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Artificial Intelligence and Corporate Tax Risk Management: A Systematic Literature Review

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Abstract: This study presents a systematic literature review examining the transformative role of artificial intelligence (AI) in corporate tax risk management. As globalization, regulatory scrutiny, and digitalization increase corporate tax complexity, AI technologies including machine learning, predictive analytics, and automated compliance systems are reshaping how organizations identify, assess, and manage tax-related risks. The review synthesizes research across taxation, corporate governance, risk management, and algorithmic decision-making, exploring AI applications in enhancing tax compliance, fraud detection, tax planning, and governance frameworks. It reveals that AI offers significant potential to improve efficiency and effectiveness in tax risk management, yet successful implementation requires robust governance structures, ethical organizational cultures, and supportive regulatory environments. Critically, the study examines challenges associated with algorithmic decision-making, including transparency, fairness, accountability, and trust. It identifies persistent research gaps concerning developing economies, long-term organizational impacts, and unintended consequences of automated tax decisions. By consolidating fragmented literature streams, the paper provides a conceptual foundation for strategically integrating AI into corporate tax risk management and offers directions for future research and policy development in this evolving field.

Keywords: *Artificial Intelligence; AI; Corporate Tax Risk Management; Tax Compliance and Governance; Algorithmic Decision-Making; Digital Transformation in Taxation; Predictive Analytics and Tax Risk; Automation and Tax Strategy.*

1. Introduction

In terms of the world of taxation, the increasing impact of digital technologies on economic activities, corporate structures, and regulations is now a reality. Governments and tax authorities are overhauling their tax systems to make them more efficient, transparent, and lucrative, and businesses are facing higher levels of scrutiny in their tax dealings.

Digital transformation has turned the traditional way of assessing and collecting taxes on its head and has also raised the stakes of corporate tax risk management, especially in a fast-changing environment of regulations and data-driven control, according to Andi in 2025 and Nugroho in 2025.

What was once the chief concern of corporate tax was being in compliance and pushing the limits of what is acceptable in the way you pay your taxes. Today, companies are confronted with a broader spectrum of threats, and they're coming from more complex laws, border crossing deals, and real-time reporting requirements. Since tax systems are becoming more automated, businesses have to handle huge amounts of tax-related data, sort out new regulations, and respond quickly to questions from tax authorities. If they don't, they face financial penalties, damage to their reputation, and heavy fines.

Coming from a global perspective, the digital revolution in taxation is both an opportunity and a challenge. It allows us to monitor, combine, and enforce policies more effectively, but it lays a heavy burden on companies, especially those operating in multiple countries. New research has shown that tax reforms can modify the behavior of companies, the sustainability of their projects, and the way they are governed, and highlights the need for top-notch risk management techniques that can navigate the complexities of the digital world.

Artificial intelligence, AI, has now become an indispensable tool in tackling the knotty problem of corporate tax risk. AI-powered techniques, like machine learning, predictive analysis and automated decision support systems, could be used to shake up how corporations spot, evaluate and neutralize tax risks, and are enabled to run real-time analysis, flag up anomalies, and predict the likelihood of financial troubles. To drive operational efficiency in tax functions, AI can also be leveraged as a governance mechanism, offering transparency, consistency, and accountability to the process, according to Merola in his 2022 paper.

However, the integration of AI into corporate tax operations brings with it a whole host of governance, legal, and moral problems. The automated decision-making in tax systems introduces new kinds of risks in terms of transparency, fairness, and regulatory oversight, and has been the subject of much debate. Legal experts claim that the increasing dependence on automated systems is putting traditional principles of administrative law and corporate accountability under threat, and that when decisions become murky or impossible to contest, these principles are not respected, as Williams in 2022 noted.

One of the problems of the growing library of research in the areas of digital taxation and AI applications is that it is broken into a number of different areas of study, each coming from a different perspective, such as accountancy, economics, IT, public policy, and law. Many of the studies delve into one-sided aspects of digital change or AI deployment, but don't put the whole picture together when it comes to corporate tax risk management, nor do they investigate how these AI-driven tools work with existing tax administration, regulatory regimes, and organisational strategies, particularly in the case of systematic reviews.

Well-known in the academic community as a significant challenge in the area of AI and tax, the purpose of this study was to provide a comprehensive and methodical review of the role of artificial intelligence in changing tax risk identification, compliance, planning, and governance, and to tear apart the institutional and moral problems that go with it. With the synthesis of insights from digital taxation, corporate governance, and algorithmic decision-making, this paper aims to give us a clear understanding of how AI can be effectively incorporated into the structure of corporate tax risk management.

This study's contribution is threefold, it takes a jumbled mess of different academic viewpoints and knits them together into a cohesive conceptual framework that links AI technology and corporate tax risk and governance, brings to light some of the major hurdles and inadequacies of AI-based tax risk management, such as regulatory and accountability problems and starts to fill in the blanks where further study is needed, giving a solid foundation for both future research and policy developments in the world of digital taxation.

This systematic literature review makes several distinctive contributions. First, this is the first comprehensive systematic review specifically examining AI and corporate tax risk management, filling a critical gap where research remains fragmented across disciplines. Second, we develop a novel integrated conceptual framework connecting AI technologies with tax risk and governance structures, addressing institutional, ethical, and regulatory dimensions overlooked in prior literature. Third, we critically examine both opportunities and challenges of AI implementation, offering a balanced perspective beyond the optimistic tone of practitioner literature. Fourth, we systematically map research gaps across technological, organizational, governance, ethical, regulatory, and contextual dimensions, establishing a comprehensive research agenda. Fifth, we offer actionable insights for multiple stakeholders' managers, regulators, policymakers, and technology developers enhancing practical relevance. Finally, by consolidating fragmented literature streams, we create a common knowledge base facilitating interdisciplinary dialogue essential for effective AI governance in tax risk management.

This paper is organized as follows. The first section is the introduction that contains the background, research gaps, objectives, originality, and value added of the study. The second section explains the methodology of the systematic literature review, including search strategy, inclusion and exclusion criteria, study selection process, and data extraction procedures. The third section establishes the conceptual foundations of corporate tax risk and governance. The fourth section explores artificial intelligence and algorithmic decision-making fundamentals. The fifth section reviews AI applications in corporate tax risk management, including compliance, fraud detection, and tax planning. The sixth section examines AI integration into tax governance frameworks and discusses societal, ethical, and policy implications. The seventh section identifies literature gaps and proposes future research directions. Finally, the last section presents the conclusions and limitations of this study.

2. Research method

This systematic literature review adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021) to ensure methodological rigor, transparency, and replicability.

a. Search Strategy

A comprehensive systematic search was conducted in December 2025 across multiple academic databases to ensure broad interdisciplinary coverage of relevant scholarship. The databases included Web of Science Core Collection, Scopus, IEEE Xplore, ScienceDirect, JSTOR, and Google Scholar (limited to the first 200 results to maintain quality and manageability). These databases were selected because they are reputable, high-quality sources that provide extensive coverage of peer-reviewed literature across taxation, accounting, finance, information systems, computer science, management, and law disciplines relevant to AI and corporate tax risk management. These databases have been widely used as reliable sources when conducting systematic literature reviews (see, e.g., Casino et al. 2019; Dwivedi et al. 2019). The search covered publications from January 2018 to November 2025, a timeframe strategically selected to capture the recent surge in AI applications in corporate taxation following major advances in machine learning, deep learning, and natural language processing technologies that became widely adopted in business contexts after 2017.

