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# Mapping the Intellectual Structure of Artificial Intelligence for Tax Compliance Enhancement: A Bibliometric Review

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## Abstract

**Background**: Artificial Intelligence (AI) has revolutionized tax compliance, improving fraud detection, risk assessment, and voluntary compliance. The knowledge landscape, intellectual bases and the trends in this nearing field, however, are not sufficiently well articulated and require a systematic mapping.
**Methods**: The structured search strategy was applied to the PRISMA methodology to retrieve literature on AI and tax compliance from Scopus. The number of records analyzed is 527 records published between 2004 and 2026, and it was done through Biblioshiny and VOSviewer. The publication trends, prolific authors, journals, countries, and citations, were analyzed to explore the performance, and science mapping included co-citation, bibliographic coupling, keyword co-occurrence, and thematic evolution.
**Results**: Research has been growing at an exponential rate since 2020, thanks to developments in machine learning, big data analytics and digital tax administration. Leading contributors became China, Germany and the United States. Focusing on the dominant themes in the field of taxation, artificial intelligence, machine learning, fraud detection and data mining. The

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growing research shows the importance of explainable AI, governance, transparency, public trust and ethical AI adoption.
**Conclusion**: The research suggests a five-step framework for implementing AI for tax compliance: risk concept formulation, data integration, model selection, governance and explainability, and continuous monitoring.
**Novelty**: This review article not only offers a comprehensive bibliometric mapping of AI and tax compliance, but also combines performance mapping with science mapping, and selects emerging themes and new research directions.
**Keywords**: Bibliometric Analysis; Digital Taxation; Machine Learning; Performance Mapping; Science Mapping

## 1. Introduction

Governments across the globe are grappling with the challenge of bridging the tax revenue gap (Garg et all., 2025). Tax evasion (Ozili, 2020) calculated avoidance (Payne & Raiborn, 2018), and inefficiencies of administration (Grand, 2009) diminish fiscal revenues and threaten the ability of the government to finance public and social goods. Among the various methods designed to bridge the tax revenue gap, artificial intelligence (AI) has the potential to become a revolutionary tool (Saba & Monkam, 2024). AI can enable the creation of systems for analyzing huge amounts of transaction (Ariyibi et al., 2024)and tax data to detect anomalies, identify potentially hazardous taxpayers, and streamline the procedures for complying with tax regulations on an unprecedented scale. The examination of the use of AI for tax compliance improvement includes investigating the organization of the tools and methods of AI application (Zaim & Sahbani, 2026;Angelov, 2026), which range from conventional machine learning methods (Swenson, 2024; Yang, 2025) to deep machine learning algorithms (Saragih et al., 2023; Kamoun et al., 2025) and language models (Jones & Free, 2026), and which deal with the real problems of tax administration.

AI-based tax administration development over the last 20 years shows its change from individual tech tests to operational functions of tax systems of nations (Belahouaoui & Alm, 2025; Anjarwi, 2026). The Golden Tax System of China (Chen &He, 2024), which has seen upgrades through big data analysis (Li & Wu 2020 and machine-learning-enabled checking of invoices ( Zhang et al., 2025; Chen et al., 2026), remains a notable tax establishment, forming the basis for this country's strategy in digital tax application (Weichen & Mayburov, 2026). The same success (Alexander, 2022; Heinemann & Stiller, 2025) is represented by the European Union that has been struggling with the problem of VAT gap (Braml & Felbermayr, 2022) and has been applying automated systems (Danescu, 2020; Kudrle, 2021) to track cross-border transactions (De & R, 2019; Merkx & Calzado, 2025). Meanwhile, tax administrations in North America have also tried machine-learning solutions (Belahouaoui & Alm, 2025) for auditing and fraud detection already. Moreover, the OECD, for instance, promotes knowledge exchange between counties regarding AI usage in tax compliance risk management (Milogolov, 2020; Yigitcanlar et al.,2024). There is a large amount of research done on various

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aspects of AI-enabled tax compliance such as digital tax management, fraud detection, taxpayer risk profiling, and automated decision-making respectively. In this regard, it is essential to conduct a literature review of the issue since most of the researchers have been analyzing various aspects of the issue with help of different techniques and approaches.

The conceptual foundation of AI-enhanced taxation research is based on the principles of economic information and regulatory enforcement theory. The asymmetric information issue between tax authorities and taxpayers plays a vital role in the area (Beck & Jung, 1989; Kacamak, 2022). The problem of not aligning the tax reported income and the real earnings is due to the fact that tax/enforcement authorities can't audit every single transaction and crosscheck every report (Slemrod, 2019). The AI technology is used to overcome this issue by processing vast amounts of structured and unstructured information (Yi et al., 2023; Qatawneh, 2025) such as invoices, bank statements etc. It is important to understand that machine learning and neural networks can be applied because they are trained on previous compliance results (Singh, 2024; Olldashi et al., 2025). The method of natural language processing can help to analyze the documents that were received from the examined parties as well (Lee & Shin, 2020; Song, 2026).

Globally, the adoption of AI in tax administration evolves around national perspectives (Saragih et al., 2023; Munjeyi & Schutte, 2024), capacity of institutions and readiness of technology (Park & McShea, 2025). Rich countries have progressed with the use of predictive analytics (Bachmann et al., 2022; Khan et al., 2025), e-invoicing regulations (Rukanova et al., 2021) and automated risk engines (Zong & Guan, 2025) in tax compliance process, while poor countries are facing obstacles (Hilbert, 2016) such as lack of digital infrastructure, fragmentation of data and low technological ability to implement those instruments. In addition to public sector applications, private sector has also started to apply AI in taxation due to demand for automated tax reporting, transfer pricing and compliance solutions (Fidelangeli & Galli, 2021).

While AI technologies can provide potential benefits, they also provide a set of problems and criticisms when it comes to tax compliance (Saragih et al., 2023; Mökander & Schroeder, 2024). There are still issues (Bracci, 2023; Koshiyama et al., 2024) in relation to algorithm transparency and explainability, especially regarding the challenge of explaining the workings of the automated audit and penalty decisions. Concerns regarding data security and privacy have also increased (Zerilli et al., 2019), as tax authorities are able to access more precise financial data and behavioral data. At the same time, there are still questions regarding the fairness of applying the unknown data-based risk modeling (lepri et al., 2018), which might lead to discrimination against a particular category of taxpayers or location as well as inadequate capabilities of tax bodies malfunctioning or lacking the resources necessary to implement such systems. Considering the mentioned problems and the fast-growing development of the area of knowledge regarding AI's potential use in taxation, it is important to establish a systematic analysis of the literature on that topic.

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**Research objective**

1. To visualize the intellectual landscape, thematic development and emerging research trends of AI and tax compliance.
2. To identify key governance, ethical and institutional challenges and future research priorities about AI enabled tax compliance.

## 2. Methodology

The intellectual framework, research trends, and thematic evolution of AI for tax compliance lay at the heart of this work. A quantitative technique known as bibliometric analysis was used in this research. This approach allows for a structured evaluation of academic literature based on bibliometric parameters (Zupic & Cater, 2015; Kumar, 2025), resulting in data on significant works, authors, providers, collaborations, and developing research topics. The bibliometric data utilized in this work was collected from the Scopus database because of its reputable nature (Kumar, 2025).

The selection of articles between 2004 and 2026 used in the analysis comprised three stages: identification, screening, and inclusion based on the PRISMA framework. The process began with identification, which was conducted through Boolean search (Table1) in TITLE-ABS-KEY sections of the articles, using a combination of artificial intelligence terms (artificial intelligence, machine learning, deep learning, natural language processing, large language models, and generative AI) with the terms related to tax compliance (tax compliance, tax administration, tax audit, tax evasion, tax fraud, digital taxation).

**Table 1**

*Database and Search Syntax*

| Database | Search Syntax |
|---|---|
| Scopus | (TITLE-ABS-KEY ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "artificial neural network*" OR "natural language processing" OR NLP OR "expert system*" OR "knowledge-based system*" OR "intelligent system*" OR "data mining" OR "predictive analytic*" OR "big data" OR "big data analytic*" OR "generative artificial intelligence" OR "generative AI" OR "large language model*" OR LLM* )AND ("tax compliance" OR "voluntary tax compliance" OR "taxpayer compliance" OR "tax compliance behavior" OR "tax compliance behavior" OR "tax administration" OR "revenue administration" OR "tax audit*" OR "tax enforcement" OR "tax monitoring" OR "tax collection" OR "tax reporting" OR "tax filing" OR "electronic tax" OR "e-tax" OR "digital taxation" OR "tax evasion" OR "tax avoidance" OR "tax fraud" OR "tax risk" ) ) |

