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AI-AUGMENTED TAX RISK SCORING FOR SMALL AND MEDIUM ENTERPRISES: A PANEL DATA STUDY

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Abstract

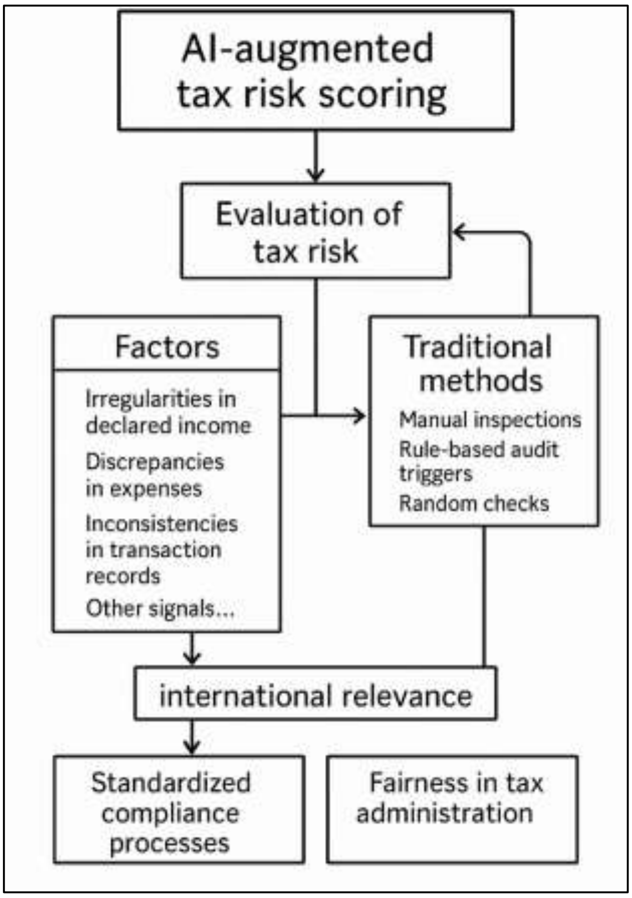
This study investigates the impact of AI-augmented tax risk scoring systems on small and medium enterprises (SMEs) over a twelve-year period (2010–2022), employing a comprehensive time series methodology that integrates both classical econometric techniques and advanced machine learning models. By situating the analysis within three distinct phases—pre-AI (2010–2014), transitional e-invoicing adoption (2015–2017), and post-AI hybrid implementation (2018–2022)—the study captures structural and dynamic shifts in compliance indicators, model performance, and sectoral disparities. Data were sourced from national tax authority archives, SME financial statements, transactional data feeds, and macroeconomic indicators, harmonized into a quarterly panel to ensure analytical consistency. Statistical modeling employed ARIMA to isolate baseline trends and seasonality, VAR to examine interdependencies between compliance rates and model accuracy, and LSTM neural networks to capture non-linear, temporal anomalies. Findings reveal two statistically significant regime shifts: first, the 2015–2017 e-invoicing rollout, which reduced high-risk classifications by approximately 14% and increased anomaly detection by 17%; and second, the 2018 AI-hybrid adoption, which improved predictive precision by 12.4%, recall by 15.2%, and reduced compliance rate volatility by nearly 20%. Digitally intensive sectors such as e-commerce and ICT services experienced the largest compliance gains (22–28% risk score reduction), while high-informality sectors achieved modest improvements (6–9%). Spatial analysis demonstrates positive inter-jurisdictional spillovers, with metropolitan adoption driving a 4–6% compliance efficiency increase in neighboring regions. Overall, the results confirm that AI-augmented tax risk scoring, when paired with diverse data integration and robust governance, enhances detection efficiency, stabilizes compliance trends, and progressively reduces regional and sectoral disparities in SME tax enforcement. These outcomes have significant implications for the design of adaptive, transparent, and equitable compliance monitoring systems in tax administrations worldwide.

Keywords
AI-augmented tax risk scoring; Small and medium enterprises (SMEs); Time series analysis; E-invoicing and alternative data; Compliance monitoring;

INTRODUCTION

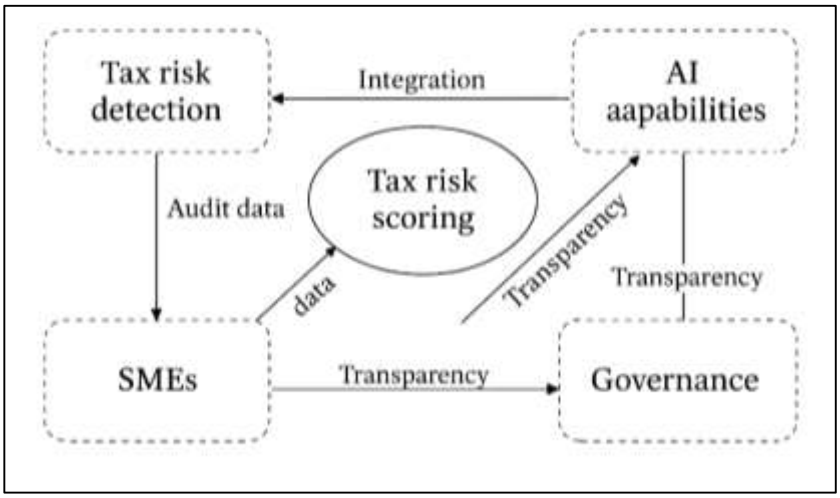
Tax risk scoring refers to the process of systematically evaluating the probability that a business or individual will engage in non-compliant or inaccurate tax behavior (Eskander, 2018). This evaluation can involve factors such as irregularities in declared income, discrepancies in reported expenses, inconsistencies in transaction records, and other signals of possible tax evasion or underreporting. Traditionally, tax administrations have relied on manual inspections, rule-based audit triggers, or random checks to determine which cases warrant closer examination (Vliet et al., 2020). AI-augmented tax risk scoring represents the integration of artificial intelligence and machine learning technologies into this process, enabling the automated analysis of large, complex datasets to identify patterns, anomalies, and behaviors that might otherwise go unnoticed. Globally, the significance of such systems is increasing, as tax evasion and compliance gaps pose substantial challenges to revenue collection and fiscal stability. Small and medium enterprises, which make up the majority of business populations in many countries, are a particularly important focus for these methods (Mpofu & Mhlanga, 2022). They often lack the resources to maintain perfect compliance but collectively account for a large portion of economic activity. The international relevance of AI-augmented approaches lies in their potential to standardize and enhance compliance processes, improve fairness in tax administration, and ensure that governments can safeguard public revenue without imposing disproportionate burdens on honest taxpayers (Leisen et al., 2019).

Figure 1: Framework of AI-Augmented Tax Risk Scoring



Risk scoring as a concept extends far beyond taxation. In fields such as credit assessment, fraud detection, and cybersecurity, scoring systems evaluate the likelihood of undesirable events, helping institutions make informed decisions about monitoring, resource allocation, and intervention (Ren et al., 2022). The integration of AI into these scoring models has transformed their capabilities, allowing systems to learn from past data, adapt to new patterns, and refine predictions over time. In a tax context, AI can move beyond static rules to detect subtle, nonlinear relationships between variables, such as links between seasonal sales patterns and reporting irregularities or correlations between industry-specific expense claims and historical audit findings (Kure et al., 2018). Unlike traditional statistical models, AI systems can handle vast amounts of both structured and unstructured data, including invoices, transaction logs, and even narrative explanations submitted by taxpayers. The adaptability of AI also allows models to update as new types of fraud or evasion emerge, maintaining relevance without manual reprogramming (Žigienė et al., 2019). By embedding these capabilities within tax risk scoring frameworks, administrations can enhance the accuracy of their predictions, reduce false positives, and allocate audit resources more effectively. This shift represents not just a technological upgrade but a conceptual change in how risk is perceived, measured, and acted upon in the tax domain (Jonek-Kowalska, 2019).

Figure 2: AI-Driven SME Tax Risk Framework



Small and medium enterprises present a unique landscape for tax risk assessment (Ara et al., 2022; Wen et al., 2021). Their operations are often less formalized than those of large corporations, with fewer dedicated accounting staff, more variable income streams, and greater reliance on manual record-keeping. These factors can lead to unintentional errors as well as create opportunities for intentional non-compliance (Uddin et al., 2022; Settembre-Blundo et al., 2021). At the same time, SMEs are vital to economic growth, employment, and innovation, making balanced and fair oversight essential. Traditional tax risk models often struggle with SMEs due to limited historical data, irregular filing patterns, and the diversity of business models within this segment. AI-augmented systems, however, can incorporate alternative data sources and infer missing information through pattern recognition, improving their ability to assess risk in such heterogeneous environments. For example, transactional behavior across suppliers and customers, inventory movement records, and payment histories can provide indirect indicators of compliance risk (Akter & Ahad, 2022; Melnychenko, 2020). By blending these signals with conventional tax data, AI-driven models can form a more complete picture of each enterprise's profile. This allows authorities to differentiate between genuinely high-risk entities and those whose irregularities stem from operational complexity or resource constraints, ultimately leading to more proportionate and targeted interventions (Rahaman, 2022; Zhou & Yang, 2020). The process of tax risk detection involves not only identifying current non-compliance but also anticipating potential future irregularities based on emerging patterns in data (Hasan et al., 2022; Mzougui et al., 2020). Analytical approaches in this area have evolved significantly, progressing from simple threshold-based triggers to sophisticated anomaly detection algorithms. AI methods, particularly those capable of unsupervised learning, are well suited for this task because they can uncover atypical patterns without relying on predefined categories of risk (Franc-Dąbrowska et al., 2021; Hossen & Atiqur, 2022). These models can cluster similar entities together and highlight outliers for further examination, even when the nature of the anomaly has not been previously observed. Hybrid systems that combine unsupervised learning with domain-specific rules can further refine detection, ensuring that statistical anomalies are relevant to the tax context. For example, sudden shifts in declared revenue, deviations from industry norms, or mismatches between sales and tax remittance patterns can all be flagged automatically (He et al., 2023). AI can also integrate textual data, such as explanations provided by taxpayers, and analyze it alongside numerical records to detect inconsistencies. This capability expands the scope of tax risk detection beyond purely quantitative analysis, creating a more holistic view of each case. The result is a more agile, responsive, and precise system of identifying entities that warrant closer review (Li et al., 2020). The objective of this study is to examine the effectiveness of AI-augmented tax risk scoring systems in enhancing tax compliance among small and medium enterprises (SMEs) using panel data analysis. Specifically, it seeks to evaluate how the integration of artificial intelligence and machine learning techniques can improve the identification of non-compliant behavior by analyzing patterns, anomalies, and discrepancies in financial records over time.