To identify all relevant articles, we constructed a comprehensive Boolean search string combining multiple keywords and operators. The search string included the following terms: ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural network*" OR "natural language processing" OR "predictive analytics" OR "algorithm*" OR "automated decision*") AND ("corporate tax*" OR "tax risk*" OR "tax compliance" OR "tax planning" OR "tax fraud" OR "tax governance" OR "tax uncertainty" OR "tax management") AND ("risk management" OR "fraud detection" OR "compliance" OR "governance"). We used the asterisk symbol (*) as a wildcard to ensure that different variations in diction across articles were covered (e.g., "algorithm," "algorithmic," "algorithms"). The search string was designed to capture studies at the intersection of AI technologies and corporate tax risk management while maintaining sufficient specificity to ensure relevance. The search was executed across article titles, abstracts, and keywords in all selected databases to maximize coverage while maintaining focus on the core research objectives. Additionally, backward snowballing (manual review of reference lists) and forward citation tracking (using Google Scholar and Web of Science) were conducted on seminal articles to ensure comprehensive coverage and minimize the risk of missing relevant studies.

b. Criteria application

Following the guidelines of Tranfield et al. (2003), we established rigorous inclusion and exclusion criteria to ensure that selected studies aligned with the research objectives and maintained high methodological quality. Inclusion criteria defined the standards for studies to be selected and incorporated into the review, while exclusion criteria specified the grounds for removing studies from consideration.

First, our literature review was limited to peer-reviewed journal articles, reputable conference proceedings, and scholarly book chapters to minimize the inclusion of documents that lack rigorous peer review or cannot be reliably accessed. Specifically, papers should have been published in highly reputable journals in the business, management, accounting, finance, information systems, computer science, and law categories. For publication quality criteria, our literature review employed the journal rankings released by SCImago, primarily based on Scopus index rankings Q1 and Q2, as well as indexing in Web of Science Core Collection. These journals are considered to be leading global scientific outlets with rigorous peer-review processes. The application of this quality criterion was adopted from previous systematic literature reviews that involved only highly reputable international journals, such as those by Wilde and Wilson (2018) and Wang et al. (2020). Articles published in Q3 and Q4 journals, as well as non-ranked journals, were generally excluded unless they made exceptional contributions to the field. Additionally, non-peer-reviewed sources, opinion pieces, editorials, and commentaries without substantial empirical or theoretical rigor were excluded.

Second, papers should explicitly address and discuss AI technologies in the context of corporate tax risk management to meet the specific purpose of this literature review. This includes studies examining AI applications in tax compliance, fraud detection, tax planning, risk assessment, or tax governance. Studies that discussed general digital taxation or tax technology without specific focus on AI-based systems or algorithmic decision-making were excluded. Similarly, we removed papers focusing exclusively on personal taxation, tax policy analysis without corporate application, or public sector tax administration without transferable insights to corporate contexts.

Third, papers should be written in English to facilitate consistent analysis and interpretation across the corpus. We excluded papers not written in English due to resource constraints and to ensure analytical consistency. Fourth, we specified a timeframe from January 2018 to November 2025 for publications, strategically selected to capture the period following major advances in AI technologies applicable to business contexts while ensuring contemporaneous relevance. This timeframe balances the need for recent, cutting-edge research with sufficient corpus size for comprehensive synthesis. Fifth, for methodological rigor, empirical studies should present clear research designs, transparent data sources, and appropriate analytical procedures, while conceptual or theoretical papers should demonstrate substantial analytical depth and clear contributions to knowledge. Finally, duplicate publications reporting the same study or dataset without additional analysis, as well as studies for which full text could not be obtained through institutional access, interlibrary loan, or author contact, were excluded.

Based on these inclusion and exclusion criteria, the initial database search yielded 487 potentially relevant articles. After removing duplicates and applying title/abstract screening, 128 articles were selected for full-text review, ultimately resulting in 60 articles meeting all criteria and forming the final corpus for systematic analysis. Figure 1 presents the PRISMA flow diagram illustrating the complete selection process.

