva, Esteve, & Mikhaylov, 2020) confirm that significant barriers hinder the adoption of big data analytics in the public sector, particularly in taxation. These barriers include limited inter-organizational cooperation and the absence of a comprehensive policy and regulatory framework capable of guiding and promoting collaboration between public authorities, the private sector, and international firms that develop artificial intelligence (AI) based fraud detection tools. Similar concerns were earlier highlighted by (wang , 2010), who emphasized two critical challenges facing the application of data mining technologies in fraud detection: the limited availability of testable, open-access data and the lack of mature, standardized analytical methods and techniques.

In response to these challenges, several pilot initiatives have emerged in developed and emerging economies, often within collaborative frameworks. For example, (Mehta, et al., 2019) examined the use of big data analytics, Android-based applications, and information technology to combat tax evasion within the Department of Commercial Taxes of the Government of Telangana, India. The findings demonstrated promising outcomes in terms of improving monitoring and compliance mechanisms.

Similarly, a joint research project between the Serbian Tax Administration and the Faculty of Sciences at the University of Novi Sad, documented by (Atanasijević, Jakovetic, Krejić, & Jerinkic, 2018), sought to develop algorithms for identifying tax evasion risks using advanced big data analytics and machine learning–supported AI techniques. The study algorithmically developed and tested risk indicators using non–personally identifiable data derived from tax return databases covering the period from April 2014 to May 2018. Prior to analysis, the data were processed in accordance with applicable data protection regulations through anonymization techniques, ensuring the privacy and confidentiality of taxpayers subject to tax control. The results demonstrated both the robustness of the proposed indicators and a notable improvement in the efficiency and effectiveness of tax control activities.

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Economic Challenges

The development of artificial intelligence (AI) and machine learning prototypes for taxation has become increasingly widespread in both academic research and practical applications within tax administrations in developed and developing countries, as well as among corporate taxpayers and tax consulting firms (Milner & Berg, 2017). In parallel, the volume of published research on advanced tax analytics has grown rapidly over the past five years, a trend that is expected to disrupt corporate tax functions in the near future. Consequently, policymakers and practitioners must develop a clear understanding of the prospective impact of AI and machine learning on taxation, particularly with respect to their economic implications.

These challenges are closely linked to global economic dynamics and structural necessities. Countries that actively attract transnational investment and host large multinational corporations face increasing pressure on their tax administrations to manage and analyze vast volumes of complex data in an increasingly digitalized environment. This challenge is further compounded by the fact that fraudulent practices also evolve alongside technological progress, continuously adapting to new systems and regulatory frameworks. As a result, tax administrations that fail to keep pace with advancements in AI-driven analytics risk significant losses in revenue, efficiency, and regulatory effectiveness.

Empirical evidence provided by (Dagiliene & Kloviene, 2019) confirms the existence of two distinct sets of motivating factors corporate and institutional driving the adoption of big data analytics. Their study indicates that large corporate clients of audit firms serve as the primary catalyst for the use of big data analytics in external auditing and legal review processes. The operational practices of large enterprises not only permit but actively facilitate the use of diverse data sources financial and non-financial, structured and unstructured by audit firms. Moreover, the study highlights the potential for a reversal in the traditional relationship between audit firms and their major corporate clients. In this emerging dynamic, audit firms, as technology-intensive actors, may assume a more proactive role, particularly in their interactions with small and medium-sized enterprises, by demonstrating the tangible value added by big data analytics.

The implications of these findings extend directly to tax administrations. Similar to large audit firms, tax authorities are increasingly unable to rely on traditional audit approaches when dealing with multinational corporations and complex economic transactions. However, the adoption of AI-based analytics in tax auditing cannot proceed without comprehensive economic feasibility studies. Such studies are essential to assess both the expected benefits such as increased tax revenues, improved compliance, and enhanced risk detection and the substantial costs associated with digital transformation. These costs include investments in data infrastructure, workforce upskilling, organizational restructuring, and ongoing system maintenance. Without careful economic evaluation, the transition toward AI-driven tax administration may pose significant fiscal and operational risks.

Ethical, Political, and Legal Challenges

A substantial body of literature converges on the ethical, political, and legal challenges associated with privacy, data security, data governance, and ethical use in the context of big data analytics and artificial intelligence. (Pencheva, Esteve, & Mikhaylov, 2020) emphasize that the absence of robust data governance frameworks particularly those that clearly define the purpose of data collection, permissible use, and data reuse principles creates significant risks and ambiguities. In this context, the use of individuals' data by tax authorities without explicit consent raises serious ethical concerns, especially given that the concept of informed consent itself has become increasingly ambiguous in the era of big data.