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**Figure 1**

*Document Selection Process*

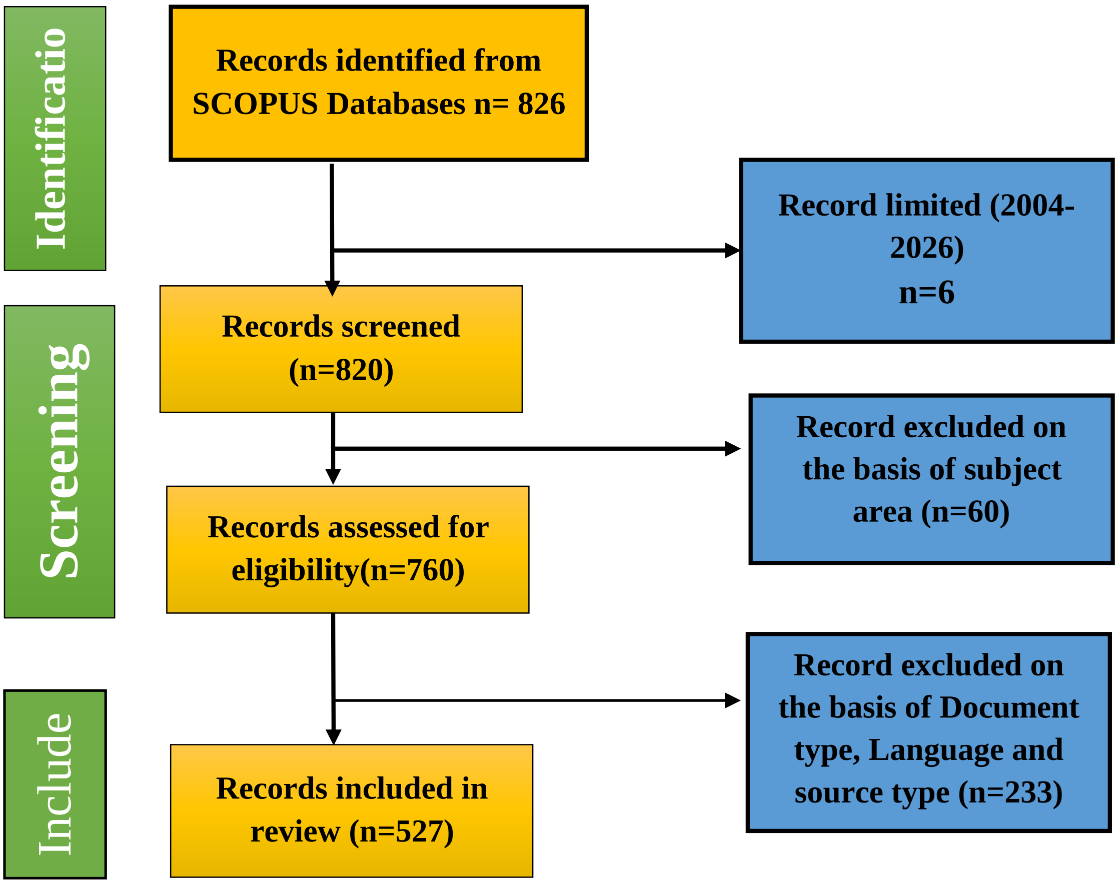


Figure 1 illustrates that the initial search resulted in the retrieval of 826 records. Records were filtered for eligible publications during the screening stage. Publications were narrowed down to relevant disciplines such as Computer Science, Social Sciences, Business, Management and Accounting, Economics, Arts and Humanities, Psychology, and Multidisciplinary studies, resulting in a total of 760 records. The screening procedure further restricted the dataset to 527 publications based on document type, language (English), and type of source (journals, conference papers, trade journals).

The analyzed documents were evaluated using VOSviewer (Version 1.6.20) and Biblioshiny®. The analysis included two stages that complemented each other. The first stage was performance analysis, which included an evaluation of annual research output, important authors and journals, countries and citation trends. The second stage was science mapping (Donthu, et al., 2021) aimed at revealing conceptual frameworks using citation analysis, bibliographic coupling, keyword occurrence analysis, thematic mapping and thematic evolution analysis. Thus, the combination of the two approaches enabled creating a full understanding of the knowledge base, research hotspots and future research strategies in the field of AI-enabled tax compliance improvement.

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## 3. Results

As stated before in this chapter, the section consists of both performance analysis and science mapping. They are complementary methodologies that form a constant understanding of the research environment.

### 3.1 Performance Analysis

Performance analysis is defined by Lowar et al. (2025) as a study of the intensity and impact of a research field's publications according to its significant indicators of bibliometric analysis. It is data-driven analytics on the development, influence, and output of the scientific domain, which contributes to the identification of the main authors and trends in research (Passas, 2024; Sahar & Munawaroh, 2025). The performance analysis in this research refers to annual scientific production, the most representative and influential authors, important publications where science is presented, as well as the most frequently shown countries.

**Main Information of Data**

The bibliometric data set has 527 articles published during the time period of 2004–2026, obtained from 383 sources (see Table 2). This indicates that there is an increasing interest in academic research on AI and its use in taxation and administration of taxes. Between the years 2004 and 2026, the number of articles published in this field has grown significantly by 20.89 % per year and has shown that this area is growing consistently and gaining more scholarly attention. The average age of the articles is around 3.83 years and there are 8.93 citations for each document which means that a good knowledge base was developed, but the field is still developing.

In total, the dataset consists of 2,222 Keywords Plus and 1,457 author keywords, which indicates the great diversity of themes covered in this research area and the multidisciplinary nature of AI implementation in tax compliance. The total amount of authors that participated in the publication of relevant papers is 1,357, where 88 have written solo works. In total, there are 96 solo works in the dataset with an average of 3.05 co-authors per paper indicating that collaborative research has entailed the emergence of a new scientific reality. Another interesting finding is that the above-mentioned percentage of cooperation among scientists from different countries constitutes 18.98%.

In terms of types of documents, journal articles dominated the dataset (293 items issued; 55.6%), followed by conference papers (207 items issued; 39.3%), thus indicating theoretical insights and technology-related advances in the developing area. Other documents include conference talks (20 items issued; 3.8%), review articles (6 items issued; 1.1%), and one editorial (0.2%), which stipulates more information from the perspective of the scholars of the area. The abovementioned bibliometric criteria provide evidence that publications related to the use of artificial intelligence in tax compliance are the growing sphere, which can be explained by the expanding collaboration of scientists from different countries, diversity of topics under the scrutiny of researchers, and the fact the scientists disseminate their findings through papers and conferences equally.

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At the same time, the young average age of publications suggests that the area is still undergoing intellectual development such as exploration of vast number of topics, improvement of research approaches, and empirical studies.

**Table 2**

*Main Information Data*

| Description | Results |
|---|---|
| ***Main information about data*** | |
| Timespan | 2004:2026 |
| Sources (Journals, Books, etc) | 383 |
| Documents | 527 |
| Annual Growth Rate % | 20.89 |
| Document Average Age | 3.83 |
| Average citations per doc | 8.932 |
| References | 17273 |
| ***Document contents*** | |
| Keywords Plus (ID) | 2222 |
| Author's Keywords (DE) | 1457 |
| ***Authors*** | |
| Authors | 1357 |
| Authors of single-authored docs | 88 |
| ***Authors collaboration*** | |
| Single-authored docs | 96 |
| Co-Authors per Doc | 3.05 |
| International co-authorships % | 18.98 |
| ***Document types*** | |
| Article | 293 |
| Conference paper | 207 |
| Conference review | 20 |
| Editorial | 1 |
| Review | 6 |

## Annual Publication Growth

According to Donthu et al. (2021), performance evaluation starts with examining the yearly scientific production, as this gives an idea of the growth trajectory of the research sphere and shows its dynamics and maturity. The growth of annual publications demonstrates the development process of the research sphere through examining annual publication evolution (Basnet et al., 2024; Hassan & Duarte, 2024). In the chart provided (Figure 2), the growth of the research on artificial intelligence and its use in tax compliance enhancement is evident and shows considerable progress achieved in the period of 2004-2026. In the first part of this period (2004-2015), the publication output remained considerably low and steady with less than ten articles per year indicating that the use of AI in tax compliance was at its nascent stage. Starting from 2016, the publications growth started developing suggesting that interest in application of AI technologies in taxation and tax compliance has been growing.

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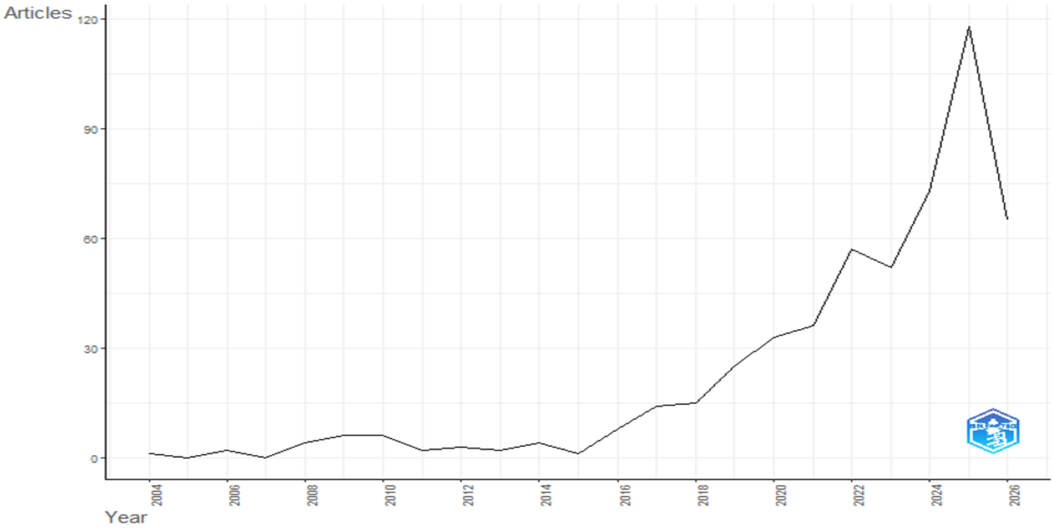
**Figure 2**

*Annual Production Growth*




The notable increase happened after 2020, when the outputs from scientific activities increased dramatically from about 33 items published in 2020 to 36 items in 2021 and 57 items in 2022. Although the output in 2023 decreased slightly, scientific activities resumed again in 2024, producing about 73 publications and peaking at 118 articles in 2025. It should be noted that the decrease to about 65 items published in 2026 should be treated with caution since the data was collected before the end of the publishing year. In general, the growth trend shows the success of long-term development and indicates strong interest in the use of artificial intelligence and machine learning in the tax field among researchers.

**Most Relevant and Impactful Sources**

As claimed by Donthu et al. (2021), source evaluation is key to performance evaluation as it determines the publishers that are mostly responsible for the creation and distribution of knowledge in a certain discipline. The most significant publications are presented in Figure 3, while Figure 4 shows the most effective outlets according to the local H-index, which reflects the amount of scholarship as well as impact of publications.