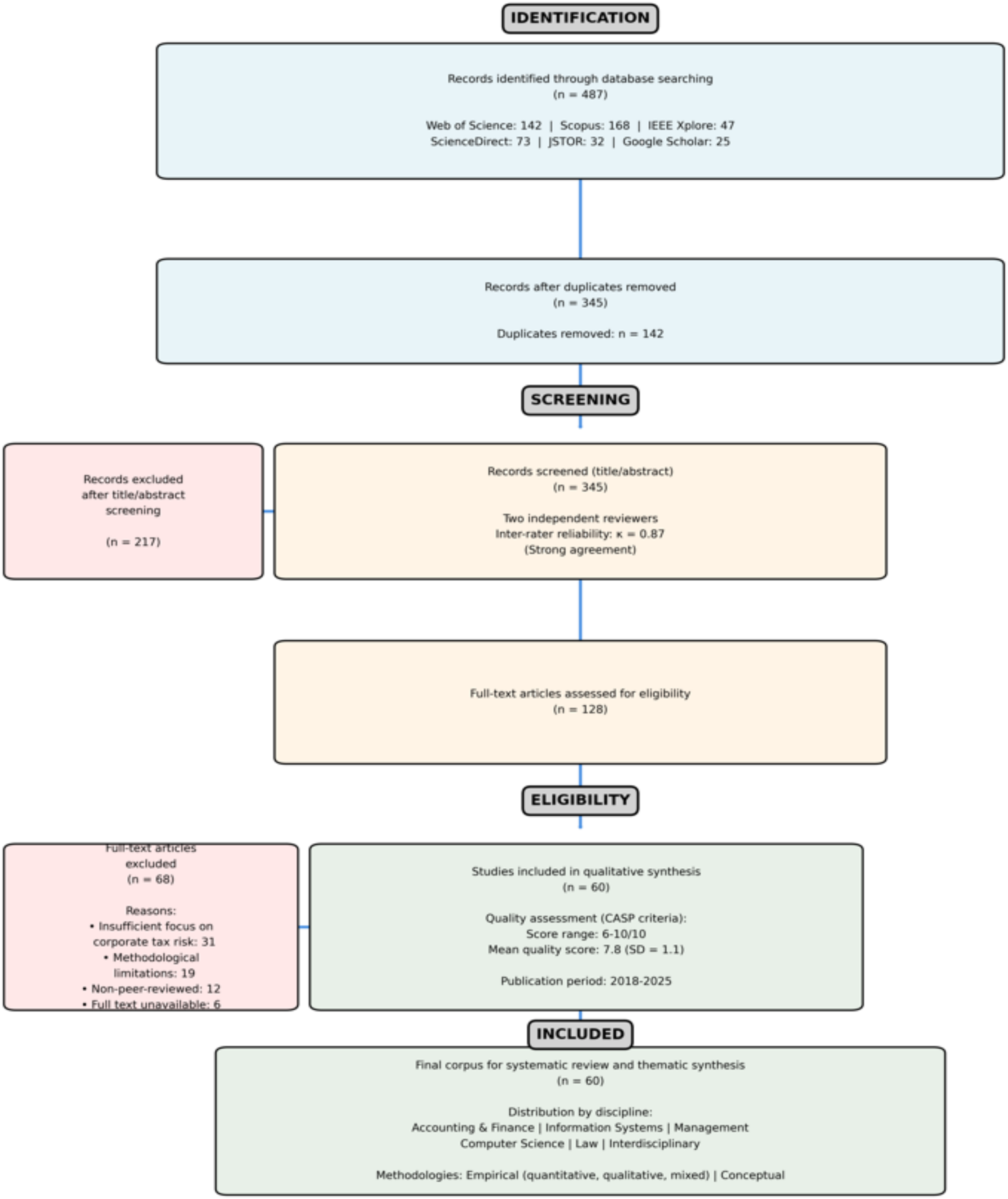
c. Study Selection Process

The study selection process followed a rigorous multi-stage screening procedure, as illustrated in Figure 1. The initial database search yielded 487 records distributed across databases as follows: Web of Science (142), Scopus (168), IEEE Xplore (47), ScienceDirect (73), JSTOR (32), and Google Scholar (25). After removing duplicates using reference management software and manual verification, 345 unique records remained for title and abstract screening. This screening was conducted independently by two reviewers who assessed each record against the predefined inclusion and exclusion criteria. Inter-rater reliability was assessed using Cohen's kappa coefficient, yielding $\varkappa = 0.87$, indicating strong agreement between reviewers (Landis & Koch, 1977). Disagreements occurred in 23 cases and were resolved through discussion between the two reviewers; for four unresolved cases, a third senior reviewer was consulted to make the final decision. Following this screening phase, 128 articles were selected for full-text review. During the full-text assessment stage, each article was thoroughly evaluated to ascertain whether it explicitly addressed AI technologies in corporate tax risk management as its primary or substantial focus, and whether it met all methodological quality criteria. This stage led to the exclusion of 68 articles for the following reasons: insufficient focus on corporate tax risk management (n=31), including studies that discussed AI in taxation generally without specific corporate risk management application or studies addressing tax risk from a tax authority's perspective rather than a corporate perspective; methodological limitations (n=19), such as unclear research designs, insufficient description of data sources, weak analytical frameworks, or lack of empirical or theoretical rigor; non-peer-reviewed sources or publications in predatory journals (n=12); and unavailability of full text despite multiple access attempts through institutional subscriptions, interlibrary loan, and direct author contact (n=6). The final corpus comprised 60 articles that met all inclusion criteria and demonstrated sufficient methodological quality for systematic analysis. Figure 1 presents the complete PRISMA flow diagram illustrating this selection process.

d. Data Extraction and Quality Assessment

The objective of quality assessment is to ensure the validity and reliability of the selected articles and to provide transparency regarding the rigor of included studies (Tranfield et al. 2003). We employed a systematic method of checking and verifying the quality of studies considered relevant (see Rasel and Win 2020). For this stage, we performed three key steps. First, all 60 articles in the final corpus were downloaded, organized, and systematically coded using a standardized data extraction form. This form captured comprehensive bibliographic information (authors, publication year, journal name, volume, issue, pages, DOI), journal quality indicators (SCImago Journal Rankings quartile, Web of Science indexing), research design characteristics (research objectives, theoretical frameworks employed, methodology and research design type, data sources and sample characteristics for empirical studies, analytical methods), AI and tax risk dimensions (specific AI technologies examined such as machine learning, predictive analytics, natural language processing, or automated decision systems; tax risk areas addressed including compliance, fraud detection, planning, governance, or risk assessment; application contexts), key findings and contributions (main results related to AI effectiveness in tax risk management, governance or ethical challenges identified, theoretical and practical implications), and research gaps (limitations acknowledged by authors, future research directions proposed). Second, to ensure consistency and reliability of data extraction, two reviewers independently extracted data from a random sample of 20% of articles (n=12); discrepancies were discussed and resolved, and the data extraction protocol was refined accordingly before completing extraction for the remaining articles. Third, each article underwent rigorous quality assessment using adapted criteria from the Critical Appraisal Skills Programme (CASP), tailored to different study designs (quantitative, qualitative, conceptual). Each article was evaluated on five dimensions: clarity of research objectives (0-2 points), methodological appropriateness (0-2 points), rigor of data collection and analysis (0-3 points), validity and reliability of findings (0-2 points), and contribution to knowledge (0-1 point), yielding a total quality score out of 10. Articles scoring below 6/10 (60%) were excluded during the full-text review stage. All 60 articles in the final sample scored 6 or above, with a mean quality score of 7.8 (SD = 1.1), indicating generally high methodological quality and substantial contributions to the field. This systematic approach to data extraction and quality assessment ensures that the subsequent synthesis is based on a robust and reliable evidence base.

Figure 1: Process of articles selection



3. Conceptual foundations of corporate tax risk and governance

A deep understanding of corporate tax risk and the governance frameworks surrounding tax-related decisions is necessary when corporations look to harness artificial intelligence in their tax risk management. Corporate tax risk is not isolated to a single component of the firm's operations, but is embedded within the broader enterprise risk management system, and is influenced by institutional, behavioral, and governance factors.

a. Defining Corporate Tax Risk

Which transcends the financial probability of a single fiscal loss and can affect a business's strategies, operations, repute, and governance, is presented by Brühne and Schanz in 2022. This concept of corporate tax risk as a result of internal decision-making and outer world uncertainty, lays out how the views on tax danger can vary from one person to another, from tax experts to executives.

Well-known in the world of corporate risk management, tax risk is becoming increasingly seen as a fundamental element of a company's total risk profile. Eastman et al. Showed in 2024 that tax planning and tax risk go hand-in-hand with the broader framework of corporate risk management, making firms weigh their need to reduce tax burdens against the potential exposure they may incur. This new perspective is quite a departure from the earlier view that saw tax risk only as a matter of compliance, and instead turns it into a top-level managerial challenge with implications for a company's value and its appetite for taking risks.

The relationship between tax risk and tax evasion is one more layer that makes the comprehension of corporate tax risk even more complicated. According to empirical evidence, bold moves to avoid taxes push up the level of tax risk, causing the chances of a tax audit, lawsuits, and damage to a company's reputation. Guedrib and Hamdi, in their 2025 study, found that higher tax risk leads to a rise in the price of borrowed money and that investors view tax risk as a significant element in deciding the financial stability of a company. Looking at tax avoidance, companies need to weigh the risks of deviating from industry norms in their tax strategies, and one of those risks is being monitored and audited more closely.

Research shows that corporate tax risk isn't purely a technical exercise, but rather has deep roots in strategic decision-making, governance, and enterprise risk management systems. Coming to grips with this complex nature of tax risk is why AI-driven systems are being increasingly used to tame the uncertainty in the area.

b. Tax Governance, Compliance, and Institutional Context

Tax governance, which covers the rules, procedures, and cultural norms within an organization, plays a significant part in how effectively companies manage their tax obligations, and therefore their tax risks. Prior studies have shown that governance quality, ethics, and institutional trust all influence the degree to which corporations stay compliant with tax laws.

Internal controls, corporate governance, and a culture of morality inside a firm are top-level contributors to tax compliance behaviour, according to studies. Musah et al. In 2025, this shows that companies with superior internal controls and ethical cultures boast higher tax compliance, especially for smaller and medium-sized companies.

Taxpayer beliefs about the level of fairness in their financial arrangements and corporate and public governance also have a large say in whether companies comply with tax laws, as Alshira'h et al In 2021 and Bello et al. (2023). In 2023 made clear. Evaluating corporate tax in South Africa, Sebele-Mpofu in 2020 showed us that governance has a huge impact on the willingness of people in the informal sector to pay their taxes. Well-known is the relationship between institutional credibility, legitimacy, and tax compliance, and cross-country research has also confirmed that the perceived quality of governance influences tax compliance. Basically how much citizens trust the people who govern them.