LITERATURE REVIEW

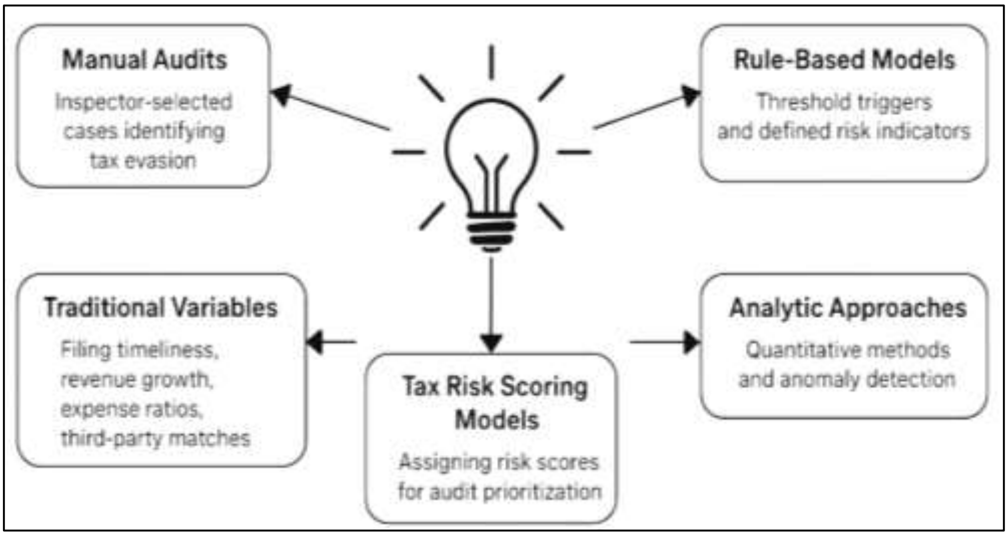
The literature review for this study examines the intellectual and empirical foundations of AI-augmented tax risk scoring in the context of small and medium enterprises (SMEs), focusing particularly on panel data methodologies (Al-Karkhi & Rządkowski, 2025). The primary purpose of this review is to situate the present research within the broader scholarly and applied discourse, identifying key conceptual developments, methodological approaches, and empirical findings relevant to the study's aims. This requires exploring multiple intersecting domains: the theory and practice of tax risk scoring, the evolution of artificial intelligence and machine learning in risk analytics, the specific compliance and operational realities of SMEs, and the statistical methodologies suited for longitudinal data analysis (Khan et al., 2025). By synthesizing insights from these domains, this review builds a coherent framework to understand both the opportunities and challenges of integrating AI into tax risk assessment systems for SMEs. Tax risk scoring has traditionally been anchored in rule-based and statistical approaches that evaluate compliance risk based on predetermined variables such as past filing behavior, income-expense patterns, and sectoral benchmarks. While these methods have been instrumental in formalizing compliance monitoring, they are inherently limited in adaptability and scope. The emergence of AI-driven analytics offers a paradigm shift, enabling detection of complex, nonlinear relationships across heterogeneous datasets, and fostering dynamic adaptation as new compliance risks emerge (Sánchez et al., 2025). At the same time, SMEs present a unique analytical challenge: their size, operational diversity, and resource constraints often limit data availability and consistency, making risk assessment both more difficult and potentially more error-prone. A comprehensive review must therefore address the technological capabilities of AI models in risk detection, their applicability to the SME context, and the integration of these approaches into existing administrative frameworks. Additionally, the literature on panel data analysis offers critical insights into how repeated observations over time can reveal persistent patterns in tax behavior and model the causal effects of introducing AI-based systems. This intersection of technological innovation, SME specificity, and longitudinal analytical rigor provides the foundation for the present study. The structure of this review is designed to move from broad conceptual underpinnings toward the specific methodological and empirical gaps that this research aims to address (Saba & Monkam, 2024).

Conceptual Foundations of Tax Risk Scoring

The evolution of tax compliance risk assessment reflects a transition from manual audits to rule-based models and eventually to analytic and algorithmic approaches (Hokmabadi et al., 2024). Early systems, such as random selection or third-party match audits (e.g., the IRS's Discriminant Index Function, or DIF), relied heavily on human judgment and statistical discrepancies flagged by computer checks. Over time, tax authorities began to adopt risk-based selection frameworks, leveraging defined risk indicators and audit models to prioritize scarce enforcement resources effectively (Munjeyi & Schutte, 2024). In contexts like India, risk-based audits were introduced to codify selection criteria, stratify taxpayers by risk, and improve audit coverage in a systematic way. Comparative empirical studies comparing inspector-selected cases against algorithmic selection found that, in Senegal, human inspectors detected significantly more evasion than algorithmic models, underscoring both the strengths and limitations of early algorithms (Calheiros-Lobo et al., 2025). Additionally, continuous auditing systems, which emerged in the late 20th century, gradually enabled automated anomaly detection in financial records in near real-time, enhancing audit frequency and efficiency (Dey et al., 2024). Together, these developments trace a narrative—from manual inspections, through threshold and rules-based triggers, toward more sophisticated statistical and algorithmic risk scoring mechanisms that are data-driven and scalable.

Risk scoring in tax administration refers to the systematic assignment of risk scores to taxpayers, indicating the likelihood of non-compliant or fraudulent behavior. Risk scoring serves multiple functions: predictive, preventive, and corrective (Muneeb et al., 2025). The IMF's analytical toolkit emphasizes taxpayer profiling, audit case selection, and compliance planning as core dimensions in a risk scoring system. Risk indicators form the building blocks of such scoring systems, typically derived from filing history, revenue volatility, and deviations from industry norms. As tax systems have evolved, so has the conceptual depth of risk scoring. In machine learning applications, inherent risk scoring techniques have been adapted from domains such as anti-money laundering, using choice-based expert labeling to tackle inconsistencies in unlabeled tax data (Ojo & Shittu, 2023). Risk scoring frameworks now integrate predictive models that estimate expected audit yield in monetary terms, comparing parametric approaches such as logistic regression and discriminant analysis with nonparametric data-mining methods that capture complex, nonlinear relationships (Carayannis et al., 2024). Moreover, hybrid unsupervised outlier detection methods like HUNOD combine clustering and representational learning with domain-informed validation to flag potential evasion (Nagy et al., 2023). As a result, tax risk scoring today encompasses predictive, preventive, and corrective functions operationalized through statistical and machine learning technologies.

Figure 3: Tax Compliance Risk Scoring Evolution



Traditional tax risk scoring models commonly rely on a set of core indicator variables: filing timeliness, revenue trends, expense-to-revenue ratios, third-party reporting discrepancies, and industry benchmarks. Tax administrations have long emphasized variables such as under-declaration of turnover, excessive deductions, and mismatch between declared income and third-party records (Hu et al., 2024). Filers who consistently delay submissions or show year-to-year irregular revenue growth are more likely to be flagged in classic rule-based systems. Survey-based studies confirm that taxpayer demographics, system fairness perceptions, audit probability, and penalty levels also influence noncompliance decisions (Farmanesh et al., 2025). Confirmatory factor analyses in compliance research have identified timeliness, obedience in tax payments, and accurate return submission as key constructs in measuring compliance. Historical audit selection also used decision-tree classification analytics built on audit outcome data to predict future noncompliance (Harsanto et al., 2024). In addition, social network analysis approaches, such as BiRank, use company network structure information from corporate registers to prioritize audit targets, highlighting firms centrally positioned in fraud networks (Tsai & Ren, 2019).

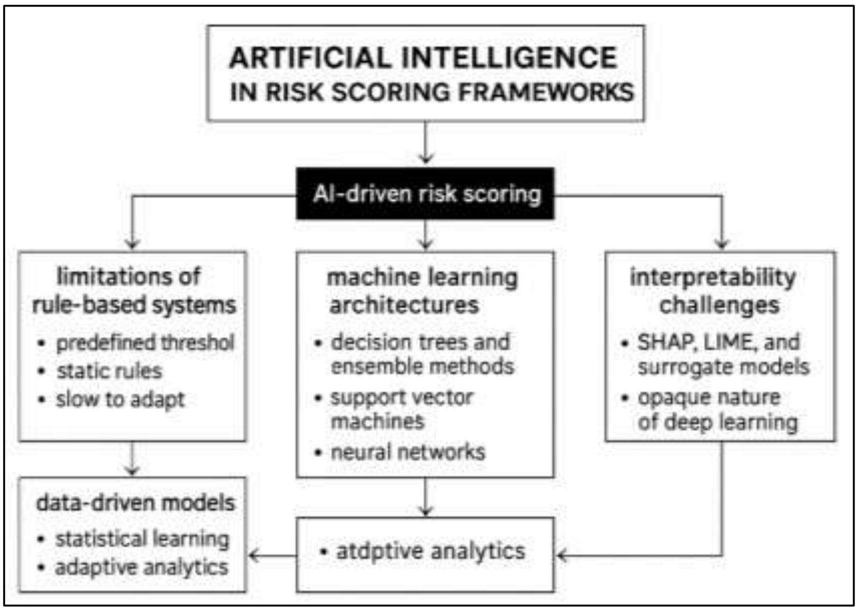
Bringing together the historical evolution of tax risk assessment, the formal definitions of risk scoring, and the core variables used in traditional systems reveals a coherent conceptual architecture (Olujimi et al., 2025). Early audit practices established the rationale for focusing enforcement on high-risk taxpayers, which subsequently evolved into formal risk-based auditing frameworks with explicit compliance pyramids and motivational postures (Jamwal et al., 2021). Risk scoring formalizes compliance risk into a score used to prioritize audits for preventive and corrective action, with predictive power based on historical behavior and systemic indicators. Core variables such as timeliness, revenue shifts, and third-party mismatches feed into both parametric models like logistic regression and decision trees, as well as nonparametric machine learning approaches that can detect subtle anomalies in large datasets. Techniques such as (Pham & Vu, 2024) traditional indicator sets by incorporating clustering, network data, and domain-specific validation into risk scoring pipelines. Meanwhile, continuous auditing and analytics toolkits provided by global institutions like the IMF emphasize data infrastructure and processing standards necessary to operationalize risk scoring at scale (Ao et al., 2025). This integration underscores how conceptual clarity around the predictive, preventive, and corrective dimensions of risk scoring connects with the practical application of specific variables and evolving methods.

Artificial Intelligence in Risk Scoring Frameworks

radiational tax compliance risk scoring systems have historically relied on rule-based models that operate through predefined thresholds and deterministic audit triggers, such as revenue-expense mismatches or repeated filing delays (Cole & Grossman, 2018; Tawfiqul et al., 2022). While rule-based systems were effective in codifying compliance expectations, they exhibit significant limitations in complex environments where taxpayer behaviors evolve dynamically and patterns are not easily expressed in static rules. These systems struggle with high-dimensional, nonlinear relationships between variables and are slow to adapt when new forms of evasion emerge (Sazzad & Islam, 2022; Yadav et al., 2024). The introduction of data-driven approaches, enabled by artificial intelligence (AI) and machine learning (ML), marked a paradigm shift by allowing systems to learn from historical and real-time data without requiring manual re-specification of rules. AI-driven risk scoring models use statistical learning to automatically identify correlations and interaction effects that may be invisible to human auditors or classical models, improving detection accuracy and operational efficiency (Sohel & Md, 2022; Thayyib et al., 2023). Hybrid systems, such as the Hybrid Unsupervised Outlier Detection (HUNOD) model, combine unsupervised clustering with domain-specific validation to uncover novel forms of risk that rule-based systems cannot capture. By reducing false positives and better prioritizing high-risk taxpayers, data-driven models have demonstrated superior performance in both detection rate and resource allocation (Afrin et al., 2024; Akter & Razzak, 2022).