(Appelbaum, Kogan, & Vasarhelyi, 2017) further highlight the challenge of encouraging organizations to grant auditors access to their big data resources a concern that applies equally to tax authorities, whether through open data initiatives or through data integration mechanisms such as electronic taxpayer accounting

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systems. This challenge is particularly pronounced when firms operate within the same industry and are audited by the same firm, as both auditors and audited entities may fear data leakage, misuse, or unauthorized sharing of sensitive information. Moreover, corporate data protection and governance policies may intentionally impose restrictions on data disclosure, thereby limiting transparency and constraining the scope of analytics. From the perspective of stakeholders, such limitations can significantly undermine the effectiveness of big data analytics in detecting creative accounting practices and, more broadly, in enhancing audit and tax compliance outcomes.

Addressing these challenges requires the development of legislative and regulatory frameworks capable of balancing data accessibility with ethical safeguards. The mere legal right of tax authorities to access data does not, in itself, render its use ethically justified. (Appelbaum, Kogan, & Vasarhelyi, 2017) argue that the increasing reliance on audit data analytics has the potential to replace traditional substantive testing procedures, thereby necessitating revisions to existing auditing standards to formally incorporate analytics-based approaches.

Related concerns are echoed by (Houser & Debra, 2018), who warned U.S. taxpayers about the tax implications of their online activities, particularly the public display of personal information and consumption patterns on social media platforms. Given the prevalence of informal and online commerce through platforms such as eBay and Amazon, such data may be scrutinized for income tax purposes. With tax authorities, including the Internal Revenue Service (IRS), having access to financial transaction data from credit and debit cards as well as payment platforms such as PayPal, the matching of transactions to individual taxpayers or small businesses has become increasingly straightforward. Consequently, taxpayers must recognize the heightened sensitivity of their digital footprints in the age of big data analytics. For instance, posting leisure-related content on social media while simultaneously claiming business travel deductions may trigger tax scrutiny and unintended compliance consequences.

Finally, the growing accumulation of sensitive and valuable data by government agencies has made them increasingly attractive targets for cybercriminals. This cybersecurity risk is expected to intensify further as tax administrations expand their reliance on big data analytics and artificial intelligence, underscoring the critical need for robust data protection, cybersecurity strategies, and ethical governance frameworks

The study by (Pencheva, Esteve, & Mikhaylov, 2020) identifies a set of political challenges that may significantly affect the funding and implementation of big data analytics within tax administrations. The authors argue that electoral cycles and the resulting shifts in political mandates can disrupt the continuity, momentum, and pace of big data–driven digital transformation initiatives. This finding is corroborated by (Sarin & Summers, 2020), who demonstrate that political will plays a decisive role in the adoption of advanced analytics, as it can either facilitate sustained financial support or act as a major constraint.

Their analysis of the Congressional Budget Office (CBO) report (July 2020) on trends in Internal Revenue Service (IRS) performance over the past decade highlights both the substantial revenue losses attributable to tax evasion and the considerable potential returns from increased investment in tax compliance. The report reveals a vast untapped revenue base, with tax gap estimates indicating an inability to collect approximately USD 7.5 trillion. During the same period, IRS funding declined by more than 15 percent, while its workforce was reduced by approximately 20 percent. Government interventions aimed at addressing these issues have remained limited and largely fail to incorporate advances in information reporting systems or technological innovation. Notably, the analysis suggests that merely restoring enforcement and compliance resources to their previous levels could generate more than USD 1 trillion in additional tax revenue.

Several structural and political factors help explain this persistent lack of support for enhanced tax enforcement. Sarin and Summers (2020) further indicate that non-compliance rates are significantly higher among less transparent income categories—such as capital gains, dividend income, rental income, and property-related earnings—where enforcement mechanisms remain weak. Given the limited capacity of the IRS to effectively monitor and enforce compliance in these areas, it is unsurprising that the Government

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Accountability Office (GAO) identifies insufficient information reporting as a major contributor to the tax gap.

Organizational, Cultural, and Social Challenges

(Pencheva, Esteve, & Mikhaylov, 2020) argue that the coordination costs associated with data sharing are likely to exceed those of other forms of collaboration within the public sector. In addition, power asymmetries and inter-agency rivalries constitute significant barriers to effective data sharing across bureaucratic organizations. The study anticipates that public agencies may strategically leverage big data as a source of power in competition for resources, influence, and institutional autonomy.

Building organizational capacity for big data analytics—beginning with information technology (IT) units and extending to change managers and data scientists—requires the redesign of existing processes and systems to accommodate the evolving needs of stakeholders. The same study identifies a critical challenge for senior managers and policymakers with decision-making authority, particularly with regard to their tolerance for risk. Individuals with higher levels of risk aversion tend to be less inclined to adopt and utilize big data effectively, while data owners may resist inter-organizational cooperation for reasons unrelated to technical constraints, such as concerns over control, accountability, or personal incentives.

Furthermore, the study emphasizes that inconsistent leadership and insufficient political commitment represent major impediments to the effective use of data in improving policymaking processes. Pencheva et al. (2020) stress the importance of a holistic understanding of big data, identifying five interrelated dimensions that managers must consider: ethics, technology, processes, organizational and institutional change, and analytics. They further recommend sustained investment in human capital to ensure that individuals acquire the knowledge and competencies necessary for the appropriate use and governance of big data.