Coming from a different direction, Nichelatti and Hiilamo in 2024 revealed that the way citizens perceive the governance in their countries has a huge effect on tax compliance in Sub-Saharan Africa, and Torgler et al in 2024 showed that tax morale, governance quality, and tax compliance go hand-in-hand, and that where governance is transparent and accountable, voluntary compliance is much more likely.

There's also the aspect of the psychology behind tax governance, as investigated by Hauptman et al. In 2024, this demonstrates how people's attitude towards the tax authorities can play a massive role in how they decide whether to comply.

Overall, we can now see that corporate tax is affected by the three main components of governance.

Institutional structure, institutional context, and behaviour come together, and as digitalisation and automation become more prevalent, these factors will only become more and more important, even with the introduction of AI to tax compliance and risk management. As summarized in Table 1, these interconnected dimensions spanning corporate tax governance, public governance quality, tax morale, institutional trust, and behavioral factors collectively shape the compliance risk landscape that AI-driven systems must navigate.

Table 1: Dimensions of Tax Governance, Tax Morale, and Compliance Risks

Dimension	Key Characteristics	Implications for Corporate Tax Risk	Supporting Literature
Corporate Tax Governance	Internal controls, ethical culture, oversight mechanisms	Reduces compliance failures and strategic tax risk	Musah et al. (2025)
Public Governance Quality	Transparency, accountability, regulatory effectiveness	Enhances trust and voluntary compliance	Alshira'h et al. (2021); Bello et al. (2023)
Tax Morale	Ethical norms, fairness perceptions, civic responsibility	Influences willingness to comply with tax obligations	Sebele-Mpofu (2020); Torgler et al. (2024)
Institutional Trust	Confidence in tax authorities and legal systems	Lowers enforcement-related tax risk	Nichelatti & Hiilamo (2024)
Behavioral Factors	Motivational postures, attitudes toward authority	Affects compliance behavior and governance effectiveness	Hauptman et al. (2024)

4. Artificial intelligence and algorithmic decision-making: foundations and risks

AI has become an integral part of the decision-making process in organizations as companies seek to leverage technology to enhance efficiency, reduce errors, and increase business value. AI technology allows organizations to analyze vast amounts of structured and unstructured data, perform repetitive and complex tasks, and make predictions to support managerial decisions. Although these benefits offer many potential advantages to organizational outcomes, they also pose new risks that arise from decision-making models such as those that involve responsibility, interpretability, and trust.

a. AI Technologies in Organizational Decision-Making

AI technology refers to a collection of computer science techniques, including machine learning, automation, and predictive modeling, that are used in organizational decision-making. A specific type of AI that can be used to recognize patterns in big data and learn through experience to improve accuracy without the need for programming is known as machine learning. Machine learning is especially beneficial when the rules of the environment are not well understood and becomes particularly useful in complex, uncertain, and changing environments. Another AI technique is automation, which allows routine, repetitive tasks to be performed automatically with little human intervention. Third, predictive analytics is a key AI application in an organizational context. Predictive analytics predicts future events by analyzing past data, facilitating timely decision-making. Haleem et al. (2022) stated that AI analytics tools have been extensively applied in the business field to plan for the future, assess risks, and monitor the performance of businesses. Vaishya et al. (2020) suggested that AI tools can instantly analyze and interpret massive data from different data sources, showing that AI technologies can be applied in any business setting.

Organizational AI adoption is a socio-organizational rather than a technical process. Horodyski (2023) stated that the perception of AI in an organization has a positive impact on its acceptance, trust, and perceived value of AI adoption. The perception of AI significantly affects how organizational members use AI-based tools and whether they incorporate AI tools into decision-making processes or not. Moreover, the fit between technology and the organization should be guaranteed for successful AI adoption, which includes strategic alignment, governance, and skill alignment.

Lastly, AI adoption differs from one industry to another or from one department to another, depending on regulation, ethical issues, and complexity in decision-making. Su and Zhong (2022) addressed how AI decision-making tools can be adapted to the structured-decision making environments through curriculum development and future-oriented planning, and how AI can be embedded in the organizational architecture. Taken together, these studies showed that AI technology can facilitate organizational decision-making but that its adoption should be preceded by good governance and institutional preparedness.

b. Algorithmic Bias, Fairness, and Trust

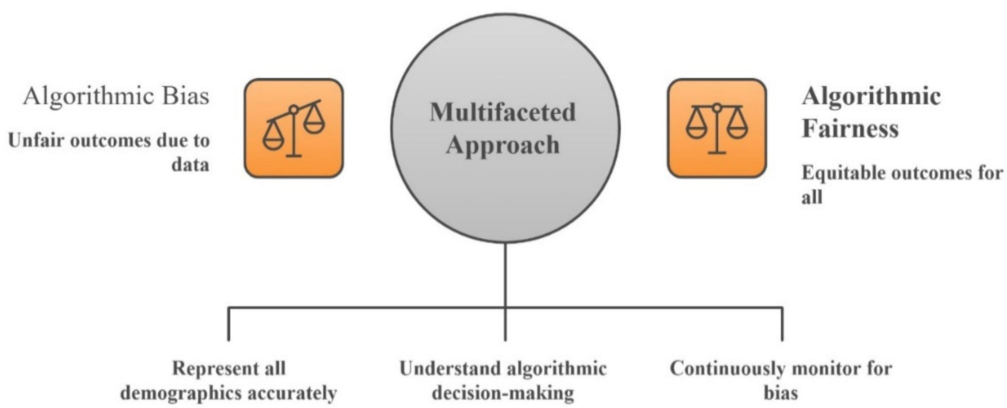
While AI-based decision support systems have the potential to provide substantial benefits, they also entail a significant governance risk concerning bias, fairness, and trust. Algorithmic bias occurs if AI-based decision support systems generate systematically biased results due to biases in the data, the model, or the application context. Köchling and Wehner (2020) provide compelling empirical evidence that algorithmic decision making can perpetuate and even exacerbate existing social and organizational biases if the data used for training are biased (e.g., because they reflect discrimination and inequality in the past). In organizational settings where fairness and legitimacy are of paramount importance, such biases can be particularly problematic. To address these interconnected challenges of algorithmic bias, fairness, and trust, a multifaceted approach is required, as illustrated in Figure 2. This approach involves representing all demographics accurately in training data, ensuring understanding of algorithmic decision-making processes, and continuously monitoring for bias.

Perceptions of fairness substantially affect stakeholder attitudes toward AI-based decision support systems. Starke et al. (2022) show that stakeholders judge decisions generated by an algorithm as fair if the decision process is perceived as fair, transparent, and subject to human control. Conversely, if AI-based decision support systems are perceived as nontransparent and unaccountable, trust in the technology and the organization using it may be negatively affected. The authors' findings are especially relevant for decision-making areas that involve high stakes, such as finance and compliance.

Algorithm aversion can cause additional problems when using AI in organizational contexts. Mahmud et al. (2022) find evidence in the literature that humans may prefer decisions made by humans over decisions made by algorithms, even when the algorithms perform better. Lack of understanding, perceived loss of control, and fear of mistakes are key drivers of algorithm aversion, highlighting the importance of explainability and human–AI collaboration in the decision-making process. Empirical examples of failed algorithmic control illustrate the importance of adequate AI system design and governance. For example, Rinta-Kahila et al. (2024) present empirical evidence on the collateral damage caused by automated decision-making in the public sector. Their work points to the need for proper control mechanisms to prevent systemic damage in the absence of adequate governance.