According to Figure 3 data, the ACM International Conference Proceeding Series is the most productive publisher, publishing 16 works in the field of AI and taxation. The next publishers are the Journal of Risk and Financial Management and Springer Proceedings in Business and Economics with 9 publications each, while Inter tax with 7. The other outlets with very few publications include Expert Systems with Applications, International Review of Economics and Finance, PLOS ONE, and World Tax Journal with 5 publications each and Applied Sciences (Switzerland) and Electronics (Switzerland) with 4. The mentioned results suggest that the study of AI related to tax compliance involves academic journals from various areas such as AI, taxation, business and finance.

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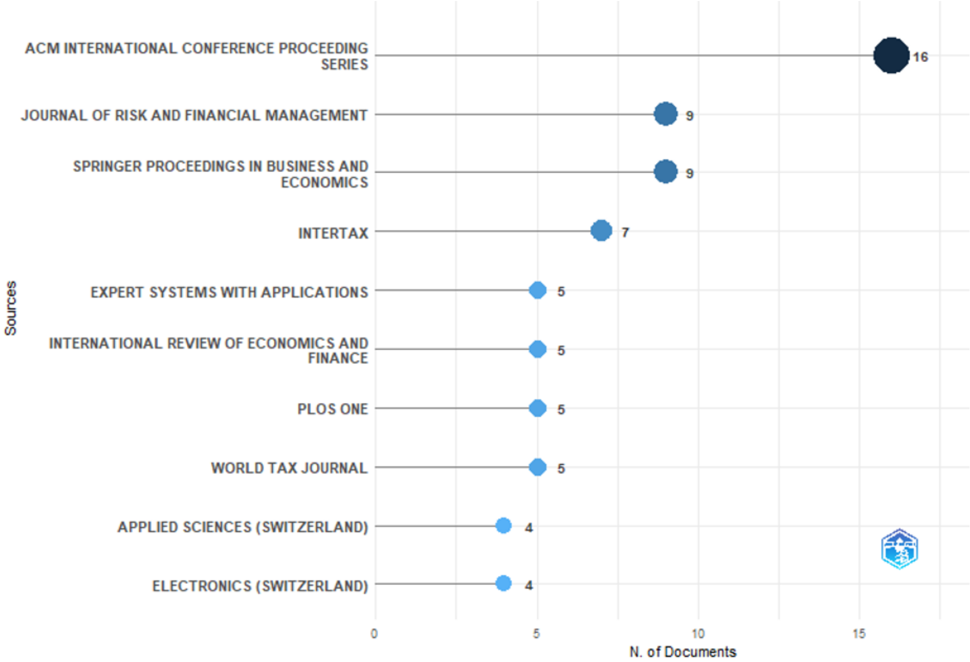
**Figure 3**

*Most Relevant Sources*




However, Figure 4 shows that the local H-index has been utilized to confirm the scholarly impact of each publication outlet. The ACM International Conference Proceeding Series, Expert Systems with Applications, and the Journal of Risk and Financial Management have the highest H-index of 5, displaying their strong influence on the researched academic literature. Additionally, the other major publication sources like Applied Sciences (Switzerland), EC Tax Review, Electronics (Switzerland), IAES International Journal of Artificial Intelligence, IEEE Access, International Review of Economics and Finance, and Inter tax have an H-index of 3 on average. A comparative analysis of figures 3 and 4 highlights that the volume of publications does not always translate to scholarly impact. Although many publishing outlets are producing a bigger volume of publications, only a handful of them are really capable of influencing citations and knowledge distribution. Thus, the progress in the intellectual know-how of AI is the result of the ability of both specialized tax journals and major interdisciplinary publications in artificial intelligence, economics, and information systems to generate knowledge on the topic.

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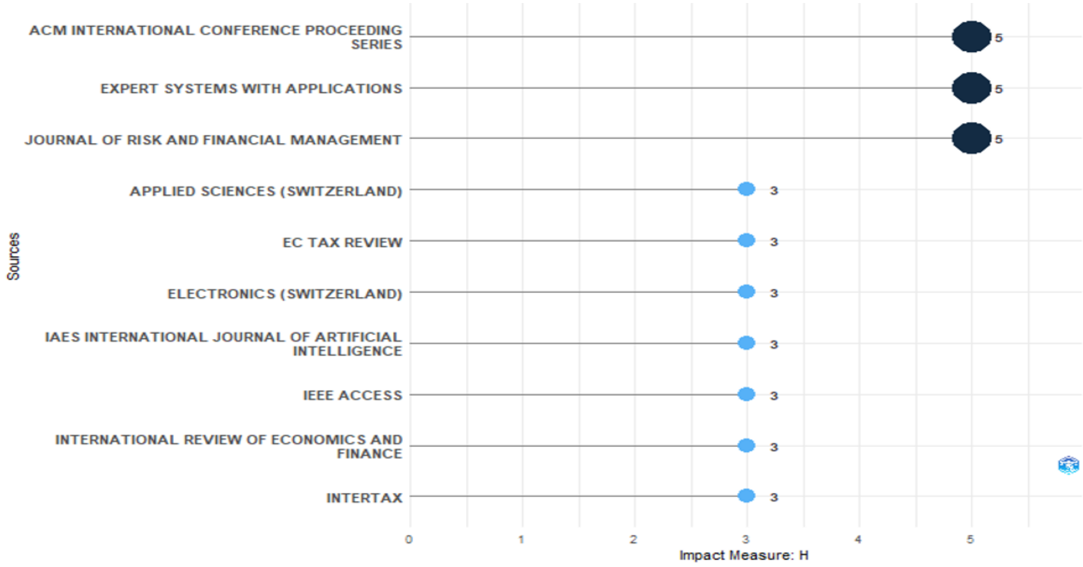
**Figure 4**

*Most Impactful Sources*

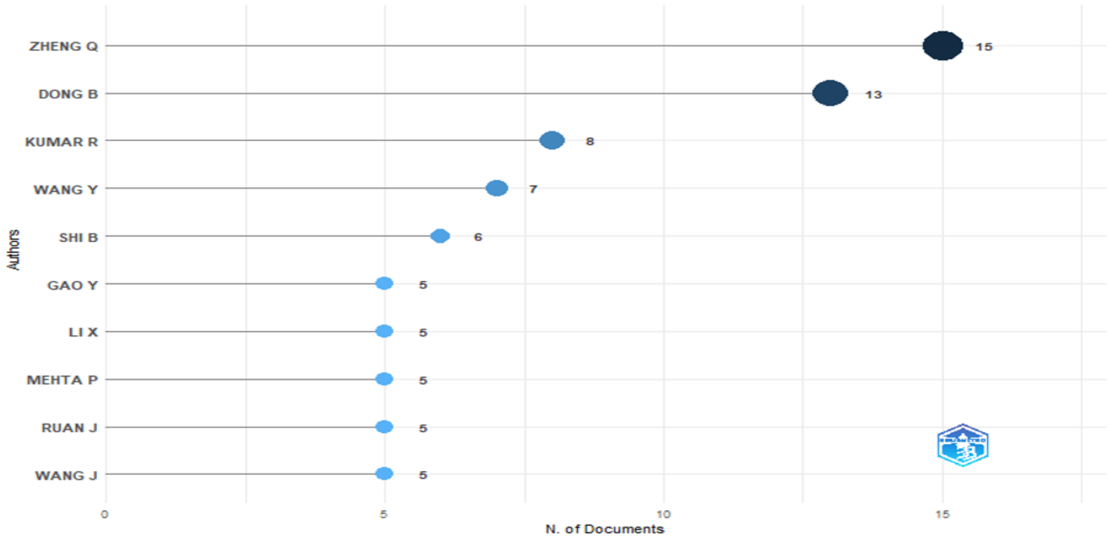



## Most Relevant and Impactful Authors

Based on the analysis of the most prominent researchers (Figure 5), Zheng Q is the most active author in this area with 15 publications, followed by Dong B with 13 works. Kumar R comes third with 8 documents. On the other hand, Wang Y and Shi B are rather productive authors with 7 and 6 publications correspondingly. A number of other researchers also published five papers—Gao Y, Li X, Mehta P, Ruan J, and Wang J. This shows that the community of researchers in this area is expanding.

**Figure 5**

*Most Relevant Authors*




It is essential to mention that productivity doesn't mean scholarly influence. According to the impact analysis of the localities done as per the H-index (Figure 6), the most influential authors

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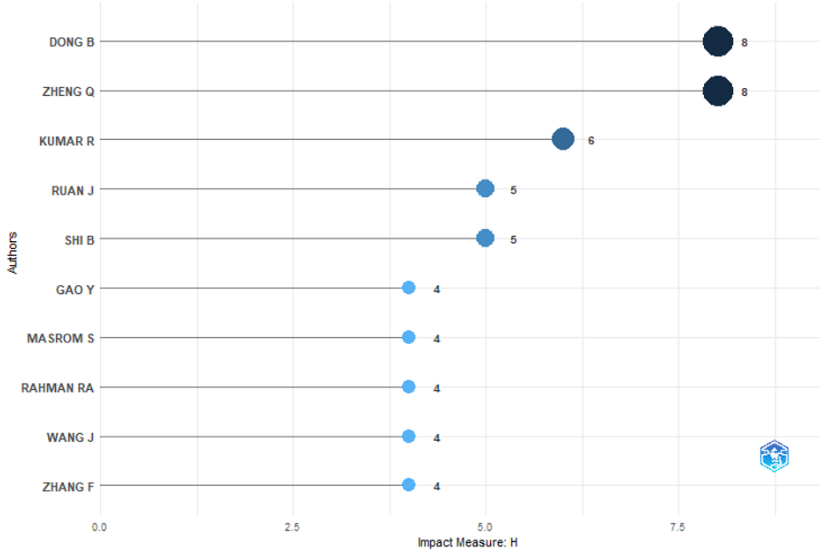
are Dong B. and Zheng Q., both having an H-index score of 8 indicating that they have consistently productive and cited publications. Kumar R comes next with an H-index of 6 followed by Ruan J. and Shi B., both earning an H-index score of 5. The other authors with an H-index of 4 include Gao Y, Masrom S, Rahman R. A., Wang J. and Zhang F, indicating that they have made a significant impact on the academic field in question. In conclusion, it can be said that Zheng Q and Dong B have been the main contributors/ authors as they have published the highest number of works with the most impact on the science.

