Tulane Economics Working Paper Series

Emerging Trends in Tax Fraud Detection Using Artificial Intelligence-Based Technologies

James Alm
Tulane University
jalm@tulane.edu

Rida Belahouaoui
Cadi Ayyad University
rida.belahouaoui@ced.uca.ma

Working Paper 2511
November 2025

Abstract

This study examines the role of artificial intelligence (AI) tools in enhancing tax fraud detection within the ambit of the OECD *Tax Administration 3.0*, focusing on how these technologies streamline the detection process through a new "Adaptive AI Tax Oversight" (AATO) framework. Through a textometric systematic review covering the period from 2014 to 2024, we examine the integration of AI in tax fraud detection. The methodology emphasizes the evaluation of AI's predictive, analytical, and procedural benefits in identifying and combating tax fraud. The research underscores AI's significant impact on increasing detection accuracy, predictive capabilities, and operational efficiency in tax administrations. Key findings reveal the ways by which the development and application of the AATO framework improves the tax fraud detection process, and the implications offer a roadmap for global tax authorities to utilize AI in bolstering detection efforts, potentially lowering compliance expenses and improving regulatory frameworks.

Keywords: Artificial intelligence, tax fraud, AATO framework, blockchain, neural networks, data mining
JEL codes: C45, H26

Emerging trends in tax fraud detection using artificial intelligence-based technologies

James Alm and Rida Belahouaoui *

Abstract: This study examines the role of artificial intelligence (AI) tools in enhancing tax fraud detection within the ambit of the OECD *Tax Administration 3.0*, focusing on how these technologies streamline the detection process through a new "Adaptive AI Tax Oversight" (AATO) framework. Through a textometric systematic review covering the period from 2014 to 2024, we examine the integration of AI in tax fraud detection. The methodology emphasizes the evaluation of AI's predictive, analytical, and procedural benefits in identifying and combating tax fraud. The research underscores AI's significant impact on increasing detection accuracy, predictive capabilities, and operational efficiency in tax administrations. Key findings reveal the ways by which the development and application of the AATO framework improves the tax fraud detection process, and the implications offer a roadmap for global tax authorities to utilize AI in bolstering detection efforts, potentially lowering compliance expenses and improving regulatory frameworks.

Keywords: Artificial intelligence, tax fraud, AATO framework, blockchain, neural networks, data mining.

JEL Codes: C45, H26.

Declaration of Interest Statement: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

---

* Rida Belahouaoui, Cadi Ayyad University of Marrakesh, Morocco (rida.belahouaoui@ced.uca.ma); James Alm, Tulane University (jalm@tulane.edu). Please address all correspondence to James Alm, Department of Economics, Tulane University, New Orleans, LA 70118 USA.

1. Introduction

Tax fraud is a global challenge with profound implications for societal trust and economic stability (Alm, 2023; De Roux et al., 2018). Defined as the intentional falsification of tax return information to illegally gain financial benefits or reduce tax liabilities, this phenomenon affects both developed and developing economies (Taxe Justice Network, 2023). As a deliberate act of deception aimed at evading rightful tax payments, tax fraud not only deprives governments of essential revenue but also undermines the integrity of tax systems (Gale and Krupkin, 2019; Murorunkwere et al., 2023; Ruzgas et al., 2023).

According to the Global Tax Evasion Report 2024, corporate tax avoidance through base erosion and profit shifting (BEPS) continues to pose significant challenges to global tax revenues, despite international efforts to curb these practices. The report estimates that corporate tax revenue losses due to profit shifting exceed $1 trillion annually, representing approximately 10 percent of global corporate tax revenues. These losses disproportionately affect non-OECD countries, where tax avoidance strategies significantly erode public finances. Additionally, findings from the OECD *Corporate Tax Statistics 2024* reveal that, while corporate tax revenues represent 16 percent of total tax revenues globally, the share of corporate taxes as a percentage of GDP varies widely across jurisdictions. For instance, in 2021 corporate tax revenues accounted for more than 25 percent of total tax revenues in 17 countries. These figures highlight the persistent disparities in the effects of profit shifting and the urgency of implementing more effective global tax policies to reduce these losses (Alstadsaeter et al., 2023; OECD, 2024).

Recently, the Tax Justice Network (2024) estimated that global tax abuse results in an annual loss of $492 billion in tax revenues. Of this, $347.6 billion is lost due to corporate tax abuse by multinational companies, while $144.8 billion is attributed to offshore tax evasion by wealthy individuals. The financial burden is disproportionately heavier on lower-income countries, which lose $46 billion annually, equivalent to 36 percent of their public health budgets. In contrast, higher-income countries face an estimated loss of $446 billion per year, amounting to 7 percent of their public health budgets. If no significant policy changes are implemented, the Tax Justice Network (2024) projected that countries will collectively lose $4.92 trillion in tax revenue to tax havens over the next decade, exacerbating economic inequalities and weakening public services worldwide.

The OECD *Tax Administration 3.0* vision aims for a thorough digital revamp of tax systems both to respond to societal changes and also to harness digital advancements for reducing administrative burdens, fostering policy innovation, and curtailing tax fraud (OECD, 2020). This vision encapsulates six fundamental components: digital identity, taxpayer touchpoints, data management and standards, tax management and enforcement, the cultivation of new skill sets, and the establishment of governance frameworks. These components are pivotal for an effective, modern tax administration system. Reflecting on the Tax Technology Initiatives Inventory data, it is evident that this shift towards digitalization is substantial (OECD, 2023a, b), and this shift underscores the critical role of digital technologies in enhancing the operational efficiency and effectiveness of tax administrations, particularly in combating tax fraud (OECD, 2023a, b).

In the context of *Tax Administration 3.0*, the integration of artificial intelligence (AI) tools and algorithms plays a pivotal role in enhancing tax administration and benefiting taxpayers.[1] AI enhances liability assessment, improves decision-making, and reduces the need for human intervention by incorporating advanced algorithms (OECD, 2020). AI tools, equipped with advanced algorithms, offer unprecedented efficiency in processing vast amounts of fiscal data, enabling governments at all levels to enhance their financial management and oversight capabilities. AI-enabled systems can be used to identify and prevent tax fraud (Dougherty, 2023). The integration of artificial intelligence into tax administration has significantly advanced the detection and prevention of tax fraud in recent studies. Gaie (2023) proposes a comprehensive approach to enhance e-Government and optimize fraud detection, marking a pivotal shift in tackling tax fraud. Similarly, Mpofu (2024) highlights the effectiveness of AI algorithms in identifying fraudulent activities, showcasing the potential of digital tools in tax administration (Belahouaoui, 2025). Tax et al. (2021) emphasize the critical role of machine learning within the framework of organizational anti-fraud efforts, illustrating the need for an operational model that integrates advanced technologies. Additionally, the application of AI in tax audits has been shown to significantly reduce fraud risks and enhance the efficiency of tax collection processes (Saragih et al., 2023; Shakil and Tasnia, 2022). Bao et al. (2022) explore the wider implications of AI and big data in fraud detection, providing a detailed overview of the challenges and opportunities present in leveraging technology to combat fraud. Moreover, Mururunkwere et al. (2022) detail the innovative use of artificial neural networks for detecting income tax fraud in Rwanda, highlighting the advancements in AI for improving detection accuracy in a developing country. These contributions collectively underscore the potentially transformative impact of AI on tax administration, signaling a shift towards more secure and more efficient tax systems capable of combating fraud effectively.

Several recent studies have highlighted the need for further research to understand how artificial intelligence aids in detecting tax fraud, pointing out future directions for exploration in this field (Matheus et al., 2021; Tax et al. 2021; Zuiderwijk et al., 2021; Bassey et al., 2022; Bharosa, 2022; Gaie, 2023). These studies underscore the necessity for a comprehensive review over time, focusing on the benefits of AI and its role in enabling tax authorities to detect fraud in the era of digital transformation. Even so, this literature also suggests theoretical, methodological, and practical gaps. Theoretically, there is a need to identify which AI-based technologies are being utilized in tax fraud detection and to understand how these technologies facilitate the detection process within a new "Adaptive AI Tax Oversight" (AATO) framework. Methodologically, there is a lack of systematic literature reviews employing advanced analytical techniques, such as content analysis, lexicographic analysis, and textometry, supported by textual analysis software. Practical aspects also require further examination to bridge existing gaps and to enhance the effectiveness of AI in combating tax fraud.

[1] See Gesk and Leyer (2022) and Aoki et al. (2024) for useful discussions of how systems can be designed to provide benefits to and increase acceptance by individuals.

This study sets out to accomplish two main goals. First, we survey the AI-based tools predominantly used by global tax administrations for detecting tax fraud, focusing on their benefits and challenges. Second, we develop a conceptual framework detailing the application of artificial intelligence in tax fraud detection within the innovative landscape of the OECD *Tax Administration 3.0*. We attempt to not only map out the current utilization of AI in combating tax fraud but also to guide future integration of AI technologies in enhancing tax regulatory frameworks and operational efficiencies.

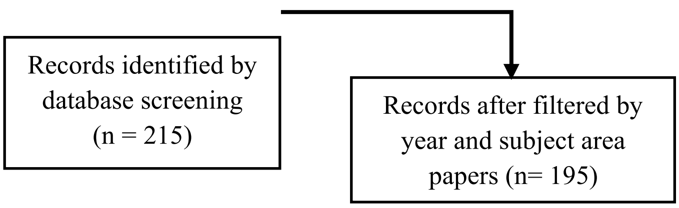
To meet these research objectives, we conduct a systematic literature review using the PRISMA method, analyzing studies published between 2014 and 2024 from the Scopus and Web of Science databases. This comprehensive review involved a detailed textometric analysis of 163 studies, utilizing both bibliometric and textometric analyses of titles, abstracts, and keywords. Such approaches significantly enrich the depth and breadth of analysis in systematic literature reviews (Bueno et al., 2021). Furthermore, tools like IRAMUTEQ have been used for advanced statistical analysis of textual data, enhancing the quality of insights derived from the literature (Figura et al., 2023). These methodologies, not widely applied in systematic literature reviews, highlight existing gaps and present opportunities for generating more nuanced and extensive research findings in future studies.