The papers cited collectively imply that AI represents a promising opportunity for management accounting decision-making, but that the introduction of AI entails novel risks not covered in the current research. Bias, fairness, and trust are key considerations for AI control and thus influence AI effectiveness and reliability. This is especially relevant in the context of corporate tax as AI applications might influence, for example, tax compliance, risk, and stakeholder trust.

Figure 2: Algorithmic Bias, Fairness, and Trust.



5. AI applications in corporate tax risk management

Regarding corporate tax, the widespread digitalization of tax systems and the growing availability of financial data have given rise to the use of artificial intelligence in tax risk management. No longer is corporate tax compliance limited to reactive approaches; AI has the capacity to be an industry game-changer in the world of corporate tax as it shifts from basic data analysis towards predicting and proactive tax strategies.

a. AI-Driven Tax Compliance and Fraud Detection

In the corporate tax arena, AI has found its primary uses in amplifying tax compliance, finding tax scams, supporting financial planning, and bringing clarity to decisions made in the face of uncertainty. Figure 3 illustrates the comprehensive process through which AI applications transform corporate tax risk management, from identifying tax risks through data analysis and strategy optimization to enhanced decision-making and ultimately achieving tax compliance. This section will delve into three AI-based methods in corporate tax risk management. Tax compliance, fraud detection, and predictive tax planning will zero in on these subjects.

AI-powered systems have, for example, become more prevalent in helping companies stay on top of their tax compliance and outsmarting scammers, and are best suited for environments with tangled tax regulations and mountains of transactional data. Machine learning and automated monitoring enable us to dissect and make sense of tax-related data in real time, flag potential irregularities, and tell us which areas of the tax system need more attention, cutting down the chance of human error that was previously prevalent in these processes. Table 2 provides a comprehensive overview of the specific AI tools deployed in tax compliance and risk detection, detailing their core functions, applications in tax risk management, and the empirical evidence supporting their effectiveness.

Research has proven that machine learning-based systems can significantly kickstart the process of identifying and stopping tax fraud and irregularities. Olabanji et al. In 2024, demonstrated that AI-based systems can cut tax avoidance and boost revenue hauls by picking up patterns that regular audits may miss, and Pamisetty in 2024 made the point that predictions and forecasts are not the only capabilities of AI; it's also able to bolster the workings of tax administrations, and alerting them to potential problems before they escalate. The digitization of tax systems has also catapulted the use of AI-based compliance systems, as shown by Erasashanti et al. In 2024, in their example of tax platforms that allow for flexible compliance and seamlessly integrate automated reporting, data cleansing, and monitoring functions. These systems, aside from just fixing compliance, add sustainability to the tax systems by bringing in transparency and honesty.

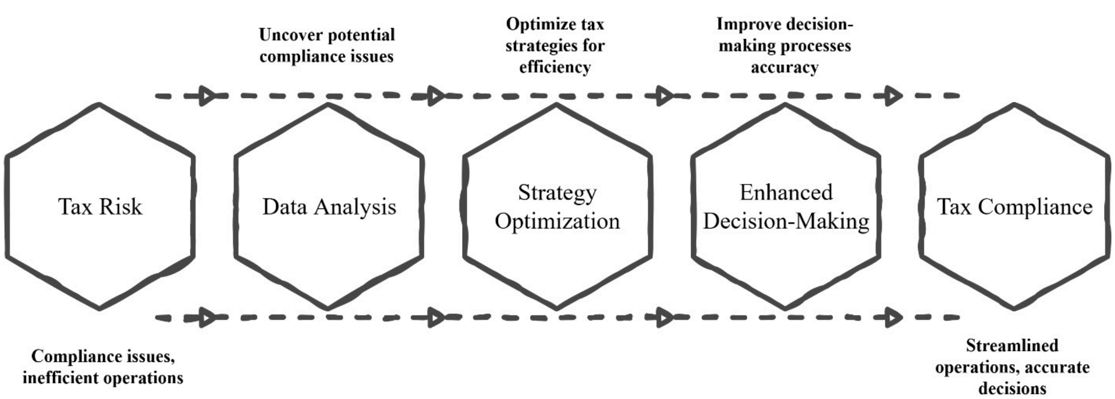
The range of AI tools available for tax risk management is diverse and complementary. As illustrated in Table 2, machine learning algorithms excel at pattern recognition and anomaly detection, making them particularly effective for identifying fraud and non-compliance risks. Predictive analytics systems complement this capability by forecasting risks and analyzing trends, enabling early detection of potential compliance failures before they materialize. Automated tax platforms integrate data and provide real-time monitoring, enhancing both compliance accuracy and reporting efficiency. Finally, advanced tax administration systems offer system-wide automation and oversight, facilitating strategic risk control and ensuring institutional alignment. Together, these AI tools form an integrated ecosystem that addresses different aspects of corporate tax risk management, from operational compliance to strategic governance.

In a corporate context, the way forward for AI-driven compliance tools is clear-cut. It's to be the first warning system that shields companies from financial penalties, brand reputation damage, and regulatory sanctions. Continuously scanning financial transactions and tax regulations, these tools enable businesses to zero in on areas of non-compliance and leap into action, and in doing so, give a boost to their overarching tax risk management frameworks. As depicted in Figure 3, this integrated AI-driven approach transforms initial compliance issues and inefficient operations into streamlined operations with accurate decisions, optimizing tax strategies for efficiency while improving decision-making process accuracy.

Table 2: AI Tools and Their Functional Roles in Tax Compliance and Risk Detection

AI Tool	Core Function	Application in Tax Risk Management	Supporting Literature
Machine Learning Algorithms	Pattern recognition and anomaly detection	Identification of fraud and non-compliance risks	Olabanji et al. (2024)
Predictive Analytics Systems	Risk forecasting and trend analysis	Early detection of potential compliance failures	Pamisetty (2024)
Automated Tax Platforms	Data integration and real-time monitoring	Enhanced compliance and reporting accuracy	Erasashanti et al. (2024)
Advanced Tax Administration Systems	System-wide automation and oversight	Strategic risk control and institutional alignment	Nugroho (2025)

Figure 3: AI Applications in Corporate Tax Risk Management.



b. Predictive Analytics and Corporate Tax Planning

Looking at corporate tax planning, artificial intelligence is becoming increasingly important, giving companies a more proactive approach to risk assessment and decision-making. Predictive analytics allows them to run simulations of what might happen in the future and calculate the consequences of different tax strategies.

Well-known studies in the field, by Lismont et al in 2018, showed how advanced analytics could be used to forecast tax avoidance, and get a look at how a company's relationships and corporate structure affect its tax risk. Building off that foundation, Barik and Ranawat in '2024 demonstrated that AI-driven corporate tax planning systems can completely change the face of traditional tax planning, merging real-time data analysis, scenario modeling, and automated advice to let companies see exactly what the risks are and what the rewards will be.

The connection between AI and risk management is one that's becoming increasingly clear. Eastman, et al in ‘2024 said that tax planning decisions should be right at the heart of a company's risk management plans so that tax savings don’t come at the price of taking on too much risk. AI-based tools can now help to weigh up the costs and benefits and send corporations down a more well-rounded and intelligent decision-making route.

Deviation from industry norms in tax planning can be very perilous for a firm and make it more exposed to audits and enforcement. AI’s ability to help out in this area is also key, by zeroing in on regulatory trends, industry behaviour, and past enforcement actions. The use of predictions and scenario analysis lets companies plan tax strategies that are on top of their financials, defensible, and aligned with what the governing bodies expect.