**Figure 6**

*Most Impactful Authors*




**Most Cited Countries**

The citation analysis provided in Table 3 illustrates clearly the world distribution of outstanding research in this field. The results show that China is the most prominent country in terms of citations with 578 total citations, far ahead of all other countries and demonstrating its leading role in the intellectual development of this area. Germany comes second with 256 citations, followed closely by the USA with 252 citations. India with 192 citations and Italy with 170 citations are also among the leaders, while Chile (147 citations), Canada (146 citations), the UK (134 citations), the Netherlands (128 citations) and Indonesia (127 citations) complete the top ten countries. Although China is at the top of the list in terms of total citations, in terms of average citations per article (5.8) it is rather low, which means that its influence is largely due to a large number of publications. On the contrary, Chile (73.5) and Canada (73.0) are leaders in terms of average citations per article, showing the remarkable research impact of the countries though with smaller number of publications. Other countries, including the Netherlands (25.6), Serbia (26.5), Italy (15.5) and the UK (12.2) show quite good citation results proving the international involvement and collaboration in research.

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**Table 3**

*Most Cited Country*

| Country | TC | Average Article Citations |
|---|---|---|
| CHINA | 578 | 5.8 |
| GERMANY | 256 | 51.2 |
| USA | 252 | 11.5 |
| INDIA | 192 | 7.4 |
| ITALY | 170 | 15.5 |
| CHILE | 147 | 73.5 |
| CANADA | 146 | 73 |
| UNITED KINGDOM | 134 | 12.2 |
| NETHERLANDS | 128 | 25.6 |
| INDONESIA | 127 | 7.5 |

### 3.2 Science Mapping

Khanal et al. (2025) describe science mapping as the analysis of the intellectual, conceptual, and social structure of a research discipline that studies the relationship between authors, publications, and keywords involved. Science mapping provides answers with regard to knowledge progression, evolution in themes used, and collaboration patterns (Donthu et al., 2021; Basnet et al., 2024). The current study understands science mapping to entail co-citation analysis, bibliographic coupling, co-occurrence analysis, a tree-map analysis process, thematic mapping, and thematic evolution.

**Co-authorship Analysis**

The analysis of co-authorship involved studying the networks of scholars and research partners among 950 eligible authors by applying a maximum threshold of 100 authors per document, at least one publication, and one citation. Upon analyzing the co-authors, it is determined that there is a significant hub and spoke pattern with a strong central hub. The foremost authors creating the hub are Qinghua Zheng (15 works) and Bo Dong (13 work), who collaborates closely with the main co-author Jianfei Ruan and Yuda Gao. Another subgroup of connections is created through Fan Zhang, who facilitates connections between important partners such as Kuo-Ming Chao and Nazaraf Shah.

The temporal overlay visualization (2016–2024) presented in Figure 7 shows the transformation path of this field very clearly. The developmental phases have included the structural foundational works done by Nick Godwin and Feng Tian from 2016 to 2018, followed by the peak consolidation phase around the period 2019–2021 under the leadership of Zheng and Dong. It can also be seen that in the latest years of 2022–2024, some new collaborative clusters have formed, led by Bin Shi (who authored 6 documents) together with Jiaxiang Wang and Yiming Xu, indicating the continuous progress and growth of the area of research.

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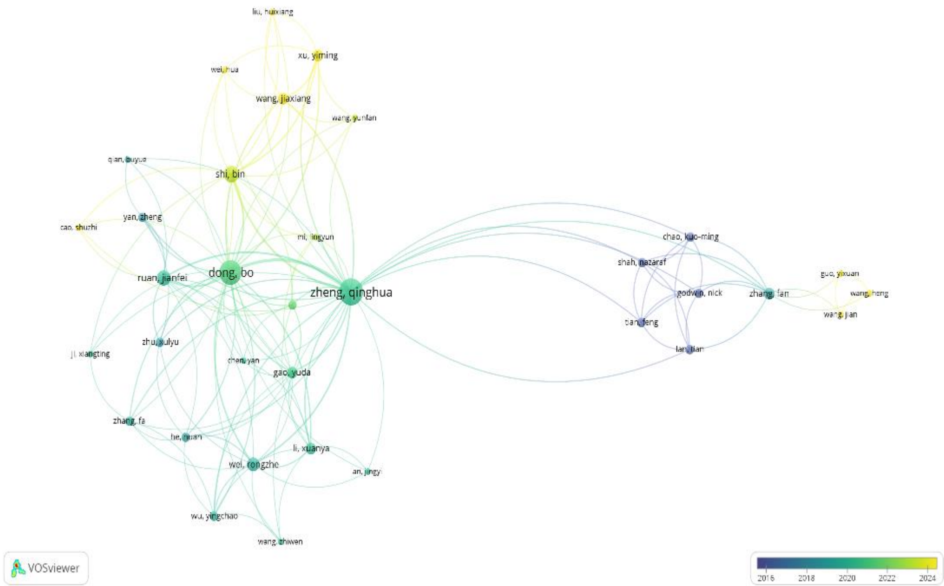
**Figure 7**
*Co-authorship Analysis based on Author*




**Co-citation Analysis of Cited References**

According to co-citation analysis, it can be established that the contemporary research in AI for tax compliance relies not on the fragmented series of disciplines but on the well-integrated common body of knowledge. The various links between clusters (Figure 8) that revolve around different topics such as artificial intelligence, corporate taxation, fraud detection, and data mining as represented by leading authors provide evidence that field in question is based on cumulative use of knowledge in the domains of computer science as well as tax policy. It also shows that the mature discipline now develops from theoretical standpoints to the applied frontiers with a focus on other interesting topics including digitalization, recognition of suspicious transactions, accounting and auditing, and more peripheral themes like transfer pricing, digital transformation, and governance. The future contributions in this area would be stronger in case they would concentrate on network between the established technical basis and peripheral subjects which concentrate on governance.

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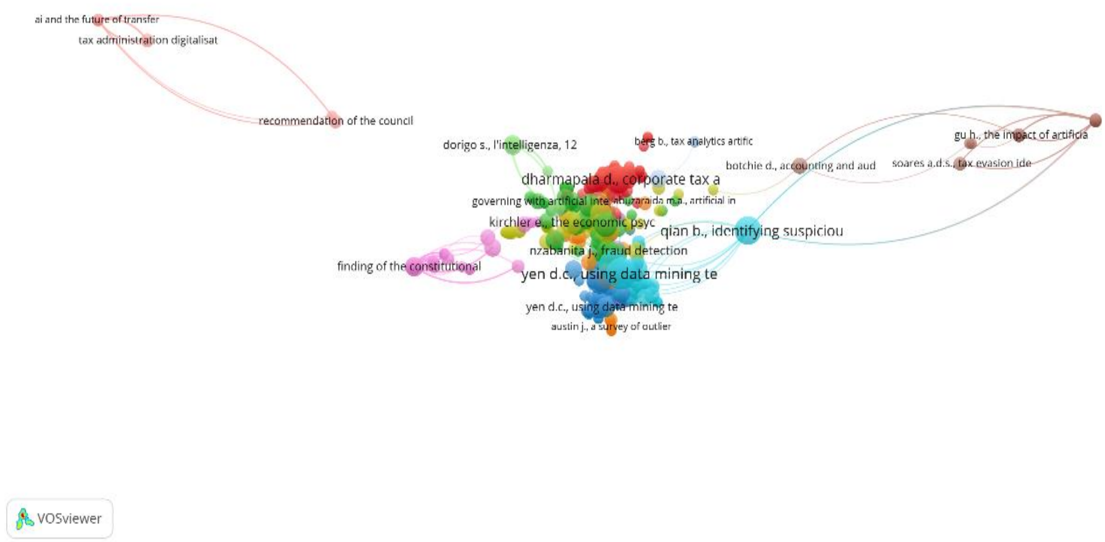
**Figure 8**
*Co-citation Analysis based on Cited References*




## Citation Analysis

Through the citation analysis of authors, the influence of scholarship and citation relation of authors is assessed in 1391 authors who meet both the document and citation threshold. The graphical representation shown in Figure 9 shows that there are both strong routes and connections involving the discussion between the two scholars and Figure 9 also shows the distinctive styles of their proper thinking. As far as the left side is concerned, one can say that there is a solid technical network involving Jianfei Ruan, Xulyu Zhu, and R. Sridhar shaped on scientific field including basic operational operations for the field. When it comes to the right side, the applied systems are represented by Feng Tian, Fan Zhang, and Kuo-Ming Chao. The temporal overlay map shows the evolution from the initial classical literature (2016-2018; Nick Godwin and Una-May O'Reilly), through a peak period (2019-2021; Zheng and Dong), bringing one to the current positions in the literature (2022-2024; G. Priyanka and N. Naveen Kumar).