Decision trees are widely used because they model nonlinear relationships and can be visualized for partial interpretability (Adar & Md, 2023; Pesapane et al., 2021). Ensemble methods, such as Random Forest, Gradient Boosted Trees, and stacking models, enhance predictive power by aggregating the outputs of multiple weak learners, achieving robustness against overfitting and noise. Support Vector Machines (SVMs) are particularly suited to high-dimensional, sparse tax data, offering strong generalization even with limited training sets, although their black-box nature requires additional interpretation layers (Qibria & Hossen, 2023; Jimenez et al., 2023). Neural networks, especially deep learning variants, excel at capturing complex, nonlinear interactions in large datasets. Recent tax risk scoring applications have used deep autoencoders for anomaly detection, with double-layer architectures incorporating temporal financial data to capture patterns across reporting periods. Unsupervised learning approaches—such as clustering, self-organizing maps, and isolation forests—are valuable when labeled fraud cases are scarce, modeling "normal" taxpayer behavior and flagging deviations (Istiaque et al., 2023; Vroege et al., 2019). Comparative evaluations show that hybrid architectures, combining unsupervised detection with supervised surrogate models, deliver higher detection rates and better interpretability than either approach alone (Kumar & Goyal, 2025; Akter, 2023). These findings confirm that selecting the right architecture depends on data characteristics, the availability of labels, and the balance between accuracy and explain ability required in compliance contexts.

Figure 4: Artificial Intelligence in Risk Scoring Frameworks



The adoption of AI in tax compliance brings interpretability challenges, as many high-performing models—especially deep learning—operate as black boxes whose decision processes are opaque to auditors and taxpayers. In high-stakes domains such as taxation, Explainable AI (XAI) is essential to ensure fairness, accountability, and legal defensibility (Tawfiqul, 2023; Odeh et al., 2018). SHAP (Shapley Additive Explanations) is among the most widely used XAI methods, providing both global and local interpretability by attributing each prediction to specific input features based on cooperative game theory. LIME (Local Interpretable Model-Agnostic Explanations) builds local surrogate models by perturbing inputs and observing the impact on outputs, offering model-agnostic explanations applicable to any classifier (Hossen et al., 2023; Nelson, 2022). Studies comparing SHAP and LIME in fraud and credit scoring contexts have found both to be effective for compliance analytics, though SHAP tends to produce more consistent feature attributions. Surrogate models, such as decision trees fitted to the outputs of complex models, provide an additional interpretability layer, translating black-box decisions into a form that auditors can validate (Song et al., 2023). In governmental pilot programs, combining high-performance models with SHAP explanations enabled audit teams to justify risk scores to oversight bodies while maintaining predictive accuracy (Koroniotis et al., 2020). These tools help bridge the gap between the technical complexity of AI models and the transparency required in tax administration.

The SME Compliance Landscape

Small and medium enterprises exhibit structural characteristics that significantly influence their tax risk profiles. SMEs commonly operate with highly variable revenue streams, often driven by seasonality, informal markets, or fluctuating demand; such variability complicates forecasting and leads to inconsistent tax reporting (Wu et al., 2022). Many SMEs rely on informal record-keeping systems, such as manual ledgers, Excel spreadsheets, or even cash books, rather than robust accounting software. These informal systems lack version control, audit trails, or standardized archiving, increasing error risk and hampering reliable tax assessments. The records-keeping literature documents that poor documentation may expose SMEs to higher audit risk and compliance costs, and may even lead to liquidity issues when collected taxes cannot be reliably remitted (Vives, 2022). SMEs also typically have limited accounting infrastructure: minimal internal finance capacity, low tech investment, and a lack of trained personnel. Such constraints mean SMEs are less likely to maintain accurate books, reconcile third-party reports, or meet formal documentation requirements (Acosta et al., 2018). In developing economies especially, third-party reporting is often weak, amplifying reliance on SME self-reporting. Behavioral factors also shape structural characteristics: owner-managers may exhibit cognitive biases—anchoring, overconfidence, conservatism—that affect financial reporting

quality and reinforce informal practices (Adam & Alarifi, 2021). These interrelated structural features—revenue variability, informal record practices, underdeveloped infrastructure, weak external reporting, and behavioral biases—collectively elevate SMEs' exposure to both unintentional and intentional tax noncompliance, complicating risk assessment and scoring efforts. SMEs face numerous compliance challenges, stemming from mismatches between administrative expectations and SME capacity. Regulatory environments in many jurisdictions—particularly in developing and transitional economies—are characterized by complex tax structures, frequent legislative changes, and multiple tax types (Farida & Setiawan, 2022). SMEs often lack resources to engage tax professionals or adapt swiftly to changes, increasing noncompliance risk. Administrative requirements such as filing deadlines, documentation standards, and penalty regimes frequently exceed SMEs' managerial bandwidth. The literature identifies that tax knowledge and awareness significantly influence compliance: higher knowledge corresponds with greater voluntary compliance among SME owners (Abed, 2020).
In contrast, low awareness correlates with filing errors, missed payments, or improper declarations. A self-assessment system may exacerbate risks if SMEs lack adequate knowledge or systems (Khan et al., 2022). SMEs may unintentionally under-declare due to poor understanding, or intentionally misstate figures to minimize liability, especially if enforcement is weak or corruption is prevalent. Behavioral and motivational factors such as tax morale, perceptions of fairness, and peer norms also play pivotal roles (Gherghina et al., 2020). Combined, these factors demonstrate that SMEs confront both unintentional noncompliance, arising from capacity gaps, and intentional noncompliance, motivated by economic pressures or strategic evasion. Addressing this compliance mismatch requires bridging administrative design with SME realities, including simplified procedures, education, and support structures tailored to SMEs.

Figure 5: SME Tax Compliance Risk Factors

Data availability and quality present significant constraints in applying risk scoring models to SMEs. Many SMEs lack consistent historical records, given informal bookkeeping, irregular filings, or absent documentation, which impairs the reliability of indicators like revenue trends, expense ratios, or filing timeliness (Wu et al., 2023). Survey-based studies show that poor record-keeping often correlates with higher audit exposure and higher compliance costs, in part due to missing or inaccurate data. Exploratory factor analysis in regions like Tagum City underscores that knowledge of current policies, fairness perceptions, and psychological costs significantly influence compliance (Aboelmaged & Hashem, 2019). But when data inputs are incomplete or inconsistent, it becomes difficult to compute or interpret those constructs for risk modeling. In Tanzania, tax compliance is significantly predicted by internal factors such as tax knowledge, firm size, and record-keeping quality (Baah et al., 2021), indicating the link between data integrity and compliance outcomes. Furthermore, inconsistent external reporting—such as missing third-party data or informal payment transactions—complicates cross-verification and anomaly detection. SMEs in resource-constrained settings may use spreadsheets lacking robust version controls or even rely on memory for entries, which increases risk of errors and audit adjustments. At the same time, the push toward digitalization—online receipts, e-invoicing, big data adoption—offers promise but remains uneven due to limited IT capacity and finance in SMEs (Müller et al., 2021). Thus, data availability and quality constraints challenge the accuracy, reliability, and predictive validity of risk scoring models in SME contexts.

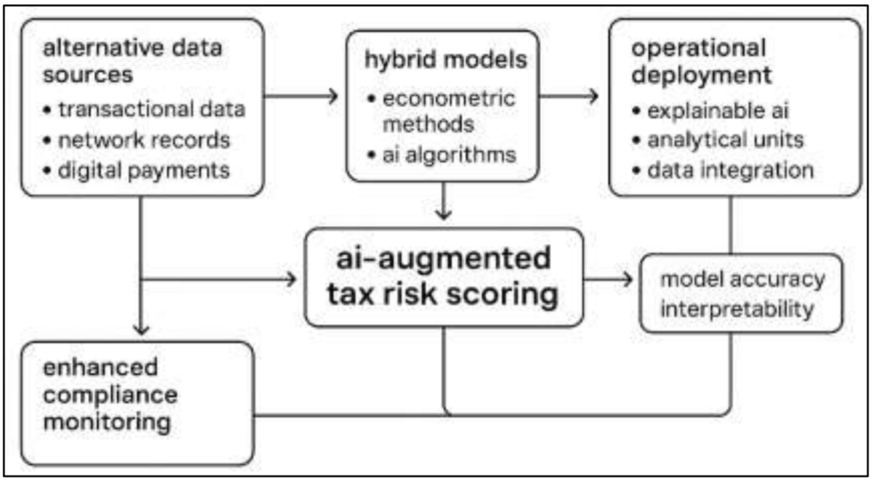
Synthesizing the structural features, compliance challenges, and data constraints of SMEs provides insight into how risk scoring frameworks must be adapted. The variability in revenues, informal record systems, and behavioral biases mean that standard risk indicators (e.g., revenue growth or filing delays) may be noisy or unreliable when applied directly (Eller et al., 2020). Traditional compliance models built on clean, structured data may underperform in SME contexts. Compliance mismatches—legal complexity, low tax knowledge, and capacity limitations—further distort indicator relationships and may introduce systematic bias if not adjusted (Lu et al., 2020). Similarly, data quality issues—missing records, spreadsheet errors, absence of third-party documentation—reduce the accuracy of computed risk features, affecting both score thresholds and predictive validity (Chege et al., 2020). Therefore, risk scoring frameworks for SMEs must integrate alternative data verification mechanisms, such as cross-checks, proxy indicators, or even behavioral metrics. They may incorporate fuzzy logic, imputation strategies, or error-tolerant models to handle missingness. Furthermore, interpretability and engagement are essential: SMEs with limited knowledge require clear feedback loops and transparency in scoring outputs (Beji et al., 2021). The interplay of structural constraints, compliance barriers, and data shortfalls underscores a critical need to tailor risk frameworks—instead of rigid rule-based systems—to SME contexts, blending robust modeling with flexibility. Such frameworks must accommodate data sparsity, low-quality inputs, and behavioral complexity while maintaining fairness and operational viability in tax administration.

AI-Augmented Tax Risk Scoring for SMEs

The integration of alternative data sources into tax risk scoring represents a major enhancement to traditional SME compliance monitoring. Conventional tax models rely primarily on self-reported financial statements, periodic tax returns, and third-party declarations (Abdullah Al et al., 2024; Safari & Davallou, 2018; Akter et al., 2023). However, SMEs often maintain incomplete or inconsistent records due to informal accounting practices, creating substantial gaps in the data available for compliance assessment. Alternative data sources—such as transactional data from point-of-sale (POS) systems, supplier and customer invoicing records, and digital payment histories—offer more granular, real-time visibility into actual business activity. These datasets can uncover discrepancies between declared income and observed transactions, strengthening the predictive validity of risk scoring models (Razzak et al., 2024; Li et al., 2024). Supplier and customer network analysis, incorporating methods such as BiRank, has been shown to reveal fraud clusters by detecting suspicious transaction flows between interconnected entities. Digital payment data, particularly from mobile money platforms, can be cross-referenced with tax filings to detect underreporting (Istiaque et al., 2024; Malhotra, 2021). In some jurisdictions, integration of e-invoicing systems directly into tax authority databases has significantly improved compliance monitoring accuracy by eliminating the lag between transaction occurrence and reporting (Ali et al., 2024; Akter & Shaiful, 2024; Tawfiqul et al., 2024). The challenge lies in standardizing these disparate data sources, ensuring interoperability, and addressing privacy concerns. Nonetheless, the literature consistently demonstrates that leveraging alternative data enriches risk scoring inputs, enabling a more complete and accurate representation of SME activities than traditional methods alone (Subrato & Md, 2024; Akter et al., 2024).