At the cognitive level, the authors acknowledge that adopting a data-driven mindset represents a profound organizational shift. Decision-makers often rely on a combination of empirical evidence, subjective reasoning, and heuristic judgment. Consequently, cultivating a data-driven culture requires general managers to fundamentally rethink decision-making practices and to continuously seek opportunities to extract new forms of value from data.

From a broader social perspective, significant challenges arise from the potential impact of artificial intelligence on labor markets, particularly in contexts where automation substitutes for human labor (Gupta K. , 2019) Moreover, the increasing use of AI in government operations may contribute to the dehumanization of routine administrative interactions, raising concerns about trust, accountability, and the quality of public service delivery (Valle-Cruz, Alejandro , E, & Ignacio, 2019).

Conclusion

This study synthesizes the findings of prior research to identify the most significant challenges facing innovation-oriented research in the detection of tax evasion and creative accounting practices. The literature reveals several persistent methodological, technical, and empirical limitations.

First, one of the most critical challenges concerns the implementation of classification processes using data mining techniques, particularly the difficulty of collecting representative samples of fraudulent firms and reliably distinguishing them from non-fraudulent entities (Gupta & Mehta, 2021). Although many proposed systems demonstrate effectiveness in fraud detection, they frequently suffer from methodological limitations and a lack of continuous updates to address emerging fraud schemes, a shortcoming that is both operationally complex and financially costly (Bhati , 2019)

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Second, existing data mining applications have been disproportionately concentrated in sectors such as banking and insurance fraud, while relatively limited attention has been given to other important areas, including mortgage fraud, money laundering, securities and commodities fraud, fictitious invoicing, and transfer pricing practices within multinational enterprises. As a result, significant dimensions of fraud detection using data mining techniques remain (Ngai, Hu, Wong, Chen, & Sun, 2011); (Al-Hashedi & Magalingam, 2021)

Third, there is limited consensus in the literature regarding the identification of reliable data patterns for detecting earnings manipulation. This limitation is partly attributable to the lack of strong theoretical foundations and insufficient reliance on expert judgment in model (Sanad & Al-Sartawi, 2021). Although many studies propose auditor checklists based on so-called "red flags," these approaches often rely excessively on quantitative financial ratios, thereby overlooking qualitative and contextual indicators of fraud (Dong, Liao, Fang, Cheng, & Chen, 2014).

From a methodological perspective, logistic regression remains the most widely used data mining technique for financial fraud detection, followed by supervised learning methods, which are employed more frequently than unsupervised approaches (Albashrawi, 2016) While ratio-based data have been shown to outperform raw accounting data, time-series data mining remains relatively under-researched despite its potential relevance for detecting dynamic fraud patterns (wang , 2010)

Moreover, relatively little attention has been paid to the integration of financial and linguistic data in intelligent fraud prediction models (Sanad & Al-Sartawi, 2021) Similarly, sentiment analysis and natural language processing (NLP) represent promising auditing tools that remain insufficiently explored in the context of tax evasion and creative accounting detection (Gepp, Linnenluecke, O'Neill, & Smith, 2018)

Another major limitation of prior studies lies in their predominant focus on predictive accuracy, often at the expense of interpretability. Few studies examine whether the proposed models are transparent and understandable to practitioners, a factor that is crucial for regulatory and auditing applications (Sanad & Al-Sartawi, 2021) In addition, many empirical studies rely on relatively small samples of fraud cases, which raises concerns regarding overfitting and the overestimation of model performance (wang , 2010)

Cost considerations also remain largely absent from the literature. Very few studies explicitly account for the economic costs associated with implementing and maintaining fraud detection systems based on data mining techniques, limiting the practical applicability of their findings (Sanad & Al-Sartawi, 2021) Despite these limitations, some studies demonstrate that combining financial and non-financial risk factors within hybrid frameworks integrating machine learning techniques with rule-based systems can significantly reduce both Type I and Type II error rates, thereby improving overall detection performance (SONG, HU, DU, & SHENG, 2014). Nevertheless, the scarcity of fraud data, the high dimensionality of potential explanatory variables, and the broad and heterogeneous definition of fraud continue to pose major challenges to the development of robust prediction models (Perols, Bowen, Zimmermann, & Samba, 2016)

Finally, comparisons of classification accuracy across studies remain problematic due to substantial differences in datasets, methodologies, and evaluation metrics. However, empirical evidence suggests that incorporating non-financial variables alongside financial data can significantly enhance model performance (GAGANIS, 2009) Many econometric studies also suffer from weak alignment between theoretical insights and practical applicability, limiting their comparability with operational models used in real-world settings (Stankeviciusa & Leonasb, 2015) Furthermore, the analysis of unstructured and non-financial data generated within big data environments remains technically challenging .

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