6. Integrating ai into corporate tax governance frameworks

The traditional tax governance frameworks need a rethink when corporations adopt artificial intelligence in their tax functions. The AI tools, which can significantly enhance the efficiency and accuracy of tax computations and forecasts, can pose difficult governance questions about accountability, transparency, and strategic oversight. Coming up against these challenges, tax governance needs more than just the technical chops. It needs institutional structures that ensure the AI being used is used responsibly and ethically in the decision-making process. Table 3 synthesizes how AI integrates into different components of corporate tax governance and risk management systems, outlining the specific roles AI plays, the governance implications that arise, and the institutional frameworks required to address them.

Well-known aspects of corporate tax governance, such as internal controls, communication with tax authorities, and alignment of tax strategy with corporate objectives, are now being reevaluated in the context of AI-assisted tax management. Effective tax communication can be key in controlling corporate tax risk, and so in reducing uncertainty, boosting transparency, and helping to build positive relationships with the people who regulate us. The introduction of AI systems into tax governance brings all this logic up to date by allowing for real-time monitoring, data-driven insights, and slicker communication, and makes it more important for us to watch over how the algorithms are working, Bruehne & Schanz (2018).

From a risk management standpoint, AI systems shouldn’t be seen as a standalone solution, but rather as a part of the broader picture of enterprise risk management and governance. Integrity and risk modelling frameworks that combine analysis with organisational governance and show us the value of lining up our use of risk measurement tools with high moral standards and transparency, Chang et al. (2020). In corporate tax contexts, AI-driven risk assessments require governance structures that sort out who is responsible for the decisions, verify the outputs, and make sure they align with the company's appetite for risk. With respect to corporate tax governance and the use of AI, regulatory and legal considerations can't be ignored. Algorithmic decision-making by AI systems, often found in tax-related matters, can blow apart traditional approaches to corporate accountability, making it difficult to see what's going through the mind of the decision-making algorithm and who's responsible for the outcome, Williams (2022).

Well-known tax-related decisions, where the results have massive financial and reputational implications, don't stand up well to the opacity of AI systems and can kill the trust that is fundamental to a company's survival, making it much harder to navigate the regulatory terrain. As a result, companies must make sure that AI-based tax decisions are crystal clear, auditable, and overseen by humans.

Coming from the policy perspective, the fusion of AI and taxation has a much larger social and economic footprint. Merola (2022) stresses that tax systems should be able to adapt to the change brought about by AI and automation, yet still be fair and socially just, and that corporations would be best served by fine-tuning their AI-driven tax strategies to be in line with the principles of responsible tax practice and sustainable governance.

An effective corporate tax governance structure is basically a balancing act between brand-new technologies and rock-solid governance. AI systems should be here to help, not to replace, management's wise decisions and moral oversight. Clear-cut rules are necessary to sort out who gets to make the decisions, hold the AI-generated results accountable, and ensure compliance with laws and principles, and regular monitoring is a must to catch any unforeseen effects and alter our governance plans as AI evolves. As summarized in Table 3, the integration of AI into corporate tax governance requires careful attention to four key components: tax strategy and communication (where AI enhances transparency and regulator engagement), risk assessment and integrity (where AI aligns decisions with risk appetite and ethics), accountability and oversight (where explainable AI preserves legal and managerial accountability), and policy and societal alignment (where AI supports fair and inclusive tax governance). Each component demands specific governance mechanisms to ensure responsible AI deployment.

Table 3: Integration of AI into Corporate Tax Governance and Risk Management Systems

Governance Component	Role of AI	Governance Implications	Supporting Literature
Tax Strategy and Communication	Automated reporting and analytics	Enhances transparency and regulator engagement	Bruehne & Schanz (2018)
Risk Assessment and Integrity	AI-based risk modeling and monitoring	Aligns tax decisions with risk appetite and ethics	Chang et al. (2020)
Accountability and Oversight	Explainable and auditable AI systems	Preserves legal and managerial accountability	Williams (2022)
Policy and Societal Alignment	Data-driven evaluation of tax impacts	Supports fair and inclusive tax governance	Merola (2022)

7. Societal, ethical, and policy implications of ai-based tax risk management

When corporations turn to artificial intelligence to manage their tax risks, they are not only looking to streamline and improve their financial outcomes but are also delving into uncharted territory in the ethical, social, and policy aspects of corporate governance.

The implications of AI driving tax compliance, planning, and governance are a compelling and controversial area because these systems not only determine the corporate outcomes but also define how the public perceives the fairness and legitimacy of tax systems.

An issue of note, given that taxation is basically the backbone of how public goods are funded, and social contracts between governments, corporations, and citizens are sustained.

Well-known issues about the use of AI in corporate tax decision making is how difficult it is to guarantee that AI systems are unbiased, given that they are reliant on data, algorithms and sets of assumptions that can be riddled with implicit prejudices or moral judgements, and that, algorithmic decision-making can simply copy and amplify existing unfairness if there are no appropriate oversight mechanisms in place, Köchling & Wehner (2020).

In corporate tax settings, unbalanced or poorly managed AI systems could lead to irregular tax compliance, targeted risk-taking and cunning behavior that throw a wrench into the works of fair tax outcomes, and ethical governance is, therefore, a top priority, and must consist of crystal-clear standards for the accuracy of the data, the design of the models and the accountability of the choices to guarantee that AI applications are honest and responsible, and that the outcomes are fair.

Transparency and ethical governance go hand-in-hand and are critical to the validity of AI-driven tax risk management systems, people are only going to accept and perceive as fair decisions made by AI systems if they can understand what is going on, how the decisions are made, and where they can go to review them. In tax matters, obscure AI systems can stifle internal accountability and make it difficult to work with tax officials, especially when companies are unable to provide clear justification for their AI-based tax strategies, Starke et al. (2022).

Legislative control is the other huge problem faced by AI-driven tax risk management. When looking at the use of algorithmic decision-making in taxation, Williams, in his 2022 publication, exposed a major challenge to traditional legal and bureaucratic systems. The ability to diffuse accountability and muddy the waters when it comes to decision-making rationales. Coming hustling over into the void left by unclear regulations, companies may well be left uncertain about what is and isn't permissible when it comes to using AI in tax planning and compliance.

Regulatory systems that are adaptable and capable of rebalancing innovation and accountability are necessary to ensure that AI systems are placed under legal scrutiny, and that does not cripple their potential.

In society, AI in taxation will have a big impact on how much people trust institutions, how well we perceive the way our governance is run can really influence our willingness to comply with taxes, so it's clear that institutional trust is basically the backbone of a sustainable tax system. If people don't see AI-driven tax systems as clear, fair, or aggressive, they'll lose faith in the corporate sector and the tax authorities, and on the flip side, AI systems that are well-run, transparent, and reliable can build that trust, Nichelatti & Hiilamo (2024).

The role that taxation plays in bringing people together and states that tax systems should be able to adapt to the changes brought about by automation and AI, all the while keeping social fairness and equity in check. This means that corporations need to make sure their AI-based tax strategies are not a threat to the people, but an aid to the world, so they had better get their ducks in a row and sort out their AI tax practices accordingly, Merola (2022).

8. Research gaps and future research directions

With respect to the integration of artificial intelligence in corporate tax risk management, we're still facing a lot of blanks in the research library. Studies in the field of AI, taxation, and corporate risk management are multiplying, but there is no unified framework for the best way to apply AI to corporate tax risk management. Table 4 systematically identifies the key research gaps in this emerging field, outlining current limitations, proposed future research directions, and the supporting literature that highlights these knowledge deficits.