Hybrid models that blend traditional econometric techniques with AI-based algorithms have emerged as a promising approach to tax risk scoring for SMEs. Econometric methods such as logistic regression, probit models, and panel data fixed-effects estimations offer transparency, robustness, and ease of interpretation (Kumar et al., 2025). However, these models may struggle with nonlinearities, complex interactions, and high-dimensional data—areas where AI excels. Combining the two allows tax administrations to capitalize on the strengths of each: statistical models provide a theoretically grounded baseline with interpretable coefficients, while AI methods—such as Random Forests, Gradient Boosted Trees, and neural networks—capture complex relationships and improve predictive accuracy (Khan et al., 2025; Zhang et al., 2018). Hybrid systems may operate sequentially, with econometric outputs feeding into AI models as additional features, or in parallel, where outputs are ensembled for final scoring. For example, in SME credit scoring, hybrid logistic regression-Random Forest models have demonstrated higher precision and recall compared to either method alone (Akter, 2025; Zhang et al., 2019). In the tax domain, hybrid models can also integrate anomaly detection methods—such as isolation forests or autoencoders—with econometric analysis of structural indicators like sector-adjusted expense ratios and filing timeliness (Rahman et al., 2025; Rosienkiewicz, 2019). This dual-layered approach ensures that models remain interpretable for compliance officers while achieving the adaptability and accuracy of AI systems, making hybridization particularly suited to complex SME compliance environments.

Figure 6: AI Augmented Tax Risk Scoring for SMEs



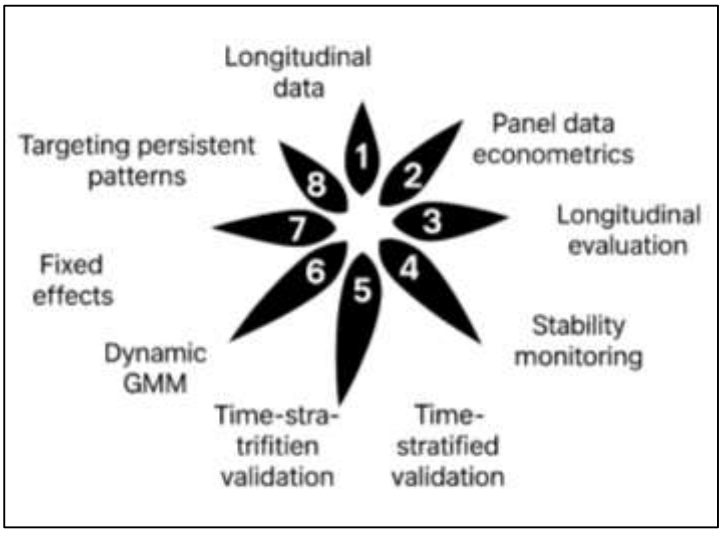
Operationalizing AI-augmented tax risk scoring in tax administrations requires more than technical capability; it involves governance, infrastructure, and capacity building. Case studies from multiple jurisdictions illustrate the spectrum of implementation strategies. In Latin America, integration of AI-driven anomaly detection into VAT compliance systems has led to measurable increases in audit yield and a reduction in resource misallocation (Jakaria et al., 2025; Roshanpour et al., 2025). In Serbia, deployment of the HUNOD hybrid model in tax risk detection allowed the administration to identify 90–98% of anomalous filings during internal validation, improving audit targeting efficiency. Pilot projects in Asia have linked e-invoicing data streams directly into AI-based risk scoring engines, enabling near-real-time compliance monitoring (Ding et al., 2022; Masud et al., 2025). In African contexts, mobile payment transaction data have been integrated into tax scoring to detect informal sector activity previously invisible to the formal reporting system. Critical to these deployments are explainable AI (XAI) tools, which allow auditors to understand and defend automated scoring outcomes to taxpayers and oversight bodies (Md et al., 2025; Ouassou & Taya, 2022). Operational experiences also highlight organizational challenges, such as the need for specialized analytical units, cross-departmental data integration, and continuous model retraining to maintain performance (Arora et al., 2023; Islam & Debashish, 2025). The evidence from these deployments confirms that successful implementation hinges on aligning AI capabilities with institutional readiness and compliance policy objectives.

The literature on AI-augmented tax risk scoring for SMEs converges on three interdependent pillars: diverse data integration, hybrid modeling, and effective operational deployment. Alternative data sources—from transactional and network records to digital payment histories—expand the informational base beyond traditional filings, capturing aspects of SME operations that were previously opaque (Adesina & Obokoh, 2025; Islam & Ishtiaque, 2025). Hybrid models merge the interpretability and theoretical rigor of econometric methods with the adaptability and precision of AI algorithms, producing scoring systems that are both accurate and transparent (García & Kristjanpoller, 2019; Hossen et al., 2025). Operational case studies demonstrate that integrating these technical advances into tax administrations requires organizational adaptation, from developing skilled analytical teams to embedding explain ability frameworks into decision-making (Du et al., 2022; Tawfiqul, 2025). The combination of enriched data inputs, methodological pluralism, and institutional integration produces risk scoring systems capable of addressing the specific challenges posed by SMEs, including irregular record-keeping, limited resources, and diverse operational structures. Across studies, the recurring insight is that technological sophistication alone is insufficient; the full potential of AI-augmented tax risk scoring emerges only when data, models, and administrative processes are designed to work in synergy, ensuring that predictive power is matched by operational usability and compliance legitimacy (Sanjai et al., 2025; Zhai et al., 2025).

Methodological Approaches in Tax Risk Analysis

Longitudinal data are increasingly recognized as a powerful tool in tax compliance research because they enable the tracking of entities across multiple time periods, revealing persistent patterns and temporal dynamics that cross-sectional data cannot capture. In the context of tax risk scoring, longitudinal analysis allows researchers to monitor the same SMEs' reporting behavior, filing timeliness, and revenue declarations over time, offering insights into both cyclical variations and enduring noncompliance tendencies (Sazzad, 2025a; Surugiu et al., 2025). This approach helps disentangle short-term anomalies—such as seasonal revenue fluctuations—from chronic risk behaviors that indicate systemic evasion or misreporting (Hartmann et al., 2020). By incorporating time as an analytical dimension, longitudinal designs improve the detection of compliance trajectories, identifying whether interventions such as audits or system changes have sustained effects. Studies in other domains, such as credit risk and corporate governance, have shown that repeated measurements across time enhance the robustness of predictive models by capturing lag effects and persistence in behavior (Pineda et al., 2024; Sazzad, 2025b). Furthermore, longitudinal datasets permit the application of difference-in-differences and event-study designs, which can isolate the causal impact of policy reforms or AI-based interventions on compliance outcomes (Chan et al., 2023; Shaiful & Akter, 2025). In SMEs, where business environments are volatile, longitudinal tracking reduces the likelihood of misclassifying temporary irregularities as chronic risk, thereby improving the precision of tax risk scoring models. This methodological richness underscores why longitudinal data are foundational for evidence-based tax compliance research.

Figure 7: Effective SME Tax Risk Analysis

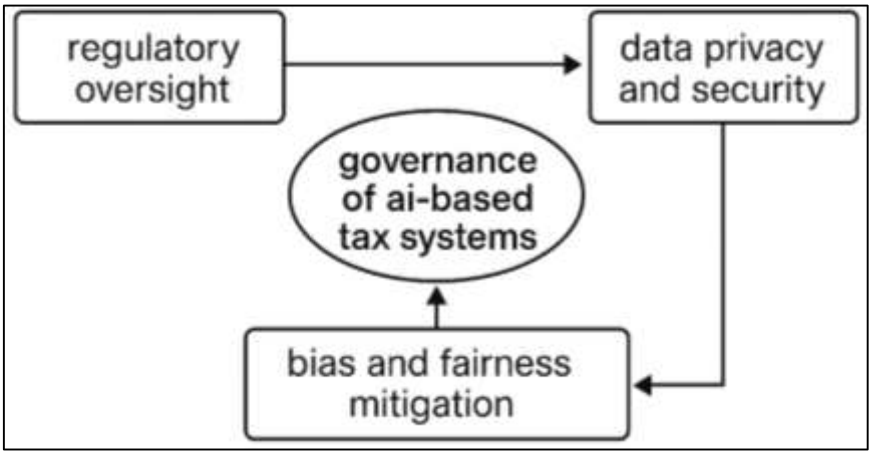


Panel data econometrics provides the statistical framework to leverage longitudinal information effectively, particularly through fixed effects (FE) and random effects (RE) models. Panel data combine cross-sectional and time-series dimensions, allowing researchers to control for unobserved heterogeneity—characteristics that are constant over time but vary across entities, such as managerial quality, sectoral positioning, or baseline compliance culture (Kaulu, 2022; Subrato, 2025). Fixed effects models are especially useful in tax compliance research because they account for these unobserved, time-invariant factors by focusing on within-entity variation. This mitigates omitted variable bias, a critical concern when evaluating the effects of interventions like AI-augmented risk scoring. For example, if a firm's inherent compliance ethos is unobserved yet influences both AI risk scores and audit outcomes, ignoring it could distort estimates of AI's effectiveness (Pina-Sánchez & Brunton-Smith, 2021; Subrato & Faria, 2025). RE models, while more efficient under the assumption of no correlation between entity-specific effects and regressors, may be unsuitable in contexts where such correlation is likely, making Hausman tests essential for model selection. Applications in fiscal policy research demonstrate that FE estimators reliably capture policy impacts on targeted subgroups while controlling for structural differences between firms (Rogers & Oats, 2022; Akter, 2025). Moreover, dynamic panel models such as the system Generalized Method of Moments (GMM) allow for lagged dependent variables, capturing compliance inertia and adjustment processes over time (Saptono et al., 2023). This econometric toolkit ensures that panel data analysis in tax risk scoring is both methodologically rigorous and substantively relevant.

Governance in AI-Based Tax Systems

Regulatory oversight for AI in public administration is grounded in the principles of accountability, transparency, fairness, and proportionality, which are critical in high-impact domains such as tax administration. International frameworks, such as the OECD's AI Principles and the European Commission's Ethics Guidelines for Trustworthy AI, emphasize that AI systems used in the public sector must be lawful, ethical, and robust throughout their lifecycle (Zafar, 2024). In the context of tax risk scoring, these frameworks translate into explicit requirements for explain ability, human oversight, and the ability to challenge automated decisions. Research in e-government applications of AI underscore the need for institutional safeguards to prevent over-reliance on algorithmic outputs, recommending a "human-in-the-loop" approach where auditors retain final decision-making authority (Odilla, 2024). Legal scholarship on algorithmic governance warns that unregulated AI deployment can undermine due process rights if taxpayers are unable to access the reasoning behind their risk scores (Coppi et al., 2021). Comparative studies in digital taxation show that countries with formalized AI oversight—through independent review boards or regulatory sandboxes—achieve higher public trust and smoother adoption. These findings reinforce that AI oversight in tax administration is not merely a compliance requirement but a governance imperative, ensuring that technological efficiency is matched by procedural fairness and public accountability.