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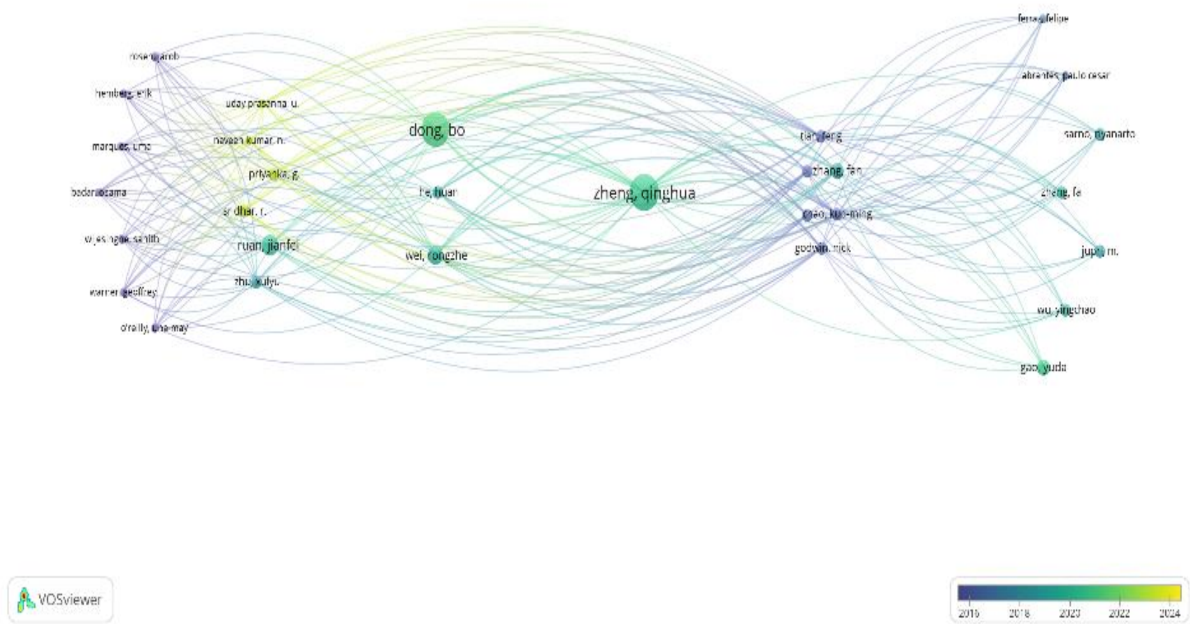
**Figure 9**
*Citation Analysis based on Authors*




## Bibliographic Coupling of Documents

Analysis of bibliographic coupling depicted in Figure 10 reveals that modern studies pertaining to artificial intelligence in tax compliance have coalesced around a common and highly interconnected network of references rather than being pursued along multiple unrelated lines of research. The importance of seminal works produced during 2017–2020, recently published papers within 2023–2026, indicates that the discipline is evolving cumulatively, as newer papers rely heavily on both methodological and theoretical foundations established by seminal works. This illustrates that the continuum encompasses multiple topics in AI-based tax administration, including fraud detection, digital governance, and intelligent decision-support systems. Further, it shows that this body of knowledge has progressed beyond proof-of-concept studies involving singular methodological and theoretical contributions and passed toward the establishment of a coherent body of knowledge with a clear intellectual history. Therefore, future research involving this bibliographic network will likely yield valuable contributions by building on or disputing established clusters of reference.

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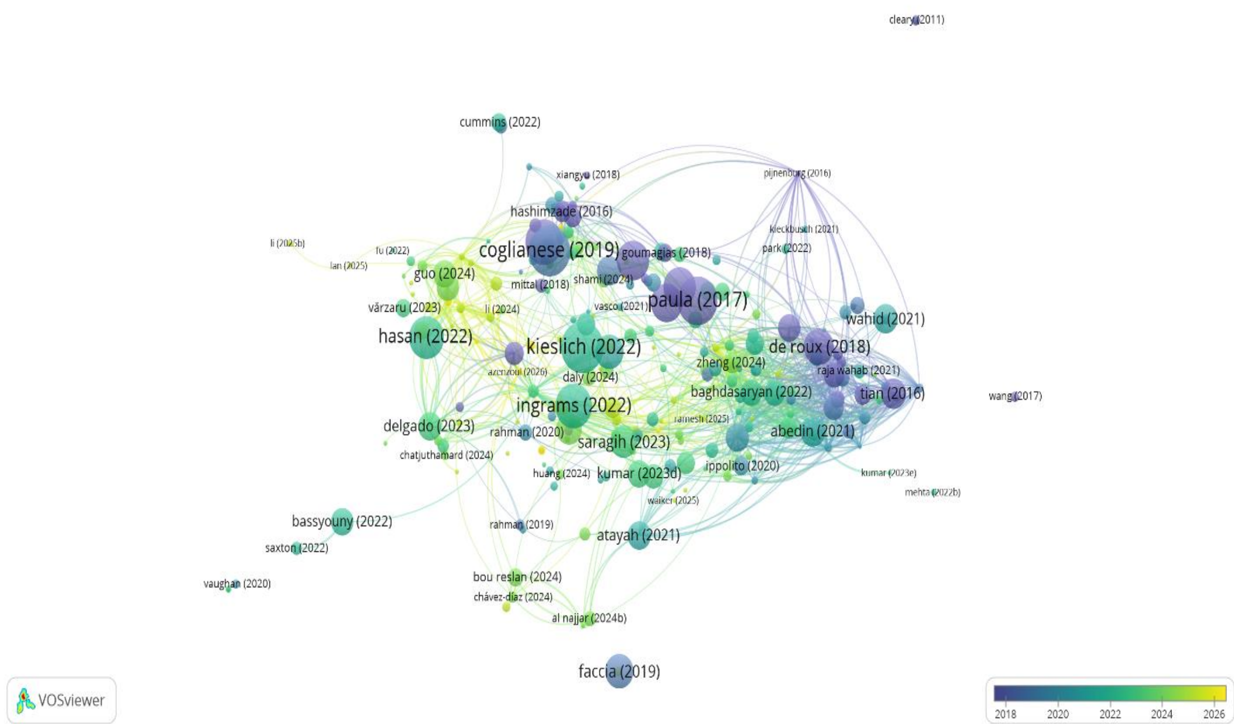
**Figure 10**
*Bibliographic Coupling based on Documents*




## Co-occurrence Analysis of Keywords

The visualization of the co-occurrence network in Figure 11 uses VOSviewer to display structural connections and the chronological evolution of keywords within the database consisting of 3,114 keywords meeting the minimum threshold (n = 1). Taxation is the most dominant node as per density of node and strength of connection. The main thematic clusters emerging from it are advanced analytics such as deep learning, interpretable Artificial Intelligence, and graph analytics, as well as governance models such as tax compliance, risk management, and digitalization. The peripheral nodes reflect its extension to socio-economics and areas of sustainability, data sharing, and trust. The time gradient (2018-2026) shows a shift in focus: the past publications were mainly related to foundational algorithms and commerce (colors blue and purple), whereas recent studies focus on the topics of explainable AI, sustainability, digitalization in taxation, trust very heavily (colors bright green and yellow) indicating the emerging combination of artificial intelligence and taxation.

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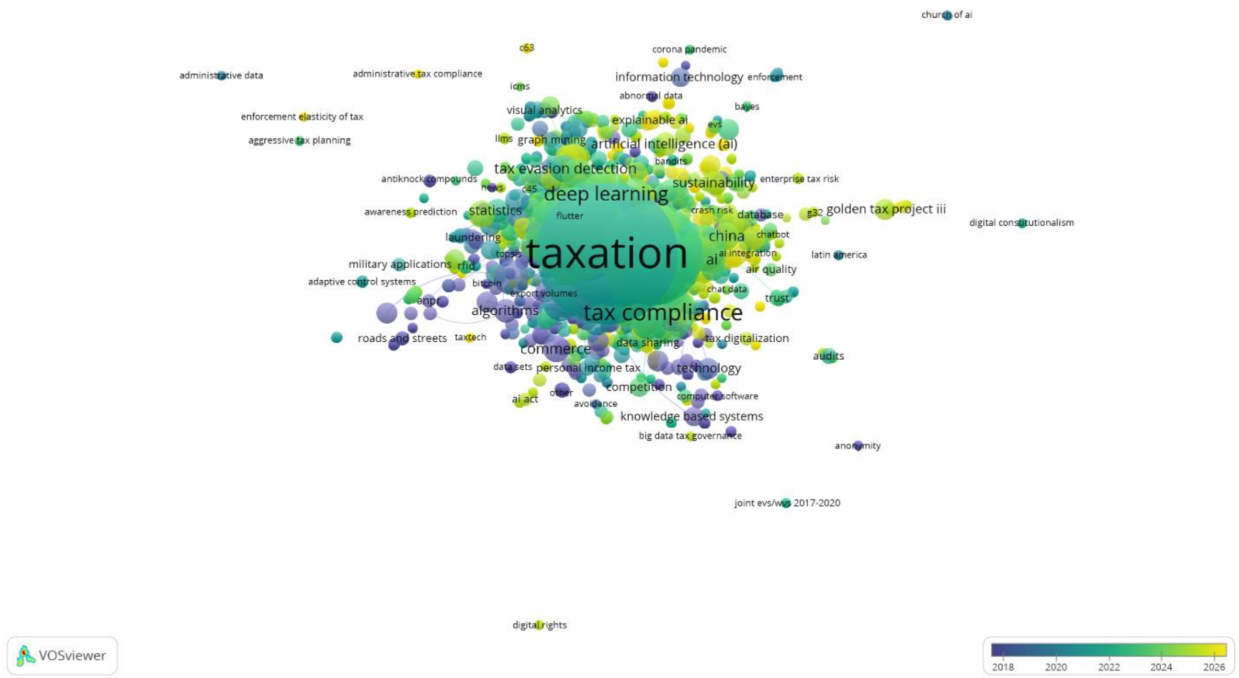
**Figure 11**

*Co-occurrence Analysis*




## Tree map Analysis

Figure 12 shows the thematic composition and frequency of significant terms in the pure data set (N = 527) that was produced through different filtering steps: time window (2004–2026, N = 820), disciplines such as Computer Science, Social Science, Business, Economics, Arts, Psychology, and Multidisciplinary (N = 760), form (Articles, Conference Papers, Reviews, Editorials) (N = 672), language (N = 638) and type of the source (Journals, Conference Proceedings, Trade Journals) (N = 527). Among this selection, the word taxation is the most popular (n = 215, 14%). The majority of mentions are made in regard to the most technologically advanced instruments including: artificial intelligence (n = 114, 8%), machine learning (n = 95, 6%), data mining (n = 66, 4%) and big data (n = 63, 4%). The image depicts the environment where the use of data analytics significantly contributes to tax and governmental regulations, like tax avoidance or tax compliance systems, or fraud detection interventions.