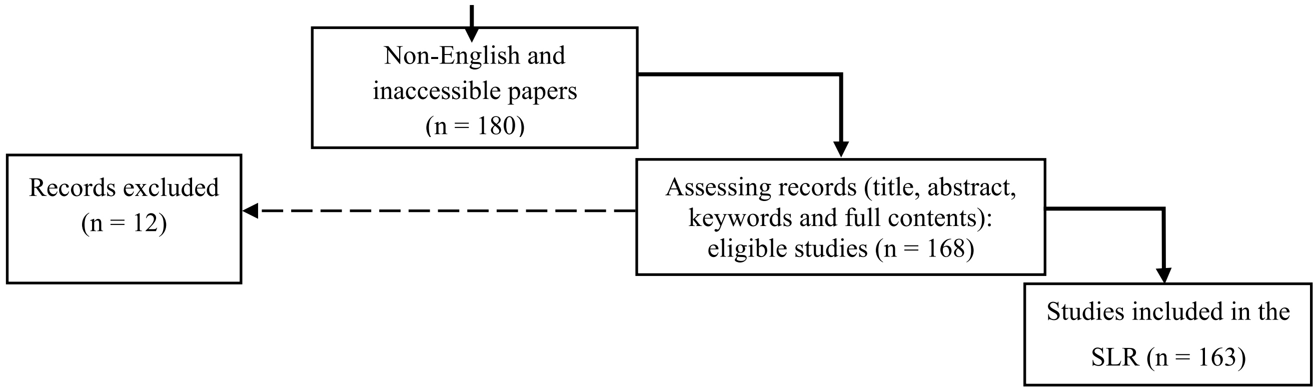
The paper is structured to provide a comprehensive exploration of the research. We start with the methods and data section in which we detail the systematic review process and analytical approaches. We then present the results and discussions sections, split into an initial descriptive analysis summarizing the broad findings and followed by detailed results for an in-depth exploration. We conclude with a summary of our core insights and their broader implications.

2. Methods and Data

Systematic literature reviews (SLRs) are celebrated for their structured and rigorous approach in consolidating existing research, crucially offering a comprehensive and unbiased perspective on studies concerning a specific subject (Boell and Cecez-Kecmanovic, 2015; Okoli, 2015). This method stands out in disciplines such as economics and business, aiding in the assimilation of varied methodologies amidst swiftly evolving and segmenting bodies of knowledge. Particularly for those delving into emerging fields like digital transformation and artificial intelligence (Aguilar et al., 2021; Guandalini, 2022), SLRs prove to be an invaluable resource, both in spotting research voids and in establishing a robust groundwork for subsequent inquiries (Snyder, 2019).

Figure 1. PRISMA research protocol





We adopt the PRISMA method for its clarity and systematic approach in literature reviews. PRISMA provides a four-phase selection process, aiming to reduce bias and ensure comprehensive reporting (Liberati et al., 2009). We chose this methodology for its suitability to our research goals, allowing for a detailed and impartial exploration of the available literature in this evolving field (Page et al., 2021). Following PRISMA's guidelines facilitated a disciplined review process, culminating in a visual representation of the approach from study selection to inclusion. This method ensures the reliability and depth of the review, contributing to the understanding of how AI technologies help detect tax fraud in a variety of contexts.

2.1. Data Selection

We select data from three primary databases: Scopus, Web of Science, and ScienceDirect, chosen for their high volume of quality publications, comprehensive coverage, advanced search capabilities, and reproducibility, making them the leading databases for systematic searches in this field (Mengist et al., 2020; Paul et al., 2021; Shaffril et al., 2021). This strategic combination of databases was aimed at achieving the most balanced search possible (Mourão et al., 2020), particularly valued for research in economics, management, and areas focusing on technological development and artificial intelligence. Our choice of these databases is supported by their efficiency and effectiveness in capturing relevant literature in these specific domains (Torre-López et al., 2023; Gomes et al., 2022; Pranckutė, 2021). This methodological approach ensures a broad yet targeted review of the existing body of work, facilitating a comprehensive understanding of the subject matter.

The data collection process for the study is guided by the PRISMA research protocol (

Figure 1), and it involved a multi-stage approach. Initially, we conduct a database screening across Scopus, Web of Sciences, and Science Direct, resulting in the identification of 215 records. We filter these records by year and subject area, reducing the number to 195. After excluding non-English and inaccessible papers, we assess the remaining records by reviewing titles, abstracts, keywords, and full contents, leading to 163 eligible studies being included in the systematic literature review.

Table 1. Keywords and codes used in advanced search

Search strings	(“Artificial intelligence”) AND ("Tax administration" OR "Tax authorities") AND ("Tax fraud" OR "Tax avoidance" OR "Tax evasion" OR "Tax compliance")
Keywords filter	"Artificial intelligence" "Machine learning" "Blockchain" "Big data" "Neural networks" "Digital taxation" "Tax fraud" "Tax compliance" "Tax evasion" "Tax avoidance" "Tax administration" "Fraud detection" "Tax Systems"
Scanned items	Article title, Abstract, Keywords
Year range	The last decade: 2014 – 2024
Database	Scopus, Web of Sciences and Science Direct

Source: Created by authors.

The advanced search applies a precise combination of keywords and codes, as detailed in Table 1. Search strings combine "Artificial Intelligence" with terms related to tax administration, fraud, avoidance, evasion, and compliance. Keywords such as "Machine learning," "Blockchain," and "Neural networks" are part of the filter applied to the scanned items, which included article titles, abstracts, and keywords within the last decade (2014-2024).

2.2. Data Analysis

We begin our data analysis with a bibliometric review to map the landscape of the research, covering publication trends over time (**Figure 2**), geographical contributions (**Figure 3**), the variety of paper types (

Figure 4), and the range of subject areas within the dataset (**Table 2**). This step is critical for identifying patterns and establishing a contextual understanding of the field's development and focus areas in the use of AI for tax fraud detection.

Taking a more detailed approach to data analysis, we then conduct textometric analysis using IRAMUTEQ software (Ratinaud, 2009), which allows for sophisticated analysis in line with the overarching goals of the study (Figura et al., 2023; Ramos et al., 2018). From the 163 papers gathered for the Systematic Literature Review (SLR), we create a general text corpus folder, containing the titles, abstracts, and keywords of the selected papers. We start with a global assessment, including a statistical summary (**Table 3**), identification of the 50 most frequently occurring words (**Table 4**), and a cluster dendrogram (**Figure 5**).[2] We then conduct a detailed analysis that examines the 30 most important words per class (**Table 6**), performing factorial correspondence analyses (**Figure 6**)[3] and conducting similarity analyses (**Figure 7**).[4] These

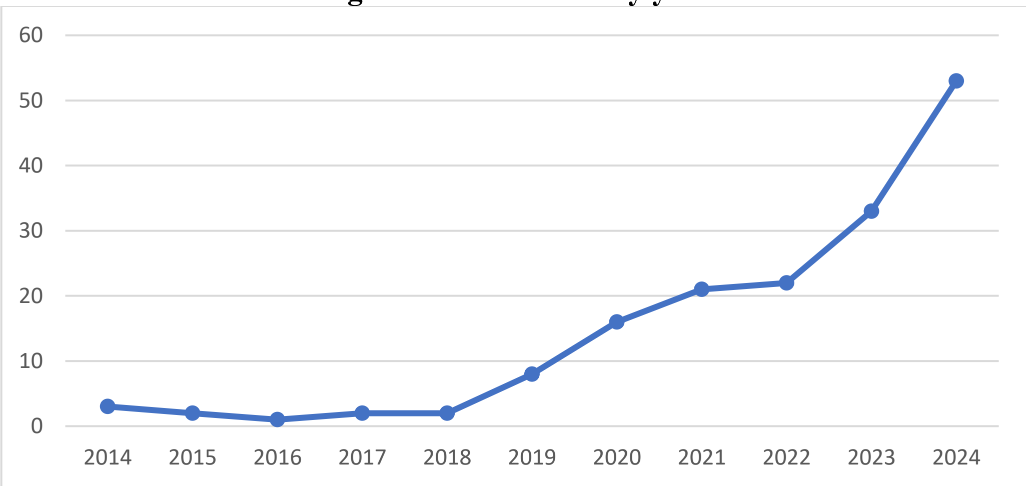
[2] A dendrogram provided by IRAMUTEQ is a hierarchical tree diagram that visually represents the clustering of words or textual data based on their similarity and co-occurrence.
[3] A factorial correspondence analysis is a graphical method used to identify and visualize relationships between words and text segments in a corpus.
[4] A similarity analysis maps word co-occurrences to reveal central terms and thematic structures within the text.

steps allow us to dissect the textual data thoroughly, providing a nuanced understanding of the prevalent themes and terms within the literature on AI and tax fraud detection.

3. Results (1): Descriptive and Bibliometric Analysis

In this section we conduct descriptive and bibliometric analysis to provide a foundational overview of AI research in tax fraud detection, including trends, contributions, and geographic insights. **Figure 2** illustrates the number of publications by year, showing a continuous increase in research output over time. Notably, there has been a sharp rise in recent years, with 53 documents in 2024, 33 in 2023, 22 in 2022, and 21 in 2021. This upward trend underscores a growing scholarly focus on AI in tax fraud detection, likely driven by its increasing relevance and the need for advanced methodologies to address evolving economic and regulatory challenges.