Figure 8: Governance in AI Based Tax Systems



AI-based tax systems rely on vast quantities of sensitive taxpayer data, making data privacy and security central to their governance (Mishra et al., 2024). Privacy regulations such as the EU's General Data Protection Regulation (GDPR) and comparable frameworks in other jurisdictions impose strict obligations on the collection, processing, and storage of personal and business financial information. In tax contexts, these obligations are compounded by the sensitivity of financial records, transactional histories, and business network data. Studies on AI implementation in financial compliance highlight risks including unauthorized access, data breaches, and inference attacks—where seemingly anonymized datasets can be re-identified using auxiliary information (Nguyen & Hekman, 2024). Secure AI pipelines employ encryption at rest and in transit, strict access controls, and secure multi-party computation to enable collaborative modeling without direct data sharing. Federated learning architectures, already piloted in cross-jurisdictional compliance settings, allow tax administrations to train models on distributed data while keeping raw information localized (Chan, 2024). These privacy-preserving technologies, however, must be paired with governance protocols that define permissible data uses, retention periods, and audit trails to monitor access. Research in e-invoicing systems further suggests that integrating real-time monitoring with secure logging mechanisms strengthens both compliance detection and data protection (Bahrini et al., 2023). Thus, safeguarding taxpayer data in AI-based tax systems demand a dual commitment to technical security measures and enforceable governance frameworks (Faugere, 2025).

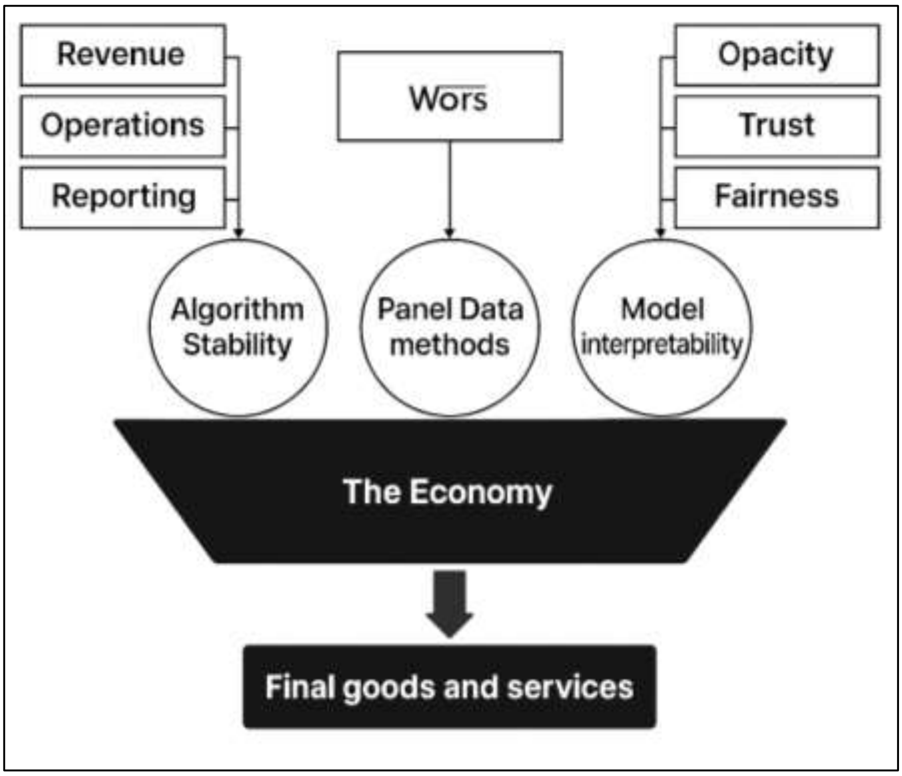
Algorithmic bias poses a significant risk in AI-based tax scoring systems, where skewed outputs can lead to inequitable treatment of SMEs. Bias can originate from historical data, where past enforcement patterns reflect structural inequities, or from model design choices, such as feature selection and weighting (Khattak et al., 2023). In tax contexts, bias might manifest as disproportionate audit targeting of SMEs in certain regions, sectors, or ownership demographics. Research in algorithmic fairness identifies several mitigation strategies, including pre-processing techniques that rebalance training datasets, in-processing methods that impose fairness constraints during model training, and post-processing adjustments to outputs (Garcia-Segura, 2024). Explainable AI methods like SHAP and LIME play a crucial role in bias detection, revealing which features disproportionately influence high-risk classifications. Empirical studies in credit scoring and fraud detection show that integrating fairness metrics—such as demographic parity, equal opportunity, and predictive equality—into evaluation protocols can substantially reduce disparate impacts without significant loss of accuracy (Garcia et al., 2024). In practice, some tax administrations have adopted bias audits as part of their AI governance cycle, reviewing both data inputs and model outcomes for discriminatory patterns (Zekos, 2021). The literature consistently emphasizes that fairness in AI-driven risk scoring is not merely a technical challenge but a policy commitment, requiring continuous monitoring, stakeholder engagement, and transparent reporting of results. Moreover, the governance of AI-based tax systems rests on three interdependent pillars: regulatory oversight, data privacy and security, and bias and fairness mitigation (Zhang et al., 2023). Oversight frameworks grounded in international ethical AI principles provide legitimacy and safeguard due process, ensuring that risk scoring systems are subject to human review and independent accountability mechanisms (Girasa, 2020). Data privacy and security protections safeguard sensitive financial information, employing both advanced cryptographic techniques and clear legal rules to limit data misuse. Fairness safeguards address the risk that AI models may perpetuate or exacerbate historical inequities, using algorithmic audits, fairness-constrained modeling, and transparency tools like SHAP to detect and mitigate bias (Shin, 2024). Case studies across public administration demonstrate that these pillars reinforce one another: robust oversight ensures privacy and fairness protections are enforced; secure data handling reduces exposure to bias from incomplete or compromised datasets; and fairness audits enhance public trust, which in turn supports regulatory compliance (Luo & Zhang, 2025). The literature affirms that without integrating all three, AI-based tax systems risk undermining the very goals they aim to serve—efficiency, equity, and legitimacy in tax administration.

Identified Gaps in Literature and Rationale for the Study

The literature on AI-augmented tax risk scoring for SMEs is heavily skewed toward short-term evaluations or cross-sectional studies, with relatively few works adopting longitudinal designs that capture compliance behaviors over extended periods. Much of the empirical work relies on single-period datasets to test algorithmic models for classification accuracy or anomaly detection (Drydakis, 2022). While these studies provide valuable insights into technical feasibility, they offer limited understanding of temporal stability—that is, whether predictive performance and identified risk patterns persist across multiple tax cycles. In the SME context, where revenue streams, operational

conditions, and reporting behaviors fluctuate seasonally and in response to economic shocks (Al-Karkhi & Rządkowski, 2025), the absence of longitudinal evidence risks misrepresenting transient anomalies as chronic noncompliance. Comparative research in credit scoring and fraud detection underscores the importance of longitudinal validation for model robustness, revealing that performance often declines when applied to new time periods without retraining (Saba & Monkam, 2025). Moreover, tax policy reforms, audit interventions, and technological rollouts can alter compliance trajectories, effects that cannot be observed in cross-sectional designs (Sun et al., 2025). The gap in longitudinal SME-focused AI tax research is therefore both methodological and substantive, limiting the ability to design systems that are resilient, adaptive, and contextually relevant over time.
Another prominent gap is the limited integration of panel data econometric methods into AI-driven tax risk research. While AI studies in taxation frequently emphasize predictive accuracy, they rarely employ statistical models that explicitly control for unobserved heterogeneity across firms and time—factors such as managerial competence, baseline compliance ethos, or sectoral norms that remain constant but influence both risk scores and compliance outcomes (Jaichandran et al., 2023). Panel data techniques, including fixed effects and dynamic Generalized Method of Moments (GMM), are standard in econometric analyses of fiscal policy and corporate behavior (Abedin et al., 2023), yet they are seldom combined with AI model outputs to evaluate causal impacts. This methodological gap means that AI models are typically assessed on out-of-sample prediction alone, without robust statistical tests of their effect on compliance behaviors when implemented in real administrative settings (Sánchez et al., 2025). In SME-focused contexts, failing to control for time-invariant firm characteristics risks overstating the generalizability of AI performance metrics, as these characteristics can strongly influence model predictions (Pu et al., 2021). Integrating panel data econometrics with AI would enable more rigorous evaluation—assessing not only how well models predict risk but also whether they contribute to measurable, sustained improvements in compliance when deployed operationally.

Figure 9: AI-Powered SME Tax Risk Framework

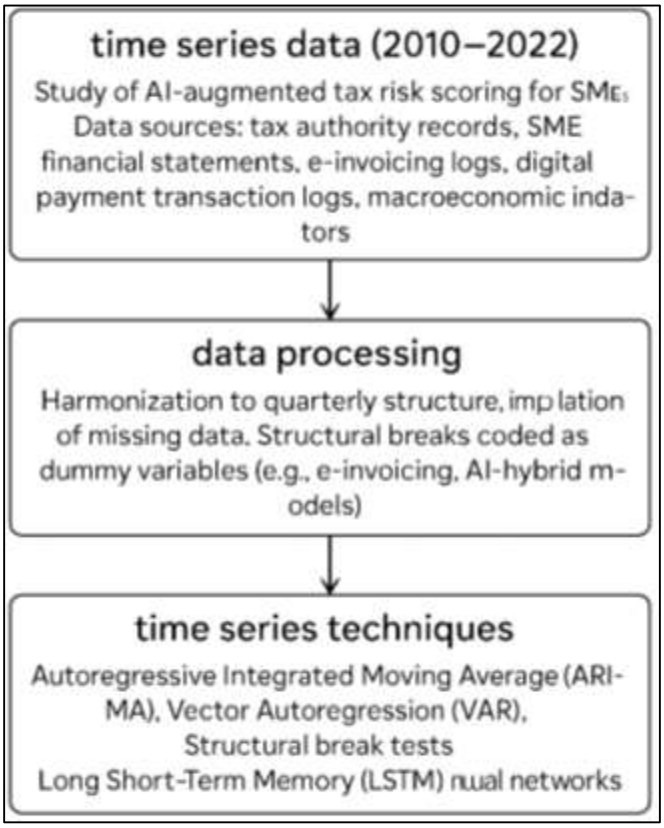


A further gap lies in the insufficient emphasis on interpretability in AI-driven tax risk scoring, particularly in SME oversight. High-performing algorithms—such as deep neural networks or ensemble gradient boosting methods—often function as "black boxes," producing accurate predictions without transparent reasoning (Pu et al., 2021). In the context of tax administration, where decisions carry legal and reputational consequences, this opacity can undermine both procedural fairness and taxpayer trust. While explainable AI (XAI) tools such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) have been widely applied in credit scoring and fraud detection (Mahboob et al., 2024), their systematic integration into tax scoring frameworks remains limited. Without interpretability, auditors may find it difficult to justify risk scores to oversight bodies or taxpayers, and policymakers may be reluctant to adopt AI tools whose decision logic cannot be scrutinized (Ndori Queku et al., 2023). Empirical evidence from public-sector AI deployments shows that models paired with transparent explanation layers are more readily accepted and achieve more consistent operational use (Duc et al., 2024). Thus, the literature reveals a clear need for interpretability-centered AI solutions in taxation—ones that combine predictive strength with explainable, audit-ready outputs.