Well-known problems are that our current understanding of the way people and organizations respond to algorithmic decision-making, such as in the case of decision aversion, isn't complete. Humans may resist AI systems even when they know the AI outperforms their own judgment, Mahmud et al. (2022).

One area that is in dire need of research is the corporate tax sector.

How tax professionals, executives, and regulators perceive and communicate with AI-driven tax tools. Future studies could focus on under what circumstances are AI-supported tax decisions accepted, distrusted, and contested, with special consideration of transparency, user involvement and company culture.

Another area that has not been fully explored is the negative consequences of AI-driven decision-making in corporate tax, poorly constructed algorithmic systems can cause irreparable damage, all the while trying to improve efficiency. Surprisingly, research about the real-life effects of AI-driven tax systems in corporate settings is very scarce, Rinta-Kahila et al. (2024). Looking at the financial and market implications of corporate tax risk in AI-driven environments, empirical research is still in its infancy. Guedrib & Hamdi (2025) showed that tax risk affects a company's cost of debt, but the way AI is changing the game is not yet fully understood by existing studies.

Well-known future directions in the field will be to see if AI-driven tax risk management makes investors and creditors feel safer or if it introduces a brand-new level of uncertainty with regard to algorithmic governance. Coming from a different angle, Musah et al. (2025) say that a company's organisational culture and internal controls are critical for tax compliance, but we don't know much about how these governance mechanisms interact with AI technologies.

We also have a shortage of studies on how internal controls, moral principles, and corporate governance affect the success and validity of AI-driven tax risk management systems. As well, the lion's share of the existing literature is from developed countries and is based on public sector tax administration, which means that there is a desperate need for cross-country and comparative studies that look at AI in corporate tax risk management in various cultural and institutional settings. As comprehensively outlined in Table 4, these research gaps span multiple dimensions: behavioral and organizational responses to AI in tax contexts (algorithm aversion), long-term and systemic effects of AI-based tax systems (unintended consequences), financial market implications of AI adoption on tax risk perceptions (market consequences), the interplay between AI and governance mechanisms (governance and internal controls), and the need for diverse empirical evidence across different regulatory and institutional contexts (institutional and cross-country evidence). Addressing these gaps will require interdisciplinary collaboration, longitudinal research designs, and comparative methodologies that capture the complexity of AI integration in corporate tax risk management.

Table 4: Identified Research Gaps and Proposed Future Research Directions

Research Gap	Current Limitation	Future Research Direction	Supporting Literature
Algorithm Aversion in Tax Contexts	Limited understanding of user acceptance of AI in tax decisions	Study behavioral and organizational determinants of AI acceptance in tax functions	Mahmud et al. (2022)
Unintended Consequences of AI	Lack of longitudinal and case-based evidence	Examine long-term and systemic effects of AI-based tax risk systems	Rinta-Kahila et al. (2024)
Market Consequences of Tax Risk	Insufficient evidence on AI's moderating role	Analyze impact of AI adoption on tax risk, debt costs, and investor perceptions	Guedrib & Hamdi (2025)
Governance and Internal Controls	Limited integration of AI into governance research	Investigate interaction between AI, internal controls, and ethical culture	Musah et al. (2025)
Institutional and Cross-Country Evidence	Overconcentration in developed economies	Conduct comparative studies across regulatory and institutional contexts	Multiple sources

9. Conclusion

This study gathered and dissected the expanding body of literature in a rapidly digitizing taxation landscape when investigating the impact of artificial intelligence on corporate tax risk management. The review shows that corporate tax risk has become a multidimensional governance problem driven by intricate regulatory complexity, astute tax maneuvers, and merciless scrutiny from the public. Coming dashing out of the last few years, recent studies emphasize that tax risk is no longer contained to trivial matters of compliance but is firmly embedded in the heart of corporate governance and enterprise-wide risk management systems, according to Brühne and Schanz (2022) and Eastman et al. (2024).

One of the key takeaways of this review was the revolutionary role that artificial intelligence has played in how corporations are able to manage their tax risks. The seismic shift in taxation systems, brought about by digitization, has opened new avenues for companies to capitalize on advanced analytical tools and techniques that can rapidly process huge volumes of data, send back real-time reports, and navigate knotty regulatory landscapes. AI-based apps, stretching from automated tax audits to predictive analysis for tax planning, give businesses the chance to transform from reactive, slapdash approaches to proactive and forward-thinking tax risk management, and in particular allow them to get a grip on the balance between risk and return, hook their tax strategies up with the company's risk tolerance and blend tax considerations into the mix of strategic planning, according to Barik and Ranawat (2024) and Eastman et al. (2024).

However, this review also stresses that AI can only be truly effective in corporate tax risk management if it is supported by robust governance arrangements. In relation to tax AI, we can see that its performance is heavily influenced by the organisational structures, moral guidelines, and monitoring bodies that are in place. Coming hurrying into the world of taxation, previous studies have shown that complete transparency, accountability, and communication are vital in the management of tax risks, so it's not about replacing the people who make decisions, but about giving them a boost.

Well-known problems that arise when AI is used in tax management include a lack of clarity, unfair bias, and the loss of public faith in the system. If not controlled, AI-driven tax tools could be used to exacerbate these issues.

This review weaves together the various pieces of research in taxation, risk management, corporate governance, and AI to create a cohesive theoretical framework. It also takes the view of AI as a governance tool that can have far-reaching implications on organisational and societal levels and zeroes in on areas where there is a need for more research.

As global digital tax reforms continue to be implemented, the role of AI in corporate tax management is likely to increase, so we will need to see a greater convergence between tech innovation, corporate governance, and regulatory policies to make sure that AI-driven tax practices put the organisation on the right track and don't betray public trust.

By laying down a foundation for future research and by positioning AI within a larger picture of corporate governance and risk management, this review is a starting point for new investigations and discussions about the sustainable and responsible use of AI in corporate taxation.

10. Reference

- Alshira'h, A. F., Al-Shatnawi, H. M., Al-Okaily, M., Lutfi, A., & Alshirah, M. H. (2021). Do public governance and patriotism matter? Sales tax compliance among small and medium enterprises in developing countries: Jordanian evidence. *EuroMed Journal of Business*, *16*(4), 431–455. https://doi.org/10.1108/EMJB-01-2020-0004
- Andi, A. (2025). Digital Transformation in the Taxation System: Global Opportunities and Challenges. *International Journal of Financial Economics (IJEFE)*, *2*(5), 360–368.
- Bello, U., Dandago, K. I., & Samaila, I. A. (2023). Hierarchical Component Model Approach on Tax Fairness, Public Governance Quality and Tax Compliance: A Mediating Role of Tax Morale. *Kelaniya Journal of Management*, *12*(3), 40–58. https://doi.org/10.4038/kjm.v12i3.7766
- Bruehne, A., & Schanz, D. (2018). Building Up a Protective Shield: The Role of Tax Communication for Corporate Tax Risk Management. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3254915
- Brühne, A. I., & Schanz, D. (2022). Defining and Managing Corporate Tax Risk: Perceptions of Tax Risk Experts*. *Contemporary Accounting Research*, *39*(4), 2861–2902. https://doi.org/10.1111/1911-3846.12785