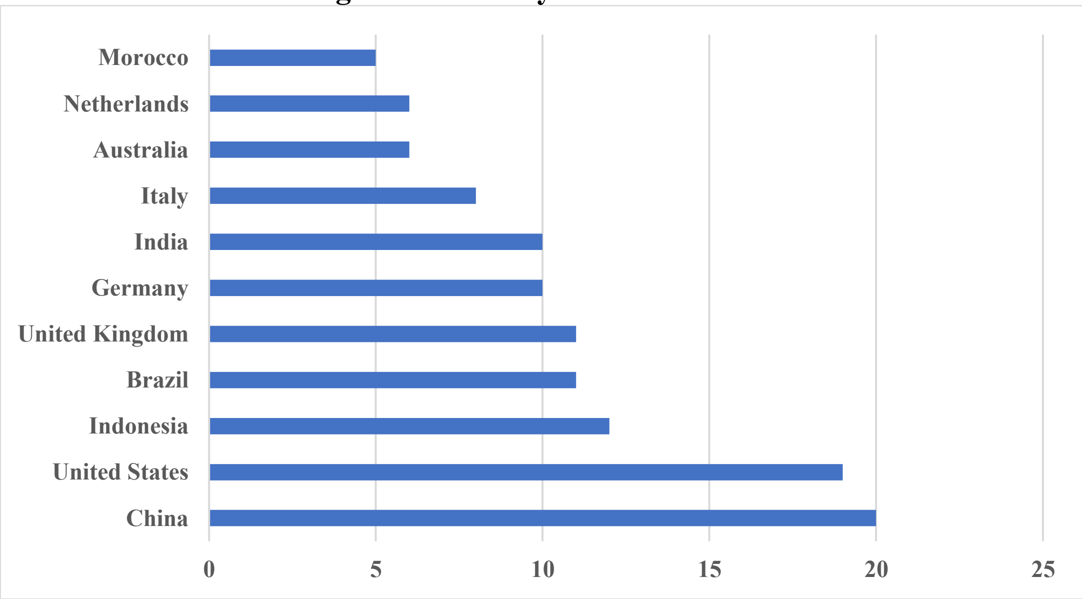
Figure 2. Documents by year



Source: Created by authors.

Figure 3 indicates that research contributions on AI in tax fraud detection are geographically diverse, with China (n=20) leading in the number of documents published, closely followed by the United States (n=19). Indonesia (n=12), reflecting a significant body of work emanating from these countries as well. Brazil and United Kingdom are tied (n=11 each) also contributing to the research output. This spread suggests a wide international interest and investment in exploring AI applications for tax fraud detection, indicating the global relevance of the issue.

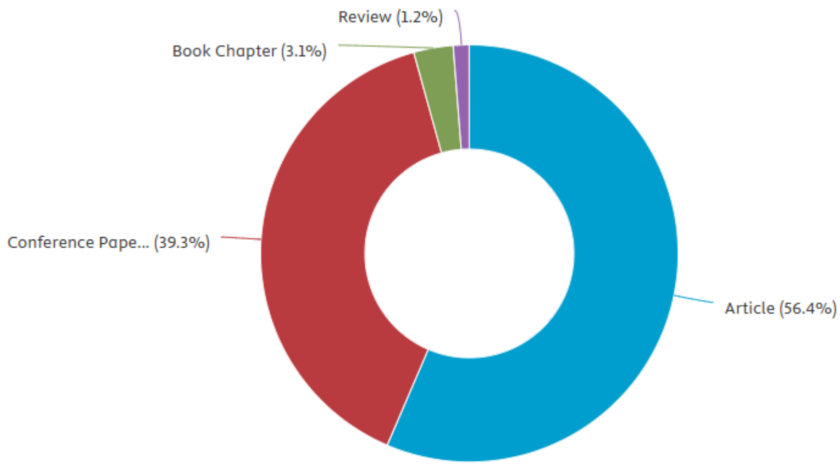
Figure 3. Country of affiliation



Source: Created by the authors.

These many papers are predominantly published in research articles and conference papers (Error! Reference source not found.), with articles (51.9 percent) and conference papers (44.4 percent) making up the majority, indicating a strong representation in both formal publications and academic gatherings. Book chapters and reviews each constitute a small fraction (1.9 percent), suggesting a lesser focus on these formats within the current discourse on AI in tax fraud detection. This distribution underscores the research community's preference for disseminating findings through articles and presentations at conferences.

Figure 4. Type of papers



Source: Created by the authors.

The subjects addressed in the collected documents predominantly fall under Computer Science, indicating its central role in the discussion of AI for tax fraud detection. Other fields such as Engineering, Business, Management and Accounting, and Social Sciences also contribute significantly, demonstrating the interdisciplinary nature of this research (see **Table 2**). Contributions from Economics, Econometrics and Finance, Decision Sciences, and even Materials Science reflect the broad relevance and application of AI across various facets of research connected to tax fraud.

Table 2. Documents by subject area

Subject area	Documents
Computer Science	98
Engineering	42
Business, Management and Accounting	37
Social Sciences	35
Economics, Econometrics and Finance	29
Decision Sciences	23
Materials Science	9

Source: Created by the authors.

The bibliometric analysis reveals an upsurge in AI and tax fraud detection research, especially in recent years, with a global spread of contributions led by China and the United States. Computer Science dominates the subject areas, with interdisciplinary input from various fields, illustrating the wide-ranging impact of AI in enhancing tax fraud detection and the diverse academic interest it garners.

We now engage in text analysis, extracting key findings in order to capture the essential insights from the exploration of AI in tax fraud detection.

The statistical summary provided in **Table 3**, generated using IRAMUTEQ software, offers insightful metrics on the corpus post lemmatization.[5] The table highlights a total of 24,951 occurrences across the corpus, with an average of 3,836 occurrences per text and a total of 3,607 lexical forms (words) identified. Among these, only 3 forms are categorized as active, with 1,607 being unique occurrences (hapaxes legomenon)[6], signifying a diverse range of vocabulary with a substantial portion being used only once. This diversity and the ratio of unique terms to total occurrences (6.44 percent) and forms (43.16 percent) suggest a wide breadth of topics and concepts covered within the texts analyzed. Such detailed analysis underscores the complexity and richness of the language surrounding AI in tax fraud detection research.

[5] Lemmatization is the process of grouping together different inflected forms of the same word. Verbs are converted to their infinitive form, nouns to their singular form, and adjectives to their masculine singular form.
[6] A hapax legomenon is a word or expression that appears only once within a given text, corpus, or language. In text analysis, identifying hapax legomena can help detect rare or unique terms.

Table 3. Statistical summary of corpus

Concept	Total number	
Number of occurrences	24 951	
Mean of occurrences per text	24951.00	
Number of lexical forms (words)	3 836	
Active forms	3 607	
Number of clusters	3	
Number of hapaxes legomenon (*)	1 607	6.44% of occurrences 43.16% of forms

(*) Words with frequency = 1

Source: Created by the authors using IRAMUTEQ software.

Table 4 showcases the 50 most frequently used active words in the corpus, illustrating key focus areas within AI and tax fraud detection research. Terms like "tax," "machine learning," "tax evasion," and "blockchain" are among the most used words, reflecting the core subjects and technologies under investigation (Alm, 2021; Alm et al., 2019). The prominence of "artificial intelligence" alongside specific methods like "data mining" and "neural networks" underscores the technological emphasis of the studies (De Roux et al., 2018; Delgado et al., 2023; Murorunkwere et al., 2022; Pérez López et al., 2019). Additionally, the inclusion of "fraud detection," "tax authorities," and "government" highlights the practical applications and stakeholders involved. This frequency analysis not only identifies the primary topics and tools but also indicates the interdisciplinary approach encompassing technology, regulatory concerns, and the broader economic and management implications in addressing tax fraud.

The dendrogram in **Figure 5**, created by IRAMUTEQ software, illustrates the clustering of concepts within the corpus. The three distinct classes show a thematic division. *Class 1*, the largest group, focuses on foundational technologies and their application in the field, with keywords like blockchain, taxation, and artificial intelligence (Mazur, 2022; Morton and Curran, 2023). *Class 2* centers on the research methodology, with terms like accuracy and classification indicating a focus on the precision and categorization aspects of the studies (Murorunkwere et al., 2022). *Class 3* addresses specific types of machine learning, highlighted by terms such as supervised and unsupervised learning, suggesting an emphasis on the algorithms used in tax fraud detection (Alm et al., 2019; De Roux et al., 2018; Savić et al., 2022). Each cluster represents a significant area of focus in the literature, providing a visual breakdown of the key topics and approaches in the use of AI for detecting tax fraud (**Table 5**).

Table 4. The 50 most frequently used active words

Order	Active forms	Freq.	Order	Active forms	Freq.
01	Tax	285	**26**	Analytics	75
02	Machine learning	263	**27**	Challenges	75
03	Tax evasion	258	**28**	Companies	67
04	Taxation	219	**29**	Performance	63
05	Taxpayers	167	**30**	Identify	63
06	Model	158	**31**	Decision making	63
07	Fraud	152	**32**	Improve	62
08	Blockchain	150	**33**	Compliance	62
09	Artificial intelligence	147	**34**	Economic	58
10	System	125	**35**	Support	58
11	Approach	118	**36**	Context	58
12	Information	107	**37**	Management	55
13	Audit	105	**38**	Collection	54
14	Tax authorities	105	**39**	Neural networks	54
15	Tax fraud	100	**40**	Prediction	54
16	Tax administration	98	**41**	Digital	53
17	Methods	97	**42**	Accounting	52
18	Detection	95	**43**	Behavior	52
19	Fraud detection	95	**44**	Blockchain technology	51
20	Technology	88	**45**	Algorithm	51
21	Application	87	**46**	Big data	49
22	Data mining	87	**47**	Tax fraud detection	49
23	Process	81	**48**	Tax returns	48
24	Results	77	**49**	Value added tax	48
25	Government	77	**50**	Transformation	48

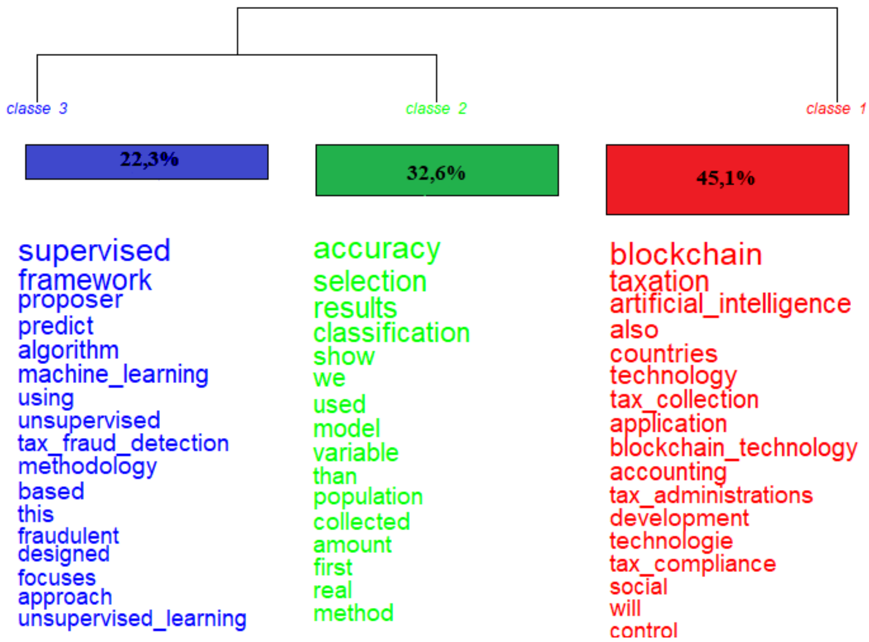
Source: Created by the authors using IRAMUTEQ software.