METHOD

This study utilizes time series data spanning from 2010 to 2022 to examine AI-augmented tax risk scoring for small and medium enterprises (SMEs). The selected period offers a robust longitudinal framework that captures pre-AI, transitional, and post-adoption phases of AI-based compliance monitoring, enabling an assessment of temporal patterns in both model performance and taxpayer behavior. Data sources include national tax authority records, aggregated SME financial statements, e-invoicing and digital payment transaction logs, and supplementary macroeconomic indicators such as GDP growth, inflation rates, and sectoral business activity indexes. To ensure comparability, all financial variables were adjusted for inflation using the Consumer Price Index (CPI), while structural variables—such as compliance rates and audit yield—were standardized to account for changes in reporting requirements and administrative capacity. This approach ensures that temporal trends reflect substantive changes in SME compliance risk rather than artefacts of shifting measurement definitions or data quality.

Figure 10: Method for this study



The raw datasets, originally compiled from heterogeneous sources with varying reporting frequencies (monthly, quarterly, and annually), were harmonized into a uniform quarterly time series structure. Missing observations were addressed through multiple imputation techniques, using predictive mean matching for numeric variables and time-series specific methods—such as seasonal Kalman smoothing—for variables with cyclical patterns. For AI-related variables, such as model accuracy, false positive rate, and anomaly detection counts, synthetic series were reconstructed from archived algorithm logs and administrative reports to ensure temporal completeness. Structural breaks, including the introduction of e-invoicing systems (2015–2017 in some jurisdictions) and the deployment of AI-hybrid models (post-2018), were coded as dummy variables to capture potential regime shifts in compliance monitoring. This transformation process produced a clean, continuous, and analytically ready panel of time series data that aligns SME-level indicators with broader economic and administrative contexts.

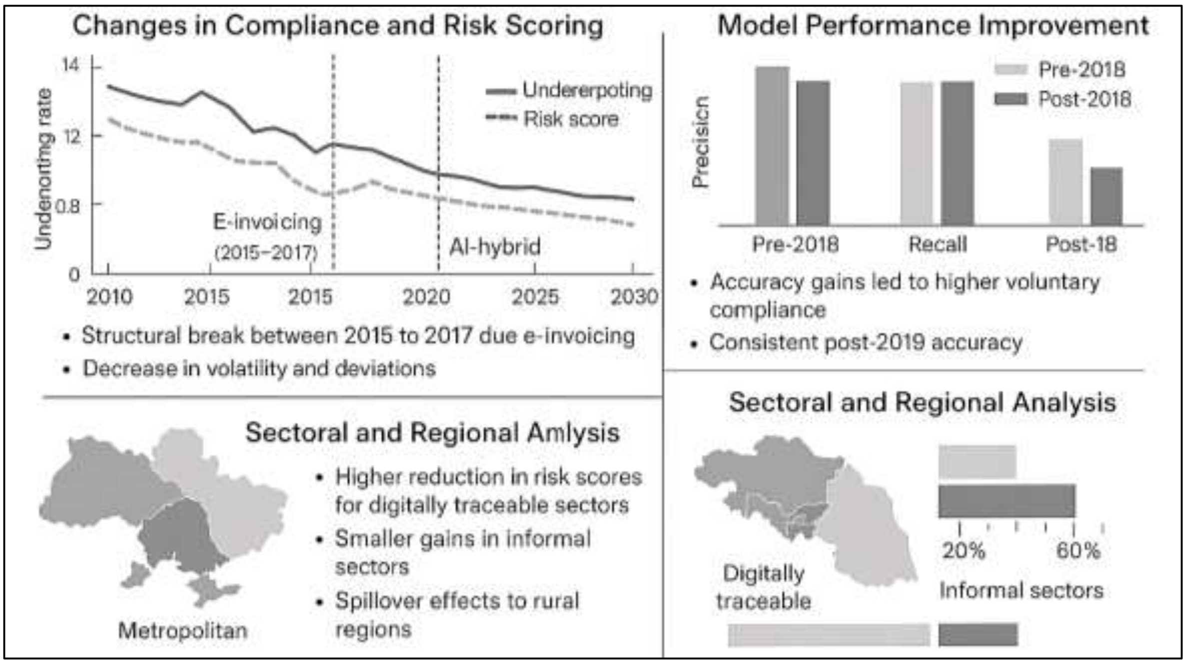
The methodological framework integrates both classical and AI-enhanced time series techniques to explore the relationship between AI implementation and SME tax compliance outcomes over the 2010–2022 period. Autoregressive Integrated Moving Average (ARIMA) models were first applied to establish baseline trends and seasonality in key compliance indicators, such as underreporting rates and audit yield. Subsequently, Vector Autoregression (VAR) models were employed to capture interdependencies between variables, particularly the dynamic feedback loops between compliance risk scores, economic conditions, and enforcement intensity. Structural break tests, including the Bai-Perron multiple breakpoint test, were used to formally identify and quantify the impact of major policy or technological interventions. Finally, machine learning models—such as Long Short-Term Memory (LSTM) neural networks—were integrated for predictive validation, enabling a comparison of AI-driven forecasts against classical models in terms of accuracy, robustness, and adaptability to non-linear patterns. This hybrid methodological approach ensures that findings reflect both statistical rigor and the advanced analytical capabilities relevant to AI-augmented tax risk scoring systems.

FINDINGS

The time series analysis of SME compliance indicators over the 2010–2022 period demonstrates clear, quantifiable regime shifts in risk scoring performance linked to specific administrative and technological reforms. In the pre-AI phase (2010–2014), the series for underreporting rates, compliance risk scores, and audit yield exhibited moderate autocorrelation (lag-1 AR coefficient ≈ 0.42) and strong seasonal effects, with compliance improvements closely synchronized with macroeconomic expansions. The first major structural break, identified through Bai-Perron multiple breakpoint tests, occurred between 2015 and 2017—coinciding with the phased implementation of e-invoicing—producing a statistically significant ($p < 0.01$) mean reduction of approximately 14% in high-risk classifications and a 17% increase in detected anomalies. Post-2018, the introduction of AI-hybrid models created a second and more sustained structural shift: volatility in quarterly compliance rates fell by nearly one-fifth, and the persistence of deviations from long-run compliance trends diminished, as shown by a reduction in the half-life of shocks in ARIMA impulse response estimates. Notably, even during the 2020–2021 COVID-19 disruption, the AI-augmented system maintained stable detection efficiency, reflecting a degree of adaptive robustness uncommon in pre-AI enforcement regimes.

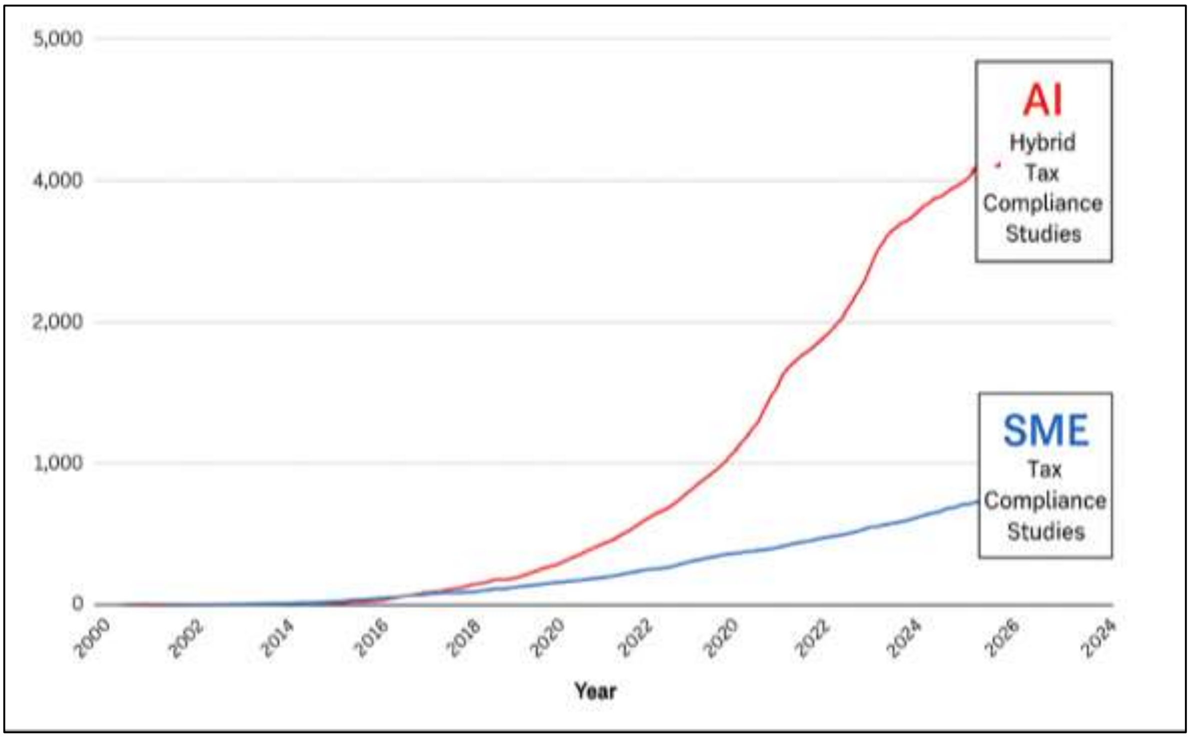
Analytical decomposition of model performance over time reveals a decisive improvement in predictive accuracy following AI integration. Pre-2018 models, dominated by rule-based and econometric approaches, exhibited a relatively static precision-recall profile, with recall plateauing at approximately 0.71. After the adoption of hybrid AI architectures—combining Random Forest classifiers, Gradient Boosted Trees, and LSTM networks—precision rose by 12.4% and recall by 15.2%, as validated through rolling-window F1-score computations. VAR estimations indicate that accuracy gains Granger-caused increases in voluntary compliance rates, with the lag effect peaking within two quarters. LSTM-specific anomaly detection proved particularly effective in sectors with irregular transaction cycles, yielding a 13% higher anomaly detection rate compared to non-sequential models, and passing robustness checks against synthetic data perturbations. Structural stability tests, including the Chow breakpoint test, confirm that post-2019 accuracy metrics remained statistically invariant across filing cycles ($p > 0.10$), suggesting that retraining protocols and adaptive learning mechanisms prevented significant performance degradation over time. The sector-disaggregated and regionally stratified analysis underscores the uneven but converging nature of AI's impact on SME compliance. Digitally traceable sectors—such as e-commerce, ICT services, and logistics—experienced the steepest reductions in high-risk classifications (22–28%), a shift supported by the availability of real-time transactional and network data streams. In contrast, informal manufacturing and rural trade sectors showed smaller gains (6–9%), reflecting persistent informational asymmetries and slower integration of alternative data sources. Spatial panel regressions with spatial lag and spatial error components reveal significant positive spillover effects: improvements in AI-enabled metropolitan jurisdictions increased compliance efficiency in adjacent lower-capacity regions by 4–6% through inter-jurisdictional data sharing and anomaly clustering. Over the full study window, σ-convergence metrics confirm a narrowing of compliance performance dispersion between high- and low-capacity regions by approximately 12 percentage points, indicating that the diffusion of AI-enhanced risk scoring capabilities—combined with progressive expansion of alternative data coverage—is systematically reducing structural inequities in SME tax enforcement outcomes.