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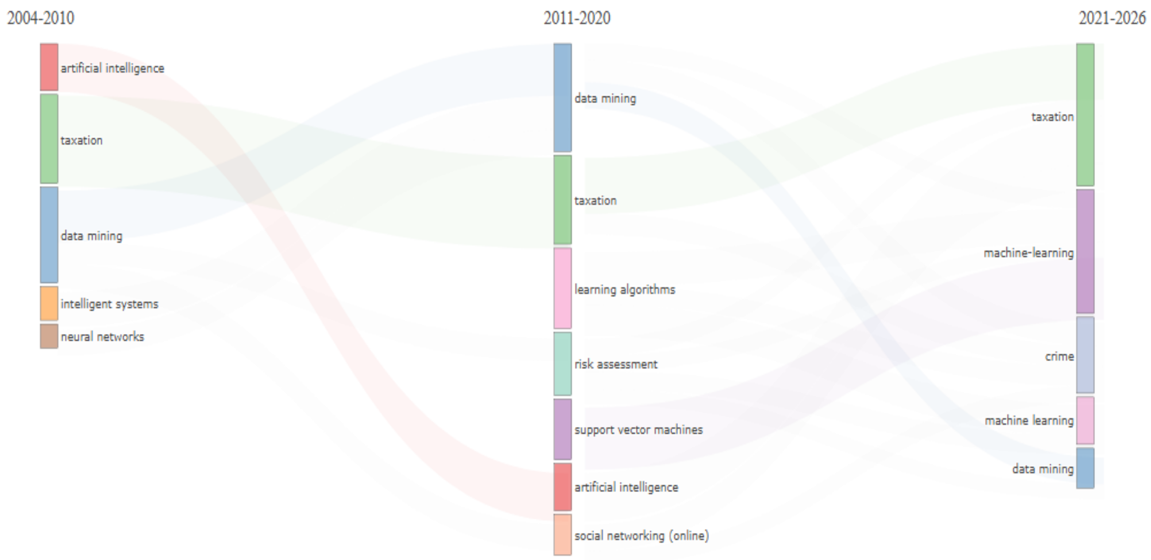
**Figure 12**

*Tree Map Analysis*


**Figure 13**

*Thematic Evolution*




## Thematic Evolution

The thematic evolution map (Figure 13) illustrates the evolution of the research landscape over three discrete periods (2004-2010, 2011-2020, and 2021-2026) by applying Keywords Plus, Louvain clustering, a minimum frequency of 5 (n=250), and 1-gram representation. In the first phase (2004-2010), early research activities focused on artificial intelligence (PageRank =

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0.346) and the core computational processes, such as data mining, neural networks, and basic taxation models. The middle phase (2011-2020) was characterized by the development of applied methodologies, such as learning algorithms, support vector machines, and risk assessment, with taxation (PageRank = 0.255, Occ = 52) and data mining (Occ = 21) being the major thematic links. The modern phase (2021-2026) is characterized by the consolidation of topics in the specificity of taxation, machine-learning, machine learning, data mining, and security-focused domains, such as solving crimes, signifying the straightforward transition to automated compliance, risk regulation, and applied financial intelligence.

**Thematic Mapping**

The thematic mapping analysis specializes in arrangement of the essential research themes discovered in the data series through the identification of four strategic quadrants about their importance and development. Figure 14 shows the main thematic axes, such as taxation, data mining, artificial intelligence, intelligent systems, commerce, neural networks, and knowledge-based systems. Taxation constitutes the largest cluster because it has the highest frequency of occurrence (18) and number of occurrences (14), as well as the highest value of betweenness centrality (17,587.02).

The strategic matrix's thematic distribution analysis indicates that the specialized techniques employed and the wider research practices influence each other. Motor Themes and Basic Themes are supported by noted clusters such as taxation (6.58 score and 11 occurrences), data mining (6.25 score and 12 occurrences) along with the main ideas relating to making decisions, finance, software engineering, etc. The above-mentioned themes are closely connected to each other and thus represent important conceptual pathways linking technological algorithms to administration and economy. In contrast, clusters such as intelligent systems and neural networks have high levels of specialization (providing such ideas as transportation, traffic control, different algorithms and intelligent vehicles for Intelligent Systems; soft computing and fuzzy inference for Neural Networks). These specialized disciplines are positioned within the Niche and Emerging Themes and are aimed at providing computer solutions and algorithms from the viewpoint of specific domains of interest.

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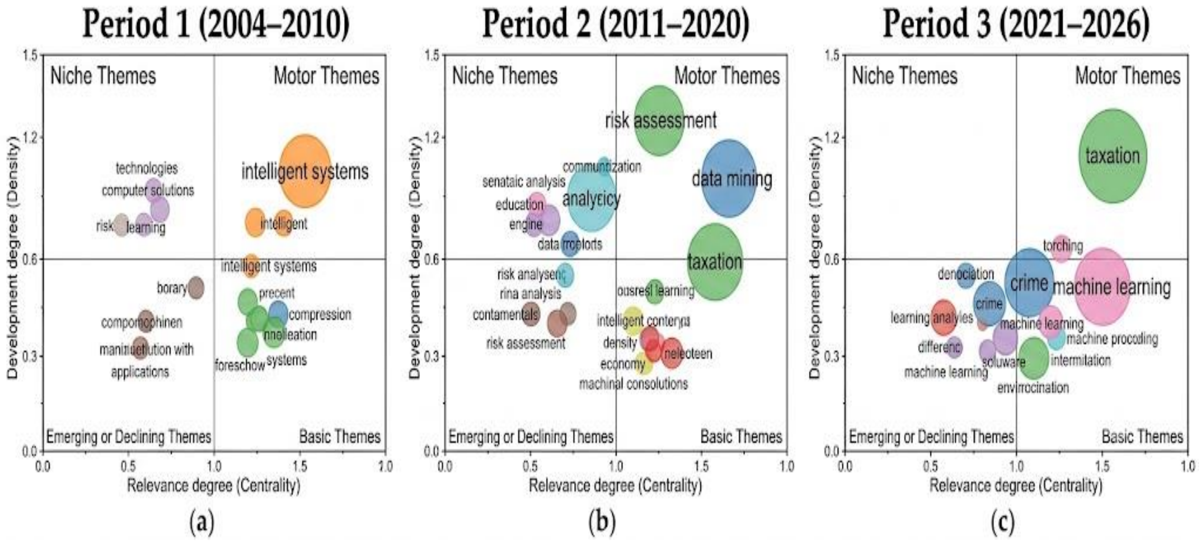
**Figure 14**

*Thematic mapping*




Apart from temporal evaluation, analyzing the impact of document affiliation also brings light to the development of the research landscape. High-impact papers, such as Liu X. (2010), with 17 citations, Kwak W. (2004), with 12 citations, and Suwisuthikasem (2008) reveal how aligned the studies in the areas of artificial intelligence, data mining, and tax are in terms of clusters. The distribution of studies in various thematic clusters has established a division of functions in the literature: while earlier works provided a basis for scientific theories like e-tax invoices processing, fraud detection, and decision-support systems, more recent papers have developed such theories further by designing automatized systems. Therefore, the current investigation shows that studies have progressed just as artificial intelligence approaches have progressed from theories to real-life applications.

**Trending Topics**

The image displayed in Figure 15 marks an obvious transition from the basic forms of computational technology to the AI-powered tax management methods. For the period from 2010 to 2017, the research was concerned mainly with the General approaches of algorithmic computing, image processing, as well as basic data mining methods. From 2018 to 2022, new data analysis and financial risk management techniques emerged through the contributions of the big data source (63 times mentioned) and tax avoidance (52 times mentioned). The biggest amount of terminology that characterizes the mid-2020s is connected with the tax legislation (215 repetitions; 2023 – median year), artificial intelligence (114 data mentions; 2024 – median year), and machine learning (95 statements; 2024 – median year). For the very last time segment (2025-2026) new trends in terms of administrative priorities can be noticed, including issues related to tax administration, information management, and information systems, as well as corporate governance, corporate tax evasion, and metadata (2026 – median year). Overall, it is possible to observe the evolution of the research from the simple algorithms of computing toward complex systems of decision-making support in the sphere of the taxation.

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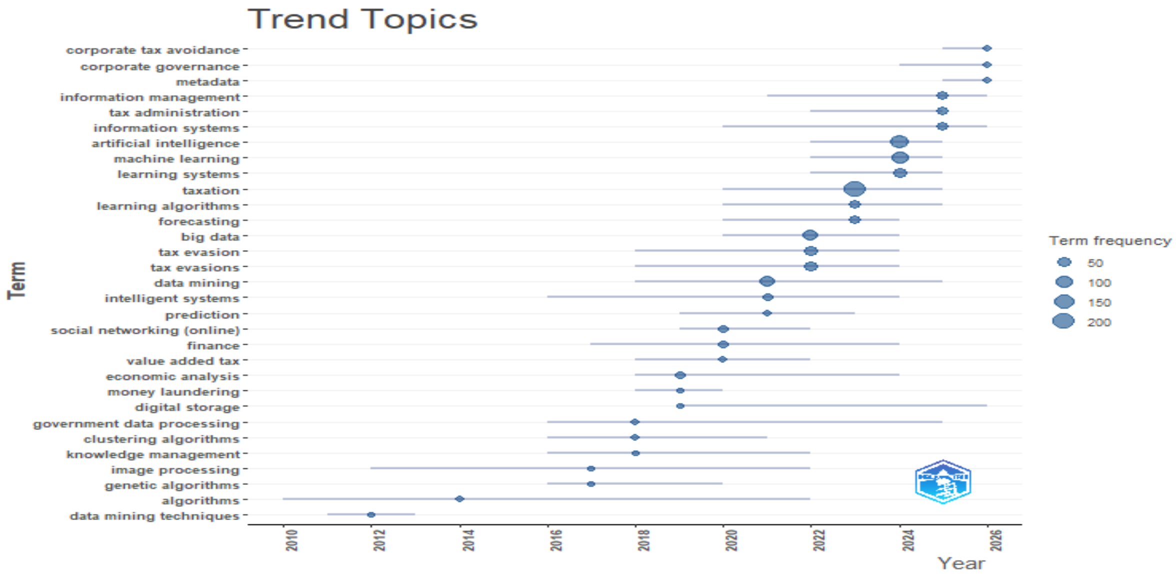
**Figure 15**
*Trending Topics*




## 4. Discussion

The bibliometric analysis shows significant increase in publications on usage of artificial intelligence for compliance in tax matters, as the number of publications began to accelerate after the year of 2020 (Chen &He, 2024), culminating in about 118 articles published in the year of 2025, which is irrefutable proof of increasing importance and relevancy of this area of research for academic and institutional audiences (Weichen & Mayburov, 2026). The leader among different countries in citation impact is China (578 citations), followed by Germany and the USA (256 and 252 respectively), which indicates these countries' meaningful contributions to the world of electronic-taxation, data analytics in tax collection and detection of tax fraud cases based on AI technological advancements (Yigitcanlar et al.,2024). The geographic data found in this analysis demonstrates the importance of advanced technologies in tax collection process.