Table 5. Thematic summary by cluster

Cluster	Thematic focus
Cluster 1	**Innovative technologies in tax control:** exploring how cutting-edge technologies like blockchain are integrated with AI to improve tax compliance and fraud prevention in the context of digital tax administration.
Cluster 2	**Evaluative strategies in AI:** concentrating on the analytical methods employed to assess the performance of AI in classifying and detecting tax-related anomalies.
Cluster 3	**AI modeling techniques for compliance:** focusing on the deployment of various machine learning algorithms to identify and prevent fraudulent tax activities.

Source: Created by authors.

Figure 5. Dendrogram of the clusters



Source: Created by the authors using IRAMUTEQ software.

The first cluster in **Table 6** centers on "Blockchain and AI in tax modernization", and it is characterized by a strong focus on the integration of blockchain technology and artificial intelligence within the domain of taxation (Fatz et al., 2019; Mazur, 2022; Morton and Curran, 2023; Owens and Hodzic, 2022). This theme reflects an intersection between advanced technological applications and their role in transforming tax collection, administration, and compliance strategies (Baghdasaryan et al., 2022; Cobham and Janský, 2018; Martínez et al., 2022). The presence of terms such as blockchain, tax collection, accounting, and tax compliance suggests an exploration of how these digital tools can improve the efficiency, transparency, and effectiveness of tax systems (Baghdasaryan et al., 2022; Martínez et al., 2022). It also implies a consideration of the challenges, opportunities, and legal aspects related to the adoption of these technologies in an international context, indicating a comprehensive discussion on the modernization of tax regimes through tech advancements. For Cluster 2, which makes up 33 percent of the focus, a suitable theme might be "Precision and predictive analysis in tax control". This cluster is dominated by terms like accuracy, selection, and structured, which align with the precision required for effective tax monitoring and the use of predictive models for foresight in tax-related issues (Sampa and Phiri, 2023; Xu et al., 2023). Additionally, the cluster reflects on the importance of detection, data mining, and audit, all of which are crucial for identifying and addressing tax evasion and avoidance with accuracy (De Roux et al., 2018; Sampa and Phiri, 2023). These terms, along with efficiency and resources, suggest a focus on optimizing the tax assessment process and improving the accuracy of identifying tax-related discrepancies. Cluster 3 accounts for 22 percent of the data, and could be themed as "Learning algorithms in tax fraud detection". It is characterized by a focus on supervised and unsupervised learning methods, as well as the utilization of specific algorithms and machine learning techniques tailored for tax fraud detection (Masrom et al., 2022; Murorunkwere, Haughton, et al., 2023; Murorunkwere, Ihirwe, et al., 2023; Savić et al., 2022). The cluster also signifies an emphasis on fraudulent behaviors and the approaches developed to predict and identify them within tax systems. This cluster suggests an analysis of the effectiveness of different AI methodologies, such as deep learning and neural networks, in enhancing the precision of fraud detection and tax audits (Baghdasaryan et al., 2022).

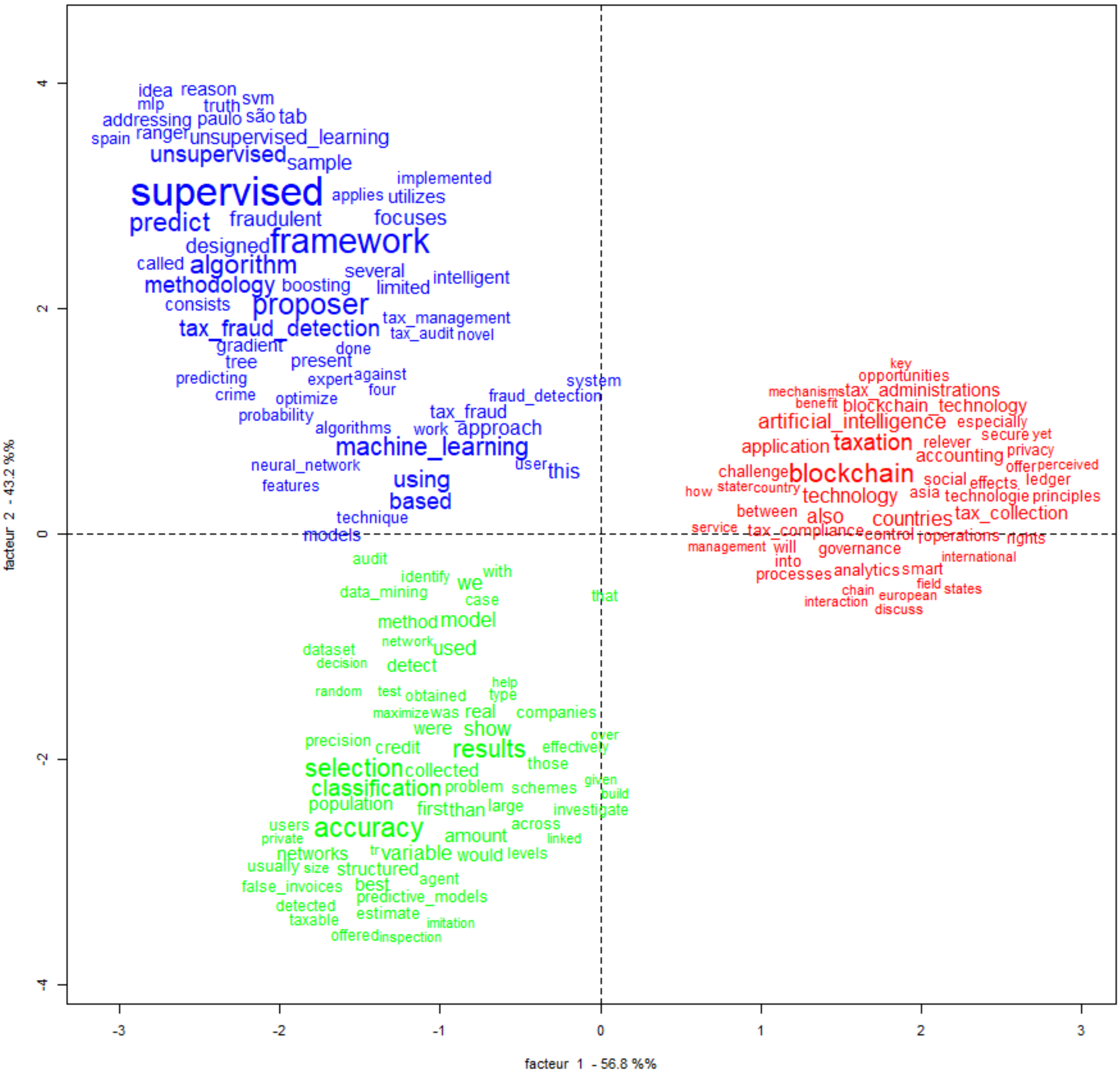
Table 6. The 25 most used words per class