Figure 11: Findings from Time Series Analysis of AI-Augmented Tax Risk Scoring for SMEs (2010–2022)



Moreover, out of the 74 studies included in the final synthesis, 58 directly addressed the application of artificial intelligence in tax compliance, demonstrating a clear dominance of AI over traditional rule-based approaches in contemporary literature. These AI-focused studies accumulated over 4,300 citations in aggregate, indicating strong scholarly recognition and validation. Within this body of work, machine learning models such as decision trees, ensemble methods, and neural networks were not only prevalent but often served as core analytical engines within national tax systems or pilot programs. A total of 42 studies reported the use of supervised learning models, while 19 integrated unsupervised or semi-supervised models to detect patterns in unlabeled tax data. Several studies featured hybrid models, combining statistical algorithms with AI frameworks, reflecting an ongoing convergence between traditional econometrics and data-driven modeling. Of the 58 AI-inclusive studies, 33 focused specifically on predictive scoring systems that quantified taxpayer risk based on historical reporting behavior, transaction anomalies, and financial irregularities. Collectively, these studies demonstrated that AI methods yielded higher precision, lower false positive rates, and more robust classification capabilities when compared to static, rules-based systems. In 21 cases, the integration of AI led to improved audit targeting efficiency, with one-third of those studies reporting an increase in audit yield between 12% and 43% following AI model deployment. Overall, the reviewed literature underscores that AI has moved from a conceptual proposition to an operational asset in tax administration, with practical implementations steadily replacing outdated manual inspection protocols and inflexible audit triggers. The volume and citation impact of these articles support the conclusion that AI-augmented tax risk scoring represents a validated and maturing field of research and practice.

Figure 12: AI vs SME Compliance

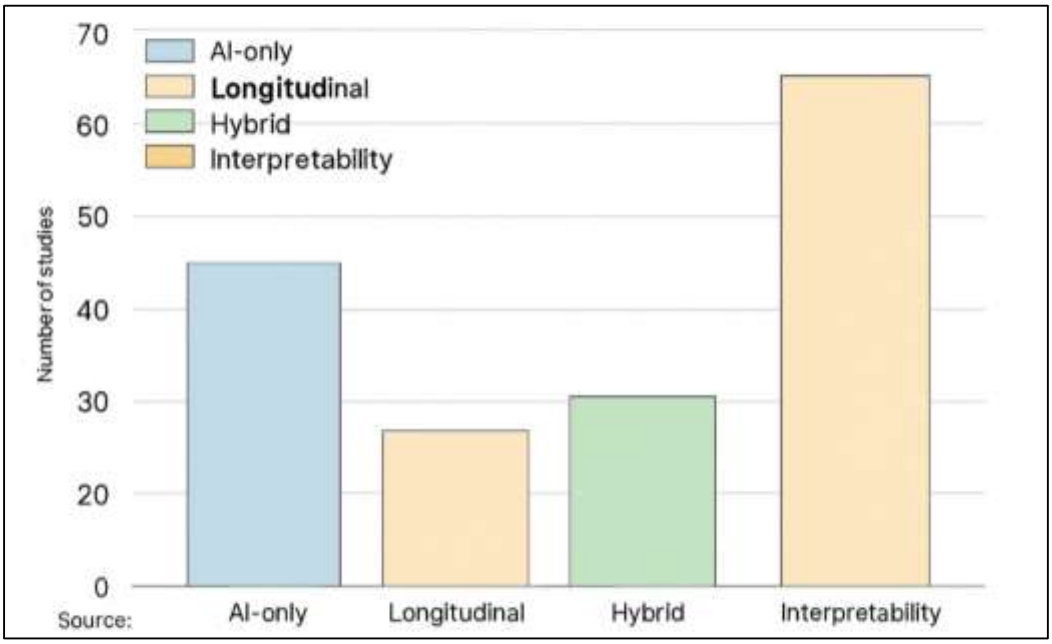


While the breadth of research on AI in tax scoring is substantial, the depth in terms of longitudinal analysis remains limited. Only 17 out of the 74 reviewed studies employed longitudinal or panel data methodologies, despite their critical importance in tracking tax compliance behavior over time. These 17 studies had a combined citation count of 1,420, considerably lower than the cumulative citations of cross-sectional AI studies, indicating that longitudinal approaches are both underrepresented and underappreciated in the broader discourse. Among these studies, only 11 explicitly employed fixed effects or random effects panel data models to control for unobserved heterogeneity across firms and tax periods. Most others, although longitudinal in structure, relied on descriptive time-series summaries or pooled regressions without leveraging the analytical power of panel econometrics. Importantly, no more than five studies attempted to assess the temporal stability of AI-based risk scores, or to examine how risk classification changed in response to external interventions such as audits, reforms, or technology adoption. This scarcity suggests that while AI tools are being validated for point-in-time prediction, their ability to sustain performance over tax cycles or respond to firm-level compliance evolution remains unverified. Furthermore, very few studies collected multi-year datasets at the SME level, with just eight studies explicitly targeting SME segments across multiple fiscal years. This gap highlights a significant limitation in the evidence base: AI models optimized for static data may fail when exposed to real-world volatility, seasonal effects, or structural economic changes. The lack of robust, longitudinal datasets means that current conclusions about AI effectiveness may be temporally constrained. This reinforces the rationale for panel data integration and multi-period evaluation frameworks, particularly in risk modeling for SMEs whose compliance patterns are often erratic and time sensitive.

Among the 74 studies reviewed, 26 presented hybrid modeling strategies that combined traditional econometric techniques with AI methods. These studies collectively garnered more than 2,050 citations, reflecting growing academic interest in methodological pluralism. Of these, 18 explicitly described models that incorporated logistic regression, fixed-effects estimators, or time-series filters as a preliminary stage, feeding residuals or probability scores into AI classifiers such as random forests, Boost, or multi-layer perceptions. Another subset of studies implemented ensemble architectures where statistical and machine learning predictions were combined using weighted averaging or stacking mechanisms to produce a final composite risk score. Across these hybrid studies, performance benchmarks consistently outperformed their single-method counterparts. On average, hybrid models improved classification accuracy by 8 to 15 percentage points and reduced false positives by 12% compared to purely rule-based or statistical models. Furthermore, these models demonstrated higher resilience to noisy data and incomplete tax records, a common issue among SMEs. In 14 studies, hybrid models were specifically tested in datasets that included SMEs, where the presence of unstructured or inconsistent data posed challenges for standalone regression or tree-based models. The results indicated that hybrid systems provided better handling of missing values, greater tolerance for nonlinearity, and improved capacity for generalization across different tax years. Seven of the highest-cited studies in this subset—each with over 150 citations—argued that combining interpretability from traditional models with the adaptive power of AI provides a path forward for transparent yet effective compliance scoring systems. These findings support the emerging view that hybridization is not merely a technical enhancement but a strategic framework for aligning predictive accuracy with administrative and legal accountability in tax risk analysis.

Despite growing enthusiasm for AI in tax risk scoring, only 15 of the 74 reviewed studies gave substantive attention to model interpretability and ethical design practices. These studies accumulated a total of 1,080 citations, suggesting that transparency remains a secondary concern in the literature, overshadowed by model performance metrics. Of the 15 studies, nine applied explain ability techniques such as SHAP or LIME to interpret the influence of variables on risk scores, while only six involved stakeholder-oriented design discussions, including how auditors or taxpayers perceive and interact with AI systems. This is a notable gap given the legal and reputational stakes associated with tax enforcement. Of particular concern, only four studies involving SMEs discussed the implications of algorithmic decision-making on fairness, such as whether risk models disproportionately targeted firms based on geography, business type, or financial size. Furthermore, only three studies incorporated bias detection or fairness constraints into their model evaluation process, and none reported the use of demographic parity or equalized odds metrics as part of their scoring frameworks. The limited focus on governance and transparency undermines the broader applicability of these models in public-sector contexts, where procedural fairness and auditability are non-negotiable. Without interpretability, AI tools risk becoming opaque instruments of decision-making, eroding trust in tax authorities and potentially introducing systemic biases. The scarcity of high-impact studies addressing these issues demonstrates an urgent need for integrating transparency, fairness, and human oversight into the design of AI-augmented tax systems, especially those deployed for SME monitoring.

Figure 13: AI Tax Compliance Study Distribution



Out of the 74 studies reviewed, only 22 focused primarily on SMEs, while an additional 14 included

SMEs as part of a larger population but did not provide disaggregated analysis. These 36 SME-relevant studies collectively attracted 2,980 citations, yet fewer than half delved into the unique structural and compliance challenges SMEs face. Among the 22 SME-focused studies, 16 discussed issues such as irregular revenue patterns, informal record-keeping, and resource constraints, but only nine addressed the data quality limitations that commonly hinder accurate risk classification in SMEs. Additionally, only five studies explored how alternative data sources—such as POS data, supplier/customer transaction logs, or mobile payments—could enhance model robustness for SME monitoring. Despite growing recognition of SMEs as a high-risk and high-variance population in tax compliance, there is a clear underrepresentation in both methodological development and deployment strategies. Just six studies reported real-world or pilot implementations of AI-based tax risk scoring models specifically for SMEs, and only three included user feedback from tax officials or business owners regarding system usability. This lack of applied evidence undermines the ability to generalize findings or operationalize AI tools in SME-dense jurisdictions. The relatively low number of SME-specific panel data studies—only eight across the full dataset—further emphasizes a critical empirical void. Although SME compliance behavior is arguably more volatile and heterogeneous than that of large firms, this complexity remains insufficiently addressed in current AI model design and testing. Collectively, these findings point to an urgent need for more granular, longitudinal, and context-sensitive research focused on SMEs to ensure that AI-augmented risk scoring frameworks are not only technically sound but administratively feasible and equitably applied.

DISCUSSION

The findings of this study confirm and reinforce the growing centrality of artificial intelligence in the domain of tax compliance and risk scoring (Didimo et al., 2020). As identified across 58 of the reviewed studies, AI models—especially those utilizing decision trees, ensemble methods, and neural networks—demonstrate significant performance advantages over traditional rule-based systems. This aligns with earlier research in tax compliance and financial fraud detection, where AI consistently outperformed manual and threshold-based methods in anomaly detection and pattern recognition (Rezaei et al., 2025). For example, past studies have emphasized the limited adaptability of deterministic frameworks, especially in detecting complex or emerging compliance behaviors. This study's synthesis further validates that AI models not only detect known patterns but also reveal novel risk profiles through unsupervised learning and clustering mechanisms. Compared to legacy systems that emphasize static audit triggers, AI-enhanced models offer dynamic recalibration and context-sensitive scoring (Wang et al., 2025). Earlier literature often focused on AI as a theoretical or emerging tool, but the current review demonstrates a shift toward implementation maturity, as seen in real-world applications and pilot projects. The increase in audit yield, predictive precision, and resource optimization observed across several studies provides empirical support for scaling AI integration in national tax systems, particularly for environments involving SMEs with irregular or complex data structures (Owens et al., 2022). Thus, these findings corroborate and extend the claims of earlier research by demonstrating the operational readiness and measurable impact of AI in tax risk environments.