- Casino, F., Dasaklis, T. K., & Patsakis, C. (2019). A systematic literature review of blockchain-based applications: Current status, classification and open issues. *Telematics and Informatics*, *36*, 55–81. https://doi.org/10.1016/j.tele.2018.11.006
- Chang, V., Valverde, R., Ramachandran, M., & Li, C. S. (2020). Toward business integrity modeling and analysis framework for risk measurement and analysis. *Applied Sciences (Switzerland)*, *10*(9). https://doi.org/10.3390/app10093145
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kumar Kar, A., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
- Eastman, E. M., Ehinger, A. C., & Xu, J. (2024). Enterprise risk management and corporate tax planning. *Journal of Risk and Insurance*, *91*(3), 529–566. https://doi.org/10.1111/jori.12469
- Erasashanti, A. P., Winarti, Ch. E., Yuniarti, R., Hikmah, & Cahaya, Y. F. (2024). Transformasi Digital Perpajakan : Adaptasi, Kepatuhan, dan Sistem Keberlanjutan di Desa Ligarmukti. *PROSIDING ABDIMAS*, *1*, 1–11. Retrieved from https://journal.perbanas.id/index.php/pkm/article/view/800
- Guedrib, M., & Hamdi, Z. (2025). Investigating tax risk's influence on tax avoidance and debt costs: evidence from France. *Journal of Financial Crime*, *32*(2), 321–336. https://doi.org/10.1108/JFC-03-2024-0111
- Haleem, A., Javaid, M., Asim Qadri, M., Pratap Singh, R., & Suman, R. (2022, January 1). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*. KeAi Communications Co. https://doi.org/10.1016/j.ijin.2022.08.005
- Hauptman, L., Žmuk, B., & Dečman, N. (2024). Tax governance in compliance: The role of motivational postures and behavioral intentions. *Problems and Perspectives in Management*, *22*(1), 500–513. https://doi.org/10.21511/ppm.22(1).2024.40
- Horodyski, P. (2023). Recruiter's perception of artificial intelligence (AI)-based tools in recruitment. *Computers in Human Behavior Reports*, *10*. https://doi.org/10.1016/j.chbr.2023.100298
- Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: a systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. *Business Research*, *13*(3), 795–848. https://doi.org/10.1007/s40685-020-00134-w
- Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159–174. https://doi.org/10.2307/2529310
- Lismont, J., Cardinaels, E., Bruynseels, L., De Groote, S., Baesens, B., Lemahieu, W., & Vanthienen, J. (2018). Predicting tax avoidance by means of social network analytics. *Decision Support Systems*, *108*, 13–24. https://doi.org/10.1016/j.dss.2018.02.001
- Mahmud, H., Islam, A. K. M. N., Ahmed, S. I., & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm

aversion. *Technological Forecasting and Social Change*, *175*. https://doi.org/10.1016/j.techfore.2021.121390

- Merola, R. (2022). Inclusive Growth in the Era of Automation and AI: How Can Taxation Help? *Frontiers in Artificial Intelligence*, *5*. https://doi.org/10.3389/frai.2022.867832
- Musah, A., Padi, A., Blay, M. W., Okyere, D. O., & Ofori, B. S. (2025). Ethical organisational culture, effective internal control systems and tax compliance of small and medium scale enterprises (SMEs): The role of corporate governance. *Social Sciences and Humanities Open*, *11*. https://doi.org/10.1016/j.ssaho.2025.101331
- Nichelatti, E., & Hiilamo, H. (2024). The Effect of Citizens' Perception of Governance on Tax Compliance: A Cross-Country Analysis Study for 32 Sub-Saharan African Countries. *European Journal of Development Research*, *36*(5), 1198–1226. https://doi.org/10.1057/s41287-024-00631-2
- Nugroho, P. A. (2025). Strategic Adaptation to Core Tax Administration System (CTAS): A Scenario Planning Analysis. *Jurnal Ilmiah Manajemen Kesatuan*, *13*(3), 1349–1362. https://doi.org/10.37641/jimkes.v13i3.3354
- Olabanji, S. O., Olaniyi, O. O., & Olaoye, O. O. (2024). Transforming Tax Compliance with Machine Learning: Reducing Fraud and Enhancing Revenue Collection. *Asian Journal of Economics, Business and Accounting*, *24*(11), 503–513. https://doi.org/10.9734/ajeba/2024/v24i111572
- 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., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, *372*, n71. https://doi.org/10.1136/bmj.n71
- Pamisetty, V. (2024). Transforming Taxation Systems through Predictive Analytics and AI-Driven Compliance Monitoring Tools. *American Data Science Journal for Advanced Computations (ADSJAC) ISSN: 3067-4166*, *2*(1), 1–20.
- Rasel, F., & Win, S. (2020). Blockchain technology in the automotive industry: A systematic literature review. *Communications of the Association for Information Systems*, *46*, 258–285. https://doi.org/10.17705/1CAIS.04612
- Rinta-Kahila, T., Someh, I., Gillespie, N., Indulska, M., & Gregor, S. (2024). Managing unintended consequences of algorithmic decision-making: The case of Robodebt. *Journal of Information Technology Teaching Cases*, *14*(1), 165–171. https://doi.org/10.1177/20438869231165538
- Sebele-Mpofu, F. Y. (2020). Governance quality and tax morale and compliance in Zimbabwe's informal sector. *Cogent Business and Management*, *7*(1). https://doi.org/10.1080/23311975.2020.1794662
- Starke, C., Baleis, J., Keller, B., & Marcinkowski, F. (2022). Fairness perceptions of algorithmic decision-making: A systematic review of the empirical literature. *Big Data and Society*, *9*(2). https://doi.org/10.1177/20539517221115189
- Su, J., & Zhong, Y. (2022). Artificial Intelligence (AI) in early childhood education: Curriculum design and future directions. *Computers and Education: Artificial Intelligence*, *3*. https://doi.org/10.1016/j.caeai.2022.100072

- Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. *BMC Medical Research Methodology*, *8*(1), 45. https://doi.org/10.1186/1471-2288-8-45
- Torgler, B. ;, Schaffner, M. ;, Macintyre, A., Torgler, B., & Schaffner, M. (2024). Standard-Nutzungsbedingungen: CREMA Tax Compliance, Tax Morale and Governance Quality TAX COMPLIANCE, TAX MORALE AND GOVERNANCE QUALITY. *Center for Research in Economics, Management and the Arts*, 1–8. Retrieved from https://hdl.handle.net/10419/214391
- Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, *14*(3), 207–222. https://doi.org/10.1111/1467-8551.00375
- Tushar Ranjan Barik, & Priyanka Ranawat. (2024). Transformation of Traditional Corporate Tax Planning into AI-Driven Corporate Tax Planning. *Involvement International Journal of Business*, *1*(4), 269–280. https://doi.org/10.62569/iijb.v1i4.68
- Vaishya, R., Javaid, M., Khan, I. H., & Haleem, A. (2020). Artificial Intelligence (AI) applications for COVID-19 pandemic. *Diabetes and Metabolic Syndrome: Clinical Research and Reviews*, *14*(4), 337–339. https://doi.org/10.1016/j.dsx.2020.04.012
- Wang, F., Xu, L., Zhang, J., Shu, W., & Carneiro, A. (2020). Textual analysis of corporate disclosures: A survey of the literature. *Journal of Accounting Literature*, *45*, 122–152. https://doi.org/10.1016/j.acclit.2020.09.001
- Wilde, J. H., & Wilson, R. J. (2018). Perspectives on corporate tax planning: Observations from the past decade. *The Journal of the American Taxation Association*, *40*(2), 63–81. https://doi.org/10.2308/atax-51993
- Williams, R. (2022). Rethinking Administrative Law for Algorithmic Decision Making. *Oxford Journal of Legal Studies*, *42*(2), 468–494. https://doi.org/10.1093/ojls/gqab032