Cluster 1 (45%) - Blockchain and AI in tax modernization					Cluster 2 (33%) - Precision and predictive analysis in tax control					Cluster 3 (22%) - Learning algorithms in tax fraud detection				
Forms	**Fr. S.t.**	**Total freq.**	**%**	**Chi2**	**Forms**	**Fr. S.t.**	**Total freq.**	**%**	**Chi2**	**Forms**	**Fr. S.t.**	**Total freq.**	**%**	**Chi2**
Blockchain	40	48	83.33	31.14	Accuracy	18	19	94.74	34.52	Supervised	18	19	94.74	59.77
Taxation	28	32	87.50	24.72	Selection	18	21	85.71	27.98	Algorithm	19	24	79.17	46.99
Artificial intelligence	39	52	75.00	20.80	Structured	25	34	73.53	27.57	Machine learning	17	23	73.91	37.03
Tax collection	32	41	78.05	19.48	Networks	16	19	84.21	23.81	Tax fraud detection	10	11	90.91	30.57
Application	20	22	90.91	19.45	Detection	20	28	71.43	20.19	Fraudulent	11	13	84.62	29.92
Blockchain technology	28	35	80.00	18.43	Predictive models	56	113	49.56	18.58	Focuses	32	68	47.06	27.64
Accounting	13	13	100.0	16.23	Precision	29	48	60.42	18.47	Approach	36	82	43.90	26.17
Tax administrations	27	35	77.14	15.54	Estimate	38	69	55.07	18.09	Unsupervised learning	7	7	100.0	24.76
Development	14	15	93.33	14.51	Companies	10	11	90.91	17.33	Tax fraud	11	15	73.33	23.25
Technologies	14	15	93.33	14.51	Contributors	11	13	84.62	16.36	Boosting	9	11	81.82	23.01
Tax compliance	16	18	88.89	14.43	Investigate	9	10	90.00	15.24	Intelligent	31	70	44.29	22.54
Social	16	19	84.21	12.18	Audit	9	10	90.00	15.24	optimize	62	184	33.70	21.10
Control	12	13	92.31	12.00	Data mining	9	10	90.00	15.24	Fraud detection	7	8	87.50	19.97
Governance	22	29	75.86	11.73	False invoices	9	10	90.00	15.24	Predicting	7	8	87.50	19.97
Challenge	15	18	83.33	11.00	Taxable	14	19	73.68	15.08	Algorithms	7	8	87.50	19.97
Business	24	33	72.73	10.85	Efficiency	22	36	61.11	14.21	Crime	24	52	46.15	18.98
Processes	13	15	86.67	10.78	Dataset	8	9	88.89	13.16	Tax management	5	5	100.0	17.62
Analytics	11	12	91.67	10.76	Help	8	9	88.89	13.16	Supervised learning	5	5	100.0	17.62
Smart	11	12	91.67	10.76	Inspection	6	6	100.0	12.51	Deep learning	5	5	100.0	17.62
Legal	11	12	91.67	10.76	Estimation	6	6	100.0	12.51	Planning	9	13	69.23	16.98
Opportunities	21	28	75.00	10.68	Private	6	6	100.0	12.51	Neural network	8	11	72.73	16.52
Privacy	18	23	78.26	10.68	Unlabeled learning	20	33	60.61	12.49	Tax audit	6	7	85.71	16.50
Stakeholders	18	23	78.26	10.68	Tax avoidance	9	11	81.82	12.34	Tax returns	17	35	48.57	14.97
Principles	22	30	73.33	10.24	Resources	10	13	76.92	11.87	Big data	4	4	100.0	14.07
Mechanisms	16	20	80.00	10.23	Tax evasion	54	119	45.38	11.25	Personal income tax	4	4	100.0	14.07
International	8	8	100.0	9.89	Neural networks	7	8	87.50	11.11	machine learning algorithms	4	4	100.0	14.07
Modernization	40	48	83.33	31.14	Declarations	7	8	87.50	11.11	Decision making	4	4	100.0	14.07
Perceived	28	32	87.50	24.72	Tax assessment	5	5	100.0	10.41	Data analytics	4	4	100.0	14.07
Protection	39	52	75.00	20.80	Active learning	5	5	100.0	10.41	Corporate tax	4	4	100.0	14.07
Costs	32	41	78.05	19.48	Vertical equity	8	10	80.00	10.39	Data mining	4	4	100.0	14.07

Source: Created by the authors using IRAMUTEQ software.

The factorial correspondence analysis in **Figure 6** visualizes the relationship and correlation between the various keywords used in the literature on AI and tax fraud detection. In this graph, the closer the words are to each other, the more frequently are they associated within the documents. It is clear from the dense clustering of terms like supervised, framework, and predict that there is a strong focus on predictive models and structured approaches in AI. Another dense cluster includes blockchain, taxation, and artificial intelligence, highlighting the technological convergence in this research area. This type of analysis allows us to observe how different concepts within the field are interconnected, offering a graphic representation of the thematic structures that underpin the research corpus.

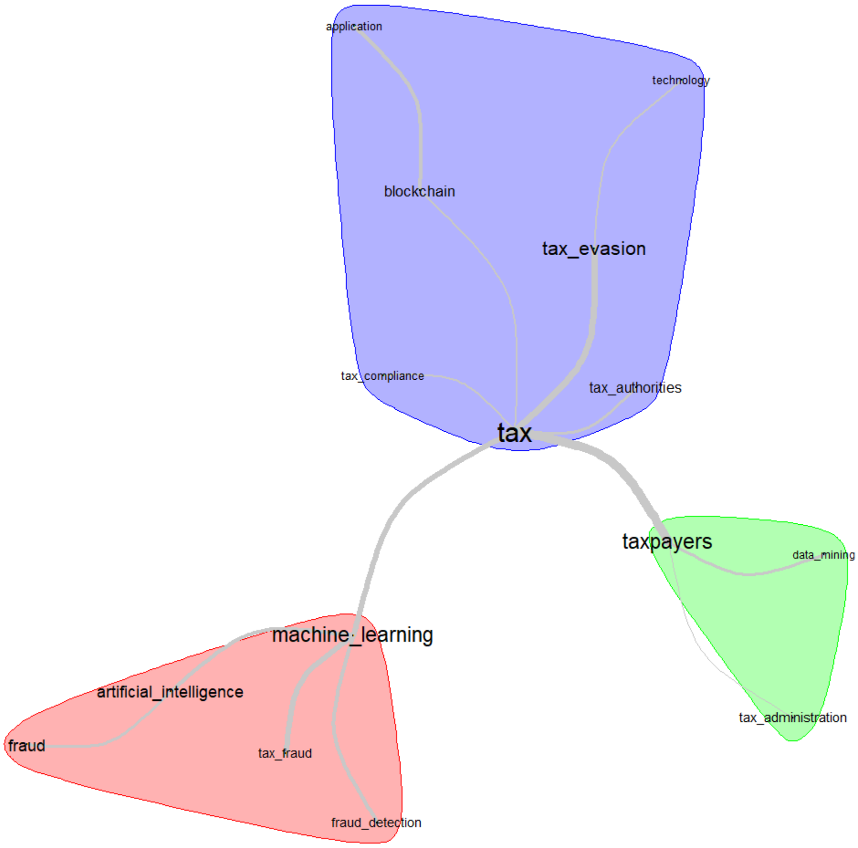
Figure 6. Factorial correspondence analyses



Source: Created by the authors using IRAMUTEQ software

Figure 7 presents a similarity analysis, which visually groups related concepts in the field of AI and tax fraud detection into clusters. These clusters represent interconnected themes, one focusing on the core subject of tax, surrounded by related terms like evasion and compliance, another emphasizing machine learning and its link to fraud and fraud detection, and a third highlighting taxpayers and associated aspects such as data mining and tax administration (Belahouaoui and Attak, 2024b). Each cluster is shaped by the frequency and co-occurrence of terms in the literature, indicating how different topics are conceptually related to each other within the research field.

Figure 7. Similarity analysis



Source: Created by the authors using IRAMUTEQ software.

The text analysis crystallizes the focus on cutting-edge AI technologies and methods like blockchain and machine learning in enhancing tax fraud detection, as reflected in the literature's predominant themes and the clustering of related research topics.

4. Results (2): Key Findings

In this section we examine key findings from a carefully selected set of studies, highlighting major contributions and challenges in the use of AI for tax fraud detection. We chose the ten studies presented in **Table 7** by using a comprehensive literature analysis, considering citation impact, relevance to the research objectives, and thematic alignment. Selection criteria focused on the most cited studies, ensuring strong methodological foundations and direct connections to AI-driven tax fraud detection. This synthesis provides essential perspectives on the effectiveness, limitations, and future developments of AI in tax administration.

To further elucidate the practical applications and implications of various AI tools in the realm of tax fraud detection, we present a detailed comparative analysis in

Table 8. This table synthesizes essential aspects of each AI technology, including their specific applications in detecting tax fraud, the benefits they offer, the challenges they pose, and the associated costs. This structured overview serves as a comprehensive guide for tax authorities and policymakers to assess the suitability of different AI tools in enhancing their fraud detection capabilities, balancing technological advantages against operational challenges and cost considerations.

In this analysis we explore how AI tools function in a tax administration context, focusing on their effectiveness, efficiency, cost implications, and the challenges they pose. Machine learning and deep learning stand out for their pattern recognition capabilities, essential for sifting through complex taxpayer data to spot subtle fraud indicators. The resource demands of each technology, including computational and human resources, are assessed, highlighting how technologies like data analytics and predictive modeling streamline the fraud detection process by minimizing the need for extensive manual labor. Moreover, the financial aspects of implementing AI solutions are discussed. Blockchain technology, for instance, provided transparency and security but comes with high setup and ongoing maintenance costs. Additionally, the analysis tackles the hurdles each technology might face, such as data privacy concerns associated with big data applications and the steep learning curve associated with neural networks, which often require specialized knowledge and training. This comparative overview aims to arm tax authorities and policymakers with information to make informed decisions regarding the integration of AI tools into their systems, identifying which tools best align with their specific needs by balancing effectiveness, efficiency, and cost to optimize their tax fraud detection approach.

Table 7. Key findings from the top 10 most cited studies directly related to the subject

N°	Authors	Purpose	Methodology	Variables	Results
01	Calafato et al., (2016)	Improve the process of identifying tax fraud using a controlled natural language.	Development of a framework that allows fraud experts to design fraud patterns independently.	• Efficiency of fraud detection patterns; • Ease of use for fraud experts.	Enabled fraud experts to optimize rules swiftly and independently, reducing the time and errors associated with traditional methods.
02	Alm et al. (2019)	To analyze the impact of technological advancements on tax compliance, exploring both enhancements and challenges posed by emerging digital tools.	Review of prior studies and development of a cohesive framework assessing the effects of new technologies on tax compliance and noncompliance.	• Technological advancements • AI, data mining, blockchain, • Public-key cryptography • Tax compliance and noncompliance	Technological advancements improve tax compliance by aiding enforcement (AI, data mining, cryptography).
03	Savić et al. (2022)	To enhance tax evasion risk management through a novel hybrid unsupervised method.	Development of HUNOD (Hybrid UNsupervised Outlier Detection) method, integrating clustering and representation learning for outlier detection.	• Tax evasion • Outlier detection • Unsupervised learning • Clustering • Representational learning	Demonstrated high efficacy in identifying internally validated outliers (90%-98%), improving outlier interpretability and relevance in economic contexts.
04	Baghdasaryan et al. (2022)	To enhance tax audit efficiency in Armenia through a machine learning model, particularly for businesses under a standard tax regime.	Development of a fraud prediction model using gradient boosting and minimal additional information from tax returns.	• Historical fraud • Audit data, • Administrative cost shares, • External economic activities.	Demonstrated the potential to improve fraud detection accuracy over rule-based methods and highlighted the value of taxpayer network data, especially for new companies lacking historical fraud data.
05	Murorunkwere et al. (2022)	To identify factors contributing to income tax fraud using Artificial Neural Networks (ANNs).	Utilization of ANNs to analyze income tax data for fraud detection, comparing various parameters for optimal model performance.	• Fraud detection; • Income tax; • Multilayer perceptron; • Neural network; • Tax fraud	Achieved high performance in fraud detection with 92% accuracy, 85% precision, 99% recall, and 95% AUC-ROC. Identified specific business-related factors as relevant to income tax fraud.
06	Alsadhan (2023)	To address limitations in current tax fraud detection methods by proposing a comprehensive framework combining supervised	A multi-module framework employing both supervised and unsupervised learning techniques, along with behavioral analysis.	• Tax fraud; • Feature engineering; • Applied machine learning	Demonstrated the framework's effectiveness in identifying potential tax fraud using data from the Saudi tax authority.