The investigation showcases some clear differences in the patterns of research impact. Zheng Q and Dong B are found to lead in the area of research influence having achieved a local H-index of 8 due to their consistent and sustained publishing of articles (15 and 13 respectively) which have been well cited. However, there is a larger group of contributors such as Kumar R, Wang Y, and Shi B who have been impactful but to a lesser extent and in a disperse way. This pattern is similar (Yu et al., 2022; Zhang et al., 2025) to the productivity-impact trade-off in emerging interdisciplinary fields showing that high productivity does not guarantee high citation impact (Higashide, et al., 2026). One can also observe a similar variation in publication sources. ACM International Conference Proceeding Series publishes the largest number of articles (16 articles) and manages to secure also one of the biggest local H-index (5) along with Expert Systems with Applications and Journal of Risk and Financial Management proving that different sources contribute to the intellectual progress in this area instead of one single source of publication. This publication strategy reflects the fact that the explorations in the area of tax compliance driven by AI are by nature interdisciplinary and combine computational methods and fiscal policies which is supported by Gorski et al. (2025).

The evolution of the field shows a clear maturation pattern: Beginning with algorithm experimentation (2004–2010), which was focused on data mining and neural networks, and continuing with methodological application (2011–2020) during which learning algorithms and risk assessments yielded bridges between computational and fiscal realms and finally to the post-2020 time where automated compliance and corporate tax risk predominate, along with security solutions such as fraud detection. This evolution reflects similar trends in other bibliometric areas (Kumar, 2025; Zupic & Cater, 2015), which go from developer concerns to practical application ultimately. The most notable trend of this progression is the emergence of explainability, sustainability, and trust as separate clusters of themes; showing that academia is just now starting to see ethical and practical challenges of using not transparent AI systems in high-risk governmental processes. This can also be seen in the network of co-citations, as works related to governance can be considered marginal on the background of more established core – corporate tax and fraud detection (Park & McShea, 2025; Chen et al., 2026; Weichen & Mayburov, 2026). All in all, the evolution shows that the ability of the field always exceeded its governance vocabulary.

However, the bibliometric analysis reveals several weaknesses in the research. For one thing, the relatively young average age of publication (3.83 years) and the emerging thematic clusters related to explainable AI, taxpayer trust, and institutional governance suggest that the intellectual framework of the field is still in its infancy (Awal & Tehlan, 2025; Merkx & Calzado, 2025), leaving many foundational issues unanswered. While the technical clusters devoted to the algorithmic efficacy—namely, fraud detection efficiency, risk scoring, and modeling—are prevalent at the heart of the co-citation and bibliographic coupling networks, the socio-institutional implications of the use of AI for tax collection, such as taxpayer privacy issues, audit selection bias, and limited adoption capabilities of the tax administrations in developing countries, have been largely marginalized.

This inequality is reflective of a broader trend within adjacent AI bibliometric domains, which tend to devote much more time and effort to examining the efficiency and precision of computational methods as compared to their equity, accountability, and capacity building aspects (Li et al., 2020; Belahouaoui & Alm, 2025). It also becomes clear that, considering the comparatively low average citation rate per paper in China (5.8) as compared to such nations as Chile (73.5) and Canada (73.0), research production and research depth may not necessarily go hand in hand – at least in terms of bibliometrics.

Three overlapping fields of inquiry need attention in future research. *First*, multi-disciplinary investigations linking computer science to public administration, law, and behavioral economics are necessary to study trade-offs involved in using more sophisticated algorithms that may infringe upon taxpayers' rights, due process, and administrative legitimacy. *Second*, comparative and regional studies, especially those involving the tax administrations of the Global South countries characterized by a different digital and institutional capacity than the currently studied (China, Germany, the USA) are crucial for comprehending how tax compliance AI performs under conditions other than highly-resourced ones. *Third*, research into explainability, auditability, and taxpayers' trust in decisions made through AI is necessary to develop effective governance structures. The significance of global tax gaps requires research that will improve detection and enforcement systems while studying at the same time its wider implications for taxpayer trust and administrative legitimacy.

## 5. Five-Phase Framework for AI-Assisted Tax Compliance

The bibliometric results revealed through this study illustrate how the research on AI for tax compliance has increased exponentially in terms of volume; however, the conceptualization thereof is inconsistent. The network maps show that the technical and algorithmic elements like machine learning, data mining, big data, and fraud detection have become dominant features in the co-occurrence network and thematic mapping; however, the governance-based elements like explainability, taxpayer trust, and institutional accountability have remained relatively insignificant, mostly appearing in the most recent trending topics but not in the core of the topic. This inconsistency reflects a general trend that has been observed in adjacent fields of bibliometrics on AI: technological capability evolves at a faster pace than the necessary framework of implementation. In order to bridge this gap, this study has developed a five-stage model of AI-assisted tax compliance.

However, the framework was synthesized through an iterative process involving the bibliometric data rather than being derived directly from any analytical cluster. In particular, the clusters found through the co-occurrence and bibliographic-coupling analyses: taxation, data mining, artificial intelligence, fraud detection, and corporate tax risk guided the identification of core activities associated with compliance and reflected in Phases 1-3 (Risk Conceptualization, Data and Evidence Integration, and Model Selection). At the same time, the disparity between highly evolving technical clusters and relatively immature explainability, trust, and governance clusters served as the basis for the human-centric focus of Phases 4-5 (Governance, Explainability, and Trust, and Continuous Monitoring and Feedback). Overall, five phases offer a pathway in Figure 16 in which AI goes from recognizing a compliance issue to the consistent application within a tax administration (Dogan et al., 2025).

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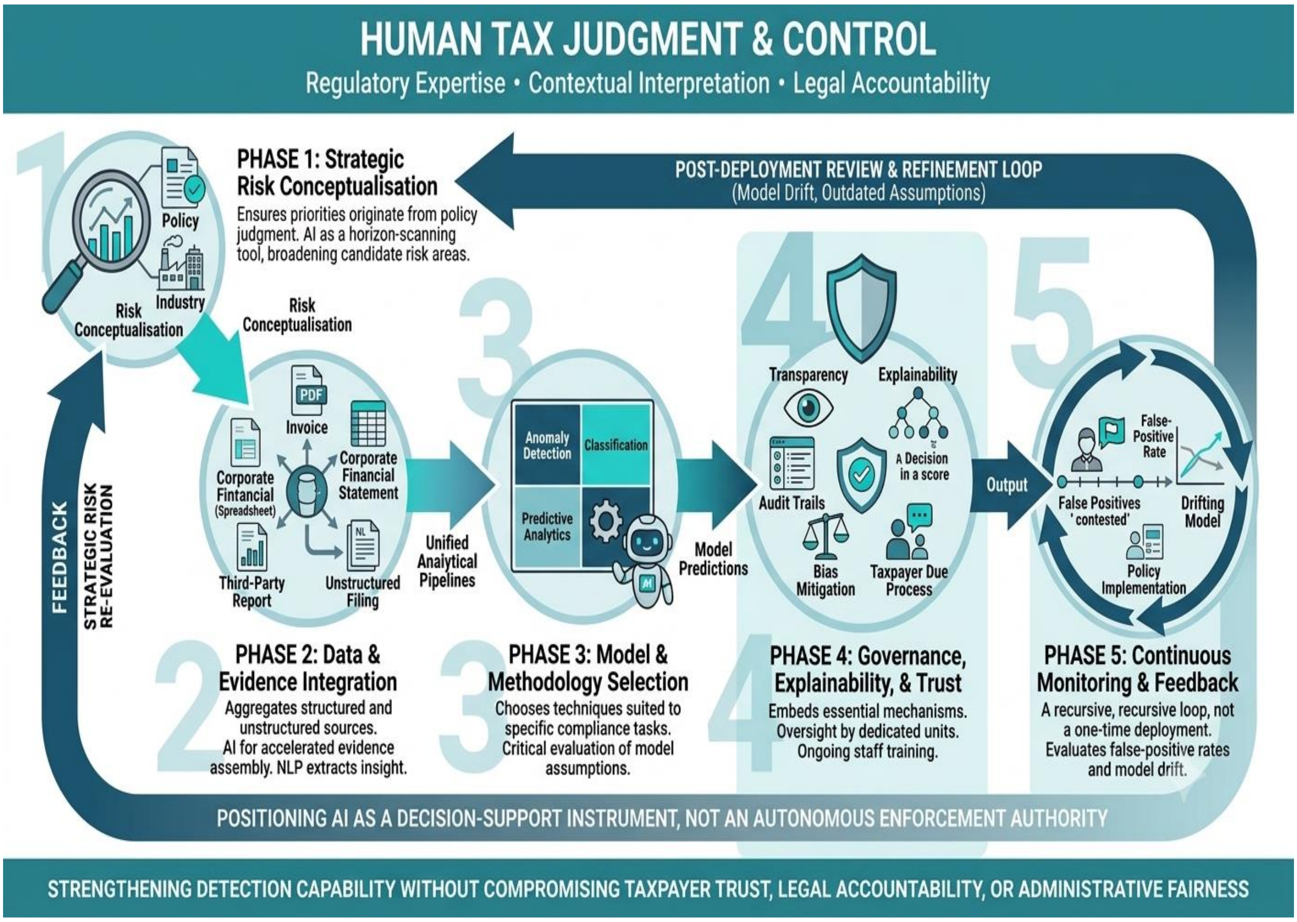
**Figure 16**