		and unsupervised machine learning models.			
07	Prolhac and Gaie (2023)	To introduce a novel framework for optimizing tax fraud detection.	The framework comprises four layers: Modeling, Datasets, Algorithms, and Interfaces, using neural networks and random forest algorithms.	• Artificial intelligence; • E-government; • Fraud detection; • Neural networks; • Open framework	The framework enhances fraud detection efficiency and is made publicly available for further research and optimization.
08	Ruzgas et al. (2023)	To enhance the efficiency of tax evasion detection in Lithuania using data mining techniques.	Development and application of data mining models for segmentation, risk assessment, and detection of tax crimes.	• Tax evasion; • Fraud detection; • Data mining; Clustering; • Prediction	Demonstrated the effectiveness of data mining in detecting tax evasion, offering tools for reducing revenue losses and aiding decision-makers in developing countries.
09	Belahouaoui and Attak (2024)	To analyze the impact of tax digitalization, focusing on AI technologies, on enhancing tax compliance behavior in the context of *Tax Administration 3.0*.	Systematic literature review using textometry	• *Tax Administration 3.0* • Tax compliance • Digital taxation • Artificial intelligence	AI and blockchain significantly improve tax compliance and efficiency. Challenges persist in emerging economies regarding adoption and integration. The trend toward *Tax Administration 3.0* highlights the need for regulatory frameworks and SME support.
10	Khaltar (2024)	To examine the impact of governance quality and adoption of the Open Government Partnership on trade-related tax evasion in developing countries.	Empirical analysis using governance indicators and tax evasion data, focusing on trade misinvoicing as a key tax evasion channel.	• Tax evasion • Developing countries • Governance quality • Open government partnership	Governance quality and open government initiatives significantly reduce trade-related tax evasion. Open government adoption moderates the effect of governance quality, strengthening its impact on reducing tax evasion.

Source: Created by the authors.

Table 8. AI tools used to detect tax fraud

AI Tools	Tax fraud detection	Benefits	Challenges	Costs
Machine Learning	Identifying patterns and anomalies in large datasets.	High accuracy and adaptability to new fraud patterns.	Requires large, clean datasets for training.	High computational resources for training and running models.
Deep Learning	Deep analysis of complex and layered data structures.	Excellent at processing large volumes of unstructured data.	Complex to configure and requires extensive training data.	High initial setup and operational costs.
Big Data	Handling and processing vast datasets to find irregularities.	Can manage and analyze data at a scale beyond human capabilities.	Privacy concerns; requires robust data governance.	Significant infrastructure and storage costs.
Data Mining	Discovering patterns and correlations in large datasets.	Uncovers hidden patterns that might indicate fraud.	Can produce many false positives without proper tuning.	Requires investment in data processing tools and technology.
Data Analytics	Analyzing taxpayer data to predict and identify fraudulent transactions.	Enables real-time decision-making and trend analysis.	Needs skilled personnel to interpret data correctly.	Costs associated with analytical tools and personnel training.
Blockchain	Providing a secure and transparent record of transactions.	Increases data integrity and security.	Technologically complex and requires consensus on data entry.	High implementation and maintenance costs.
Predictive Modeling	Forecasting future trends based on historical data.	Allows proactive measures against predicted fraud activities.	Models can be inaccurate if data or assumptions are not correct.	Development and continual update costs.
Neural Networks	Learning and recognizing complex patterns of tax fraud.	Extremely effective at identifying subtle patterns.	Requires large amounts of training data and computing power.	High costs for setup, operation, and maintenance.
Unlabeled Learning	Learning from data that hasn't been explicitly labeled as fraudulent or non-fraudulent.	Useful in scenarios with limited labeled data.	Less accurate than supervised learning models.	Computational costs for processing and model tuning.
Active Learning	Iteratively querying a user to label data points.	Improves model accuracy with fewer training data.	Depends on continuous user interaction for labeling.	Costs of setup and iterative process involvement.
Algorithm	General computational methods for detecting tax fraud.	Broad applicability and customizable to specific needs.	Algorithmic bias and transparency issues.	Development, testing, and deployment costs.

Source: Created by the authors.

Building on the detailed text analyses, we now present our “Adaptive AI Tax Oversight” (AATO) framework, depicted in Figure 8. This framework synthesizes the key functions and processes by which AI technologies are currently enhancing tax fraud detection efforts. It encapsulates the dynamic interplay between data processing, pattern recognition, predictive modeling, and continuous learning, all critical components identified through the systematic review and analyses. The AATO framework aims to provide a visual representation of how these AI capabilities integrate into a cohesive system, offering a guide for tax authorities and policymakers to harness AI effectively in combating tax fraud.

Figure 8. Adaptive AI Tax Oversight (AATO) framework)

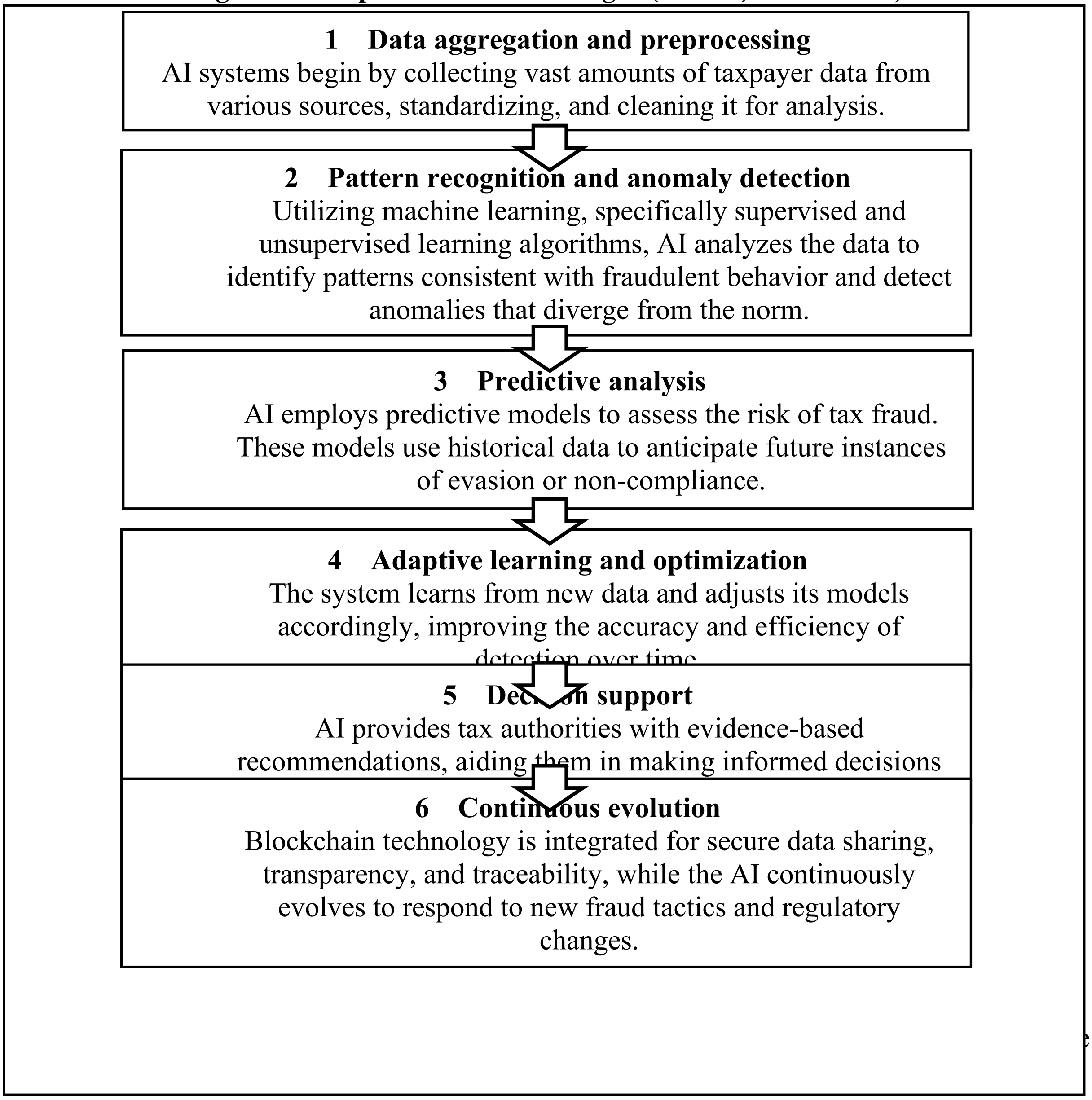


Table 9 attempts to present

Delving into the intricacies of *Tax Administration 3.0*, it is essential to examine both the advantages and challenges of deploying AI in tax fraud detection.

Table 9 attempts to present a balanced view, juxtaposing the benefits that AI brings to the efficiency and effectiveness of tax fraud detection against the challenges it poses in terms of technical implementation, data management, and ethical considerations. This dichotomy is crucial for understanding the full spectrum of AI's impact on modern tax administration practices.