*Five-Phased Framework for AI-Assisted Tax Compliance*




**Phase 1: Strategic Risk Conceptualization**

Strategic risk conceptualization forms the bedrock of AI-enabled compliance, since it ensures that priority risk areas emerge out of tax policy judgement and not just algorithmic pattern recognition (Ozmen et al., 2023). From the tree map and thematic map analyses, it was evident that the concepts of taxation, artificial intelligence, and machine learning were among the most central themes, hence, reinforcing the notion that AI is being increasingly used to identify compliance targets such as VAT-gap segments, high-risk industries, or transfer pricing discrepancies (Roux et al., 2025). Nonetheless, risks flagged out by the algorithms are based on historical patterns in the data and hence, risks that have been historically enforced or those that are not in the training data can easily be ignored. In light of this, this phase seeks to place AI as a horizon scanning tool whose role is to expand the scope of risk areas (Vignali et al., 2022; Bengston et al., 2024), with tax administrators remaining responsible for judging the appropriateness of risk priorities against statutory requirements, taxpayer categories, and revenue integrity goals.

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**Phase 2: Data & Evidence Integration**

The second phase entails the process of combining structured and unstructured data to facilitate compliance analysis. Data mining, big data, and corporate taxation have been revealed as major and closely connected topics in the co-occurrence network analysis, which is associated with the need for combining invoices, financial statements, third party information and transactional data to perform analyses. In addition, natural language processing technologies (Hirschberg & Manning, 2015; Khurana et al., 2023) help to extract structured information from unstructured tax reports, letters, and disclosures. Still, efficient data aggregation is not enough as it does not ensure high-quality compliance evidence since the process of reconciling conflicting standards, data validation, and assessing the significance of data inconsistencies requires the specific knowledge that automated processes cannot provide. Thus, this phase is dedicated to the idea that artificial intelligence is supposed to make the process of data aggregation faster (Wu et al., 2020; Xu et al., 2021), but compliance analysts should still be responsible for the interpretation of collected data.

**Phase 3: Model and Methodology Selection**

The selection of the model and the method is the third stage, at which AI can facilitate the decision (Rousopoulou et al., 2022; Abououf et al., 2023) on the most suitable classification, anomaly detection, or predictive analytics models. Bibliographic-coupling and thematic-evolution analyses reveal a strong tendency to progress from theoretical algorithms and neural networks to applied models like risk scoring, machine learning auditing model, and fraud detection models, which means that methodological development has made significant steps forward. Still, the best model for the detection of invoice fraud does not mean the best one for the detection of transfer pricing abuse or income understatement, and the overreliance on one dominant method may result in limiting the type of the evasion behavior that will be identified. That is why the third phase encourages methodological reflexivity (Bringer et al., 2004; Day, 2012; Leicht-Deobald et al., 2022): it is necessary to analyze the compatibility of assumptions, data needs, and errors of the proposed model with the given compliance task.

**Phase 4: Governance, Explainability, and Trust**

The fourth phase adds governance, explainability, and trust as crucial factors (Camilleri, 2024; Lahusen et al., 2024) in the ethical use of AI in tax administration. As revealed from the trending-topics and thematic mapping analyses, explainable AI, taxpayer trust, and governance issues have emerged in the latest literature alone and have not yet gained much linkages with the main technical clusters in the field, which implies that the governance frameworks are not as advanced as the technological ability of algorithms. With regard to the concept of governance here, it is not only about meeting legal requirements but also entails transparency regarding the way automated risk scoring works, auditable nature of decisions in using algorithms to make audit selection, protection of taxpayers from biased targeting, and clear avenues where taxpayers can challenge AI-driven decisions (Zalnieriute et al., 2019). To incorporate these aspects during all previous phases rather than making them into a compliance

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stage is the key to ensuring legality and legitimacy of automated enforcement decisions. For this to happen in reality, there must be transparency measures (Anjarwi, 2026) in showing how AI influences decisions on audits or penalties, audit trails enabling the review of individual decisions, oversight from compliance integrity units, and continuous training of staff members in challenging algorithmic outputs.

**Phase 5: Continuous Monitoring and Feedback**

The process of continuous monitoring and feedback represents the last phase in the framework. According to the results of the thematic evolution analysis, increased interest to tax administration, institutions, and policy-making has been observed recently (Belahouaoui & Alm, 2025; Olldashi, et al., 2025), which indicates that ongoing monitoring of the results of enforcement, not one-time deployment of models, has become the characteristic of the trend in the area. This phase ensures that the results of post-deployment evaluation will be used for assessing false-positive rates, identifying model drift due to the changes in behavior of taxpayers, and revising initial decisions regarding risk conceptualization based on the obtained results. The feedback obtained at this stage serves as input data for Phase 1.

The framework as a whole brings together two interrelated aspects of AI-aided tax compliance: a sequence of five interdependent stages in which implementation is arranged, and a continuous basis of human tax reasoning – regulatory knowledge, contextual understanding, and accountability – underlying each and every stage. The contribution of this framework does not consist of inventing any wholly new methods of enforcement; instead, its value resides in the fact of introducing governance, explanation, and feedback into an area of research where bibliometric data indicates that these aspects have been relatively ignored in comparison with technical innovation. By treating AI as a tool for decision support (Mökander & Schroeder, 2024; Zong & Guan, 2025) rather than an enforcement mechanism on its own, the framework provides a systematic approach to the implementation of AI for tax administrations.

## 6. Conclusion

The present study represents a bibliometric analysis of the research related to artificial intelligence (AI)-facilitated tax compliance that is based on 527 papers indexed by Scopus that were published from 2004 to 2026. The results of the study prove that there has been a rapid growth of interest to the topic; especially since 2020, when taxation, artificial intelligence, machine learning, data mining, and fraud detection became dominant research themes. In addition, China, Germany, and the USA have proved themselves to be important contributors to the field; nevertheless, analysis of productivity and citations shows that the volume of publications does not correlate with scholarly influence.

Moreover, science mapping shows how research interests have evolved from computational methods, data mining, and neural network studies to applied machine learning, risk management, fraud detection, and automated tax compliance. However, more recent themes, including explainable AI, taxpayer trust, sustainability, transparency, and governance, can be

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considered relatively underdeveloped. It means that there is an obvious gap between technical advancement and the development of corresponding institutional frameworks.

In order to fill this research gap, the study outlines a five-step framework involving Strategic Risk Conceptualization, Data and Evidence Integration, Modeling and Methodology Selection, Governance, Explainability and Trust, and Monitoring and Feedback. This framework recognizes AI technology as a tool for decision support rather than self-governance, highlighting the necessity for the involvement of regulatory judgments and human control over the process. This way, the study contributes to the existing literature by linking the technological aspects of developing AI-based tax compliance with emerging governance needs.

## 7. Recommendations and Future Research

There are a number of implications that this study raises for further researchers, tax authorities, and government policymakers.

**First**, future research in the field should transcend a technical analysis of fraud detection capabilities, risk scoring, and prediction accuracy to engage in multi-disciplinary research that integrates computer science with public administration, taxation law, behavioral economics, and ethics. This way, the impact of AI on taxpayer rights, procedural justice, accountability, and legitimacy of tax administration will be studied properly.

**Second**, more attention needs to be paid to the issues of AI explainability, transparency, auditability, and taxpayer trust. Future researchers should explore the effects of AI explainability mechanisms, algorithm auditing, human supervision, and available procedures for contesting AI-assisted decisions on taxpayer acceptance and institutional trust.

**Third**, there is a need for comparative research in both developed and developing economies. While at present there is an over-representation of technologically and institutionally advanced cases in existing literature, tax administrations of developing countries might suffer from insufficiently developed information infrastructure, poor data integration capabilities, technical knowledge, and institutional capacity.

**Fourth**, tax authorities should adopt AI through governance by design where issues of transparency, privacy, fairness, accountability, and human oversight are built into the entire AI life cycle instead of being treated as an afterthought. The suggested five-stage framework could be used as the basis for implementing governance-by-design.

Lastly, future research should empirically test and develop further the suggested five-stage framework through case studies, surveys, experiments, and longitudinal data. Because this review has used only the Scopus bibliographic database, future literature reviews must use multiple sources and include full-text literature to cover the aspects not captured by the bibliometric analysis. Updated bibliometric analysis should also be conducted regularly due to the fast-moving nature of the research field.

## Author Contributions

The contribution of authors includes the following:

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**Dinesh Bidari**: The author was involved in conceptualization, literature review and data collection, methodology, bibliometric analysis, data interpretation, formulation of the five-phase framework, writing the initial draft.

**Dr. Nasiruddin Molla**: The author took part in supervision, conceptual assistance, methodology review and evaluation of the results, interpretation of findings and conclusion, and reviewing the paper.

## Declaration of AI Use

The bibliometric analysis for this paper has been done using Biblioshiny® and VOSviewer software. Generative AI (ChatGPT) has helped in generating keywords and proofreading. All the intellectual inputs have been provided by the authors themselves. No AI has been used for the generation, interpretation, or synthesis of the research results.

**Transparency Statement:** The authors confirm that this study has been conducted with honesty and in full adherence to ethical guidelines.

**Funding:** The study received no external funding.

**Conflict of Interest:** The authors declare there is no conflict of interest.

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