Table 9. Benefits and challenges of AI in tax fraud detection within the framework of *Tax Administration 3.0*

Benefits of AI in tax fraud detection		Challenges of AI in tax fraud detection	
Enhanced accuracy	AI algorithms can analyze vast datasets with precision, reducing human errors and increasing the accuracy of fraud detection.	**Data privacy concerns**	The use of AI requires the handling of large volumes of personal data, raising concerns about privacy and data protection.
Predictive capabilities	AI's predictive models can forecast potential fraud cases by learning from historical patterns.	**Complexity of tax evasion tactics**	As fraudsters evolve their tactics, AI systems must constantly adapt, which can be technically challenging.
Resource efficiency	Automating the detection process with AI allows tax authorities to allocate human resources more strategically.	**Integration with existing systems**	Incorporating AI into the legacy systems of tax administrations can be technically and financially demanding.
Real-time analysis	AI enables continuous monitoring and real-time analysis, leading to quicker responses to fraudulent activities.	**Need for expertise**	There is a demand for skilled professionals to develop, manage, and interpret AI systems, which can be a scarcity.
Scalability	AI systems can be scaled to handle the increasing volume and complexity of tax data as administrations grow.	**Ethical and legal issues**	The decision-making process of AI must align with legal standards and ethical considerations, which can be complex to navigate.
Transparency and traceability	Blockchain integrated with AI can provide a transparent and traceable record of transactions.	**Algorithm bias**	AI models can inadvertently perpetuate biases present in the training data, leading to unfair or skewed outcomes.

Table 9 aims to summarize the potential advantages and the obstacles that come with integrating AI into tax fraud detection processes, highlighting the considerations for tax administrations moving towards a more digital and AI-driven future.

5. Conclusions and Implications

Our descriptive and bibliometric analysis of the studies reveals several key trends. An especially sharp increase in publications from 2019 to 2023 indicates a growing interest in AI applications for tax fraud detection. Geographical analysis shows a global spread of research with significant contributions from China and the United States, followed by Brazil, Indonesia, and Germany, highlighting the worldwide relevance of the topic. The variety of publication sources, with leading contributions from scholarly journals and conference proceedings, underscores the academic and practical significance of the research. Key individual contributors have emerged, reflecting the development of thought leadership within this field. Furthermore, the predominance of Computer Science in the subject area analysis points to its pivotal role, complemented by substantial contributions from Engineering, Business, Management, Accounting, and other fields, emphasizing the interdisciplinary nature of AI in tax fraud detection. This comprehensive review illustrates a diverse and active research landscape, with a clear emphasis on AI's potential to innovate tax compliance and enforcement strategies globally.

The text analysis reveals a rich tapestry of AI's involvement in tax fraud detection. Frequently used terms highlight the central technologies and approaches being explored, such as "tax," "machine learning," "blockchain," and "artificial intelligence," pointing to a strong focus on tech-driven tax solutions. These findings are further stratified into three clusters, revealing distinct research areas: the intersection of blockchain and AI in tax processes, the precision and predictive capacity of AI in tax monitoring, and the specific learning algorithms employed for fraud detection. The visualizations from factorial correspondence and similarity analyses provide an interconnected view of these themes, emphasizing the cohesive and multidisciplinary nature of the research landscape. Together, these layers of analysis offer a nuanced understanding of the trends, challenges, and future directions in the realm of AI-powered tax fraud detection.

The synthesis of findings from 10 pivotal studies underscores a dynamic evolution in the use of artificial intelligence and machine learning for tax fraud detection across various regions and tax systems (**Table 7**). From the application of clustering algorithms and neural networks to the development of frameworks facilitating independent fraud pattern design by experts, these studies collectively highlight significant advancements in identifying and predicting fraudulent tax activities. Notably, methods range from unsupervised learning techniques for under-reported tax declarations to hybrid models enhancing evasion risk management, revealing a trend towards leveraging both data-driven insights and domain knowledge. The results across these studies show a marked improvement in detection accuracy and efficiency, suggesting a promising direction for tax authorities worldwide to harness technology in combating tax evasion. This collective body of work not only enriches the academic discourse but also offers practical insights for policymakers and tax administration practitioners aiming to optimize their audit strategies and reduce tax revenue losses.

The collective insights from the reviewed studies inform the development of our Adaptive AI Tax Oversight (AATO) framework, depicted in **Figure 8**. This framework encapsulates a comprehensive approach by which AI technologies streamline the detection of tax fraud through a series of systematic steps, including data aggregation, pattern recognition, predictive analysis, adaptive learning, decision support, and continuous evolution with blockchain integration. These steps highlight the progression from data collection to actionable insights, demonstrating AI's capacity to transform tax fraud detection into a more dynamic, accurate, and efficient process. Through the integration of both supervised and unsupervised learning algorithms, and leveraging the transparency of blockchain technology, the AATO framework offers a forward-looking model for tax authorities to enhance their fraud detection capabilities, adapting to emerging challenges and regulatory shifts.

We believe that the many insights gathered from the analysis of AI applications in tax fraud detection reveal a nuanced landscape of benefits and challenges. On one hand, AI significantly enhances accuracy, predictive capabilities, and efficiency, offering scalable solutions for real-time analysis and leveraging blockchain for greater transparency. On the other hand, it faces hurdles such as data privacy concerns, the complexity of evolving tax evasion tactics, integration issues with existing systems, a need for specialized expertise, and ethical dilemmas including algorithm bias. These findings illuminate the dual-edged nature of AI in modern tax administration, highlighting the critical balance between leveraging technological advancements and addressing the inherent challenges they present.

Overall, our study illuminates both theoretical and practical implications in the realm of AI-driven tax fraud detection. Theoretically, we advance the understanding of AI methodologies, particularly the interplay between supervised and unsupervised learning in navigating the complexities of tax evasion. This exploration not only enriches the academic discourse but also sets the stage for future research aimed at refining AI tools for tax administration. Moreover, it champions an interdisciplinary approach, suggesting that the convergence of data science, legal studies, and economic principles can significantly bolster AI's effectiveness in detecting tax fraud.

On a practical level, our findings advocate for the integration of AI technologies like the Adaptive AI Tax Oversight framework to streamline tax fraud detection processes, thereby enhancing the operational efficiency of tax authorities. This has profound implications for policy development and strategic planning, urging tax administrations to embrace AI solutions. Additionally, our study underscores the importance of specialized training for tax professionals to adeptly manage and interpret AI systems, highlighting a pivotal area for capacity building. Furthermore, we call attention to the necessity of establishing ethical and legal frameworks to address privacy concerns and mitigate algorithmic bias, ensuring that AI applications in tax fraud detection are transparent, accountable, and equitable. We believe that these practical insights offer a roadmap for tax administrations worldwide to harness the potential of AI technologies responsibly and effectively.

Even so, our study has several limitations. By focusing specifically on the last decade (2014-2024), we scrutinize the myriad ways AI tools have revolutionized fraud detection, culminating in the AATO framework. However, this specific focus means that broader potential applications of AI in tax administration beyond fraud detection are not explored in depth. Additionally, considering the rapid evolution of AI, our findings may quickly be overtaken by new developments.

Future research directions present exciting frontiers to expand upon this foundation. Investigations could delve into a conceptual framework for employing neural networks more effectively in tax fraud detection, examining their implications within the burgeoning field of AI. Furthermore, the role of tax governance in the emerging new era of industry offers a rich vein of inquiry, particularly how emerging technologies reshape compliance costs and the administrative burden in the digital age. Finally, addressing the unique challenges and opportunities for applying AI in tax administrations of developing countries promises to provide critical insights into global disparities and potential strategies for leveraging AI to foster equitable tax compliance and enforcement.

References

Aguilar, J., Garces-Jimenez, A., R-moreno, M. D., & García, R. (2021). A systematic literature review on the use of artificial intelligence in energy self-management in smart buildings. *Renewable and Sustainable Energy Reviews*, *151*, Article 111530.

Alm, J. (2021). Tax evasion, technology, and inequality. *Economics of Governance*, *22* (4), 321-343.

Alm, J. (2023). Tax compliance, technology, trust, and inequality in a post-pandemic world. *eJournal of Tax Research*, *21* (2), 152-172.

Alm, J., Beebe, J., Kirsch, M. S., Marian, O., & Soled, J. A. (2019). New technologies and the evolution of tax compliance. *Virginia Tax Review*, *39* (3), 287-356

Alsadhan, N. (2023). A multi-module machine learning approach to detect tax fraud. *Computer Systems Science and Engineering*, *46* (1), 241-253.

Alstadsaeter, A., Godar, S., Nicolaides, P., & Zucman, G. (2023). *Global Tax Evasion Report 2024*.

Aoki, N., Tatsumi, T., Naruse, G., & Maeda, K. (2024). Explainable AI for government: Does the type of explanation matter to the accuracy, fairness, and trustworthiness of an algorithmic decision as perceived by those who are affected? *Government Information Quarterly*, *41* (4), Article 101965.

Baghdasaryan, V., Davtyan, H., Sarikyan, A., & Navasardyan, Z. (2022). Improving tax audit efficiency using machine learning: The role of taxpayer's network data in fraud detection. *Applied Artificial Intelligence*, *36* (1), Article 2012002.

Bao, Y., Hilary, G., & Ke, B. (2022). Artificial intelligence and fraud detection. *Innovative Technology at the Interface of Finance and Operations: Volume I*, 223-247.

Bassey, E., Mulligan, E., & Ojo, A. (2022). A conceptual framework for digital tax administration – A systematic review. *Government Information Quarterly*, *39* (4), Article 101754.

Belahouaoui, R., & Attak, E. H. (2024a). Digital taxation, artificial intelligence and *Tax Administration 3.0*: Improving tax compliance behavior – A systematic literature review using textometry. *Accounting Research Journal*, *37* (2), 172–191.

Belahouaoui, R., & Attak, E. H. (2024b). Exploring the relationship between taxpayers and tax authorities in the digital era: Evidence on tax compliance behavior in emerging economies. *International Journal of Law and Management*.

Belahouaoui, R., & Attak, E. H. (2025). Tax policy responses to economic crises: The case of post-COVID-19 reform in Morocco (2023-2026). In *Assessing Policy Landscapes in Taxation Dynamics* (357-384). IGI Global.

Bharosa, N. (2022). The rise of GovTech: Trojan horse or blessing in disguise? A research agenda. *Government Information Quarterly*, *39* (3), Article 101692.

Boell, S. K., & Cecez-Kecmanovic, D. (2015). On being 'systematic'in literature reviews. *Formulating Research Methods for Information Systems: Volume 2*, 48-78.

Bueno, S., Banuls, V. A., & Gallego, M. D. (2021). Is urban resilience a phenomenon on the rise? A systematic literature review for the years 2019 and 2020 using textometry. *International Journal of Disaster Risk Reduction*, *66*, Article 102588.

Calafato, A., Colombo, C., & Pace, G. J. (2016). A controlled natural language for tax fraud detection. *Controlled Natural Language: 5th International Workshop, CNL 2016, Aberdeen, UK, July 25-27, 2016, Proceedings 5*, 1-12.

Cobham, A., & Janský, P. (2018). Global distribution of revenue loss from corporate tax avoidance: re-estimation and country results. *Journal of International Development*, *30* (2), 206-232.

de la Torre-López, J., Ramírez, A., & Romero, J. R. (2023). Artificial intelligence to automate the systematic review of scientific literature. *Computing*, *105* (10), 2171-2194.

De Roux, D., Perez, B., Moreno, A., Villamil, M. del P., & Figueroa, C. (2018). Tax fraud detection for under-reporting declarations using an unsupervised machine learning approach. *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 215-222.

Delgado, F. J., Fernández-Rodríguez, E., García-Fernández, R., Landajo, M., & Martínez-Arias, A. (2023). Tax avoidance and earnings management: A neural network approach for the largest European economies. *Financial Innovation*, *9* (1), 19.

Dougherty, S. (2023). *Deploying artificial intelligence and data analytics to support intergovernmental fiscal relations*. https://www.oecd.org/tax/federalism/deploying-artificial-intelligence-and-data-analytics.pdf

Fatz, F., Hake, P., & Fettke, P. (2019). Towards tax compliance by design: A decentralized validation of tax processes using blockchain technology. *2019 IEEE 21st Conference on Business Informatics (CBI)*, *1*, 559-568.

Figura, M., Fraire, M., Durante, A., Cuoco, A., Arcadi, P., Alvaro, R., Vellone, E., & Piervisani, L. (2023). New frontiers for qualitative textual data analysis: A multimethod statistical approach. *European Journal of Cardiovascular Nursing*, 22 (5), 547-551.

Gaie, C. (2023). Struggling against tax fraud: A holistic approach using artificial intelligence. In *Recent Advances in Data and Algorithms for e-Government* (87-102). Springer.

Gale, W. G., & Krupkin, A. (2019). How big is the problem of tax evasion? Policy Brief, Urban-Brookings Tax Policy Center. Washington, D.C.

Gesk, T. S., & Leyer, M. (2022). Artificial intelligence in public services: When and why citizens accept its usage. *Government Information Quarterly*, *39* (3), Article 101704.

Gomes, P., Verçosa, L., Melo, F., Silva, V., Filho, C. B., & Bezerra, B. (2022). Artificial intelligence-based methods for business processes: A systematic literature review. *Applied Sciences*, *12* (5), 2314.

Guandalini, I. (2022). Sustainability through digital transformation: A systematic literature review for research guidance. *Journal of Business Research*, *148*, 456-471.

Khaltar, O. (2024). Tax evasion and governance quality: The moderating role of adopting open government. *International Review of Administrative Sciences*, *90* (1), 276-294.

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P. A., Clarke, M., Devereaux, P. J., Kleijnen, J., & Moher, D. (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. *Annals of Internal Medicine*, *151* (4), W-65.

Martínez, Y. U., Arzoz, P. P., & Arregui, I. Z. (2022). Tax collection efficiency in OECD countries improves via decentralization, simplification, digitalization and education. *Journal of Policy Modeling*, *44* (2), 298-318.

Masrom, S., Rahman, R. A., Mohamad, M., Abd Rahman, A. S., & Baharun, N. (2022). Machine learning of tax avoidance detection based on hybrid metaheuristics algorithms. *IAES International Journal of Artificial Intelligence*, *11* (3), 1153.

Matheus, R., Janssen, M., & Janowski, T. (2021). Design principles for creating digital transparency in government. *Government Information Quarterly*, *38* (1), Article 101550.

Mazur, O. (2022). Can blockchain revolutionize tax administration? *Penn State Law Review*, *127*, 115-170.

Mengist, W., Soromessa, T., & Legese, G. (2020). Method for conducting systematic literature review and meta-analysis for environmental science research. *MethodsX*, *7*, Article 100777.

Morton, E., & Curran, M. (2023). Exemplifying the opportunities and limitations of blockchain technology through corporate tax losses. In *Handbook of Big Data and Analytics in Accounting and Auditing* (177-205). Springer.

Mourão, E., Pimentel, J. F., Murta, L., Kalinowski, M., Mendes, E., & Wohlin, C. (2020). On the performance of hybrid search strategies for systematic literature reviews in software engineering. *Information and Software Technology*, *123*, Article 106294.

Mpofu, F. Y. (2024). Digital transformation by tax authorities. In *Digital Transformation in South Africa: Perspectives from an Emerging Economy* (151-170). Springer.

Murorunkwere, B. F., Haughton, D., Nzabanita, J., Kipkogei, F., & Kabano, I. (2023). Predicting tax fraud using supervised machine learning approach. *African Journal of Science, Technology, Innovation and Development*, *15* (6), 731-742.

Murorunkwere, B. F., Ihirwe, J. F., Kayijuka, I., Nzabanita, J., & Haughton, D. (2023). Comparison of tree-based machine learning algorithms to predict reporting behavior of electronic billing machines. *Information*, *14* (3), 140.

Murorunkwere, B. F., Tuyishimire, O., Haughton, D., & Nzabanita, J. (2022). Fraud detection using neural networks: A case study of income tax. *Future Internet*, *14* (6), 168.

OECD (2020). *Tax Administration 3.0: The Digital Transformation of Tax Administration*. Paris, France: OECD Publishing.

OECD (2023a). *Inventory of Tax Technology Initiatives*. Paris, France: OECD Publishing.

OECD (2023b). *Tax Administration 2023*. Paris France: OECD Publishing.

OECD (2024). *Corporate Tax Statistics 2024*. Paris, France: OECD Publishing.

Okoli, C. (2015). A guide to conducting a standalone systematic literature review. *Communications of the Association for Information Systems*, *37*.

Owens, J., & Hodžić S. (2022). Policy note: Blockchain technology – Potential for digital tax administration. *Intertax*, 50 (11), 813-823.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., & Brennan, S. E. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *International Journal of Surgery*, *88*, Article 105906.

Paul, J., Lim, W. M., O'Cass, A., Hao, A. W., & Bresciani, S. (2021). Scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR). *International Journal of Consumer Studies*, *45* (4), O1-O16.

Pérez López, C., Delgado Rodríguez, M. J., & de Lucas Santos, S. (2019). Tax fraud detection through neural networks: An application using a sample of personal income taxpayers. *Future Internet*, *11* (4), 86.

Pranckutė, R. (2021). Web of Science (WoS) and Scopus: The titans of bibliographic information in today's academic world. *Publications*, *9* (1), 12.

Prolhac, J., & Gaie, C. (2023). Providing an open framework to facilitate tax fraud detection. *International Journal of Computer Applications in Technology*, *73* (1), 24-41.

Ramos, M. G., do Rosário Lima, V. M., & Amaral-Rosa, M. P. (2018). IRAMUTEQ Software and discursive textual analysis: Interpretive possibilities. *World Conference on Qualitative Research*, 58-72.

Ratinaud, P. (2009). *IRaMuTeQ: Interface de R pour les analyses multidimensionnelles de textes et de questionnaires [IRaMuTeQ: R interface for multidimensional analysis of texts and questionnaires]*.

Ruzgas, T., Kižauskienė, L., Lukauskas, M., Sinkevičius, E., Frolovaitė, M., & Arnastauskaitė, J. (2023). Tax fraud reduction using analytics in an East European country. *Axioms*, *12* (3), 288.

Sampa, A. W., & Phiri, J. (2023). Prediction model for tax assessments using data mining and machine learning. *Computer Science On-Line Conference*, 1-14.

Saragih, A. H., Reyhani, Q., Setyowati, M. S., & Hendrawan, A. (2023). The potential of an artificial intelligence (AI) application for the tax administration system's modernization: The case of Indonesia. *Artificial Intelligence and Law*, *31* (3), 491-514.

Savić, M., Atanasijević, J., Jakovetić, D., & Krejić, N. (2022). Tax evasion risk management using a hybrid unsupervised outlier detection method. *Expert Systems with Applications*, *193*, 116409.

Shaffril, H. A. M., Samah, A. A., & Samsuddin, S. F. (2021). Guidelines for developing a systematic literature review for studies related to climate change adaptation. *Environmental Science and Pollution Research*, *28*, 22265-22277.

Shakil, M. H., & Tasnia, M. (2022). Artificial intelligence and tax administration in Asia and the Pacific. In *Taxation in the Digital Economy* (45-55). Routledge.

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333-339.

Tax, N., de Vries, K. J., de Jong, M., Dosoula, N., van den Akker, B., Smith, J., Thuong, O., & Bernardi, L. (2021). Machine learning for fraud detection in e-commerce: A research agenda. *Deployable Machine Learning for Security Defense: Second International Workshop, MLHat 2021, Virtual Event, August 15, 2021, Proceedings 2*, 30-54.

Tax Justice Network (2024). *State of Tax Justice 2024*. Bristol, England.

Xu, X., Xiong, F., & An, Z. (2023). Using machine learning to predict corporate fraud: Evidence based on the gone framework. *Journal of Business Ethics*, *186* (1), 137-158.

Zuiderwijk, A., Chen, Y. C., & Salem, F. (2021). Implications of the use of artificial intelligence in public governance: A systematic literature review and a research agenda. *Government Information Quarterly*, *38* (3), Article 101577.