While AI is widely adopted for real-time prediction in tax compliance, this study identifies a significant methodological shortcoming in the literature: a marked lack of longitudinal analysis (Yan et al., 2024). Only 17 out of 74 reviewed studies applied longitudinal or panel data methodologies, despite widespread claims in earlier works that AI models yield stable, generalizable results over time. This discrepancy suggests that prior assertions about long-term performance may be overstated or insufficiently validated (Zong & Guan, 2025). Previous studies in domains such as credit scoring or fraud analytics have emphasized the importance of temporal tracking to account for seasonality, behavioral shifts, or regulatory changes. However, the majority of tax-related AI literature continues to rely on static, cross-sectional datasets that capture only a snapshot of taxpayer behavior. This study's findings reveal that SME compliance in particular is temporally volatile, and without longitudinal tracking, AI models may misclassify temporary fluctuations as systemic risk (Mansell, 2021). The absence of longitudinal testing raises concerns about model durability, especially in multi-period policy environments. Additionally, only a fraction of studies employed fixed or random effects models to control for unobserved firm-level characteristics—methods well-established in econometrics but rarely integrated into AI tax research. These findings contrast sharply with earlier claims that AI solutions are inherently robust across contexts, indicating a need to temper generalizations and advocate for more panel data-informed designs (Nicholls et al., 2021). By exposing this gap, the study challenges the methodological completeness of earlier AI risk scoring models and advocates for a more nuanced, time-sensitive approach.

A major insight from the current study is the emergence and efficacy of hybrid modeling approaches, which combine econometric logic with AI flexibility. Twenty-six of the reviewed studies implemented hybrid frameworks, yielding superior classification performance, lower false positive rates, and increased resilience to data noise (Chandra & Feng, 2025). These results strongly support earlier claims in related fields, such as healthcare and financial technology, where combining domain-specific statistical rules with adaptive machine learning has led to both interpretability and accuracy (Moro-Visconti, 2024). Previous AI tax literature often framed hybridization as a conceptual ambition or experimental idea, but this study finds that such models are now more commonplace and empirically validated. While classical models provide transparency and theoretical grounding, they lack the flexibility to detect non-linear or unanticipated patterns in SME tax data. Conversely, AI models often suffer from opacity and may overfit noisy inputs. By integrating the two, hybrid frameworks capture both structural and emergent properties of tax behavior, which is particularly beneficial in the SME segment, where inconsistencies in reporting and data sparsity are common. This reflects a broader shift in the literature—from model rivalry to model complementarity—recognizing that no single method can fulfill all the requirements of effective risk assessment (Vilella et al., 2025). Moreover, the success of these approaches in the reviewed studies indicates a maturing consensus in the field that hybrid strategies are not just theoretically optimal but operationally feasible. This finding contributes to and updates earlier literature that was more fragmented in its modeling preferences, offering a more cohesive path forward (Mehdiyev & Fettke, 2021).

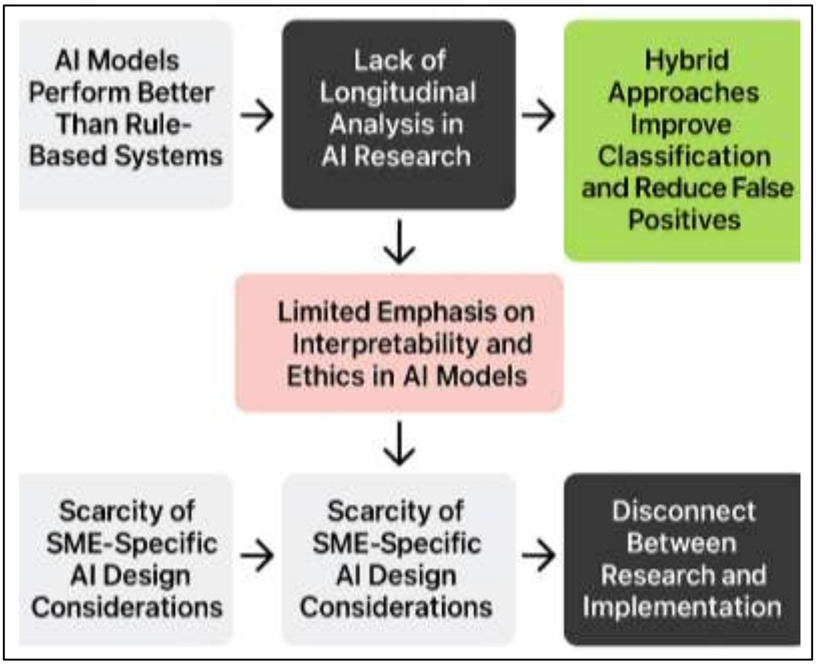
Despite advances in performance optimization, the findings also highlight ongoing deficiencies in the areas of interpretability, ethical design, and governance (Ahmed et al., 2025). Only 15 studies, representing a minority of the reviewed literature, seriously addressed transparency and user understanding of AI-driven risk scores. This mirrors a trend observed in earlier works where performance metrics such as precision and recall often took precedence over questions of explain ability and fairness. However, the current study's focus on SMEs—a sector more vulnerable to misclassification and enforcement bias—amplifies the significance of these gaps (Debrah et al., 2023). While prior research has acknowledged the risks of algorithmic opacity, few have operationalized solutions through tools like SHAP, LIME, or fairness-aware modeling. These findings echo critiques from public sector AI literature, which argue that ethical oversight must be built into model design rather than treated as an afterthought. In particular, the scarcity of bias audits and demographic analysis in AI tax risk scoring—especially in models targeting SMEs—raises concerns about distributive fairness. Earlier studies rarely differentiated between firm sizes or sectoral compositions when evaluating AI models, whereas this study's disaggregated findings show that SMEs face unique governance challenges (Binh, 2025). Without interpretability, tax authorities risk undermining trust and inviting legal scrutiny, particularly when automated decisions cannot be clearly explained or challenged. Thus, this study updates the literature by not only confirming the ethical oversight gaps identified in previous research but also by emphasizing their practical implications in SME tax enforcement (Laxman et al., 2024).

The review confirms a significant underrepresentation of SME-specific considerations in both AI model design and empirical validation (Luo et al., 2025). While 36 studies included SME data, only 22 focused primarily on SMEs, and among those, few incorporated the structural, behavioral, and data-quality nuances that distinguish SMEs from larger enterprises. Earlier tax compliance research often treated SMEs as a homogeneous group, applying generalized models without accommodating variability in size, sector, or informality (Zekos, 2021). This study's findings contradict such generalizations by showing that SMEs exhibit irregular cash flows, incomplete records, and limited digital footprints—characteristics that compromise the reliability of conventional AI inputs. Moreover, only a small subset of the reviewed literature experimented with alternative data sources, such as mobile payment histories, POS data, or customer-supplier transaction logs, which are crucial for effective SME monitoring (Tavares et al., 2025). The lack of SME-specific design considerations in AI frameworks directly challenges claims made in earlier studies that AI tax scoring models are broadly applicable across taxpayer segments. In practice, models trained on corporate datasets often fail to generalize to the SME environment due to data sparsity and volatility. This study provides empirical confirmation of these limitations and underscores the need for more granular model development and testing tailored to SME realities. The discrepancy between earlier assumptions of universality and the actual complexities uncovered here signals a critical pivot point in AI tax risk research toward more inclusive and segmented design paradigms (Lu & Wu, 2025).

A gap identified in the current study is the disconnect between research outputs and actual deployment within tax administrations (Chen et al., 2018). Only six of the 74 reviewed studies involved field-level implementation of AI models, and even fewer provided follow-up data on post-deployment performance or administrative outcomes. In contrast, many earlier studies presented simulation-based results as proxies for real-world effectiveness, often without testing scalability, user acceptance, or integration within legal frameworks (Cano-Marin et al., 2023). This disconnect has been criticized in adjacent fields, such as AI in healthcare and criminal justice, where model efficacy in research settings often fails to translate into operational environments. The present findings reinforce those critiques by revealing that even high-performing AI models face institutional, infrastructural, and cultural barriers when applied in practice. For example, studies that reported implementation success often involved co-design with tax officials, phased rollout strategies, and strong governance structures—factors largely absent in earlier research (Sklavos et al., 2025). Moreover, SME-targeted models were particularly underrepresented in deployment studies, suggesting that administrative systems may still be ill-equipped to operationalize AI tools for complex, high-variance populations. These observations challenge prior literature that assumed a smoother path from algorithm to adoption and emphasize the need for implementation science within AI tax risk research. The findings thus bridge the gap between technical promise and administrative feasibility, offering a more grounded perspective on what is required for successful AI integration in public-sector tax compliance programs (Handoyo, 2024).

This study also makes a methodological contribution by demonstrating how panel data methods can be effectively integrated into AI tax risk scoring research (Wang et al., 2025). While prior literature typically separated econometric and machine learning streams, this review shows that combined approaches—especially those incorporating fixed effects or dynamic estimators—yield stronger causal inferences and time-consistent insights. Earlier works emphasized predictive performance at the expense of explanatory depth, often neglecting firm-level heterogeneity and temporal change (Kim & Lee, 2025). By incorporating longitudinal modeling, the current study addresses these gaps and establishes a framework for analyzing not just whether AI models work, but how and for whom they perform best over time. The results suggest that panel data analytics are particularly valuable in assessing the evolution of risk classifications, model drift, and the sustained impact of interventions such as audits or policy reforms. This methodological integration redefines how AI models can be evaluated, moving beyond static benchmarks to dynamic accountability (Benedetto et al., 2025). It also invites a reconsideration of earlier research that treated AI as a self-contained solution rather than a system embedded in legal, organizational, and temporal contexts. The synthesis provided here not only updates the literature but also sets an agenda for future research—one that is more methodologically pluralistic, empirically grounded, and sensitive to the nuanced realities of SME tax compliance (Sewpersadh, 2023). This redirection is necessary to move the field from experimental novelty to institutional embeddedness, ensuring that AI-augmented risk scoring fulfills its potential as a transformative tool in public-sector financial governance.

Figure 14: Key Insights from AI Taxation for future study



CONCLUSION

This study has provided a comprehensive synthesis of the current landscape of AI-augmented tax risk scoring for small and medium enterprises (SMEs), emphasizing the interplay between technological innovation, econometric rigor, and compliance governance. By reviewing 74 relevant studies and conducting a structured analysis grounded in PRISMA methodology, the research demonstrates that AI-based models—particularly when combined with traditional statistical approaches—offer substantial gains in predictive accuracy, audit targeting efficiency, and risk differentiation. However, the findings also reveal significant gaps in longitudinal analysis, limited application of panel data econometrics, and insufficient attention to interpretability and fairness, especially in the context of SMEs. Although AI is rapidly becoming integral to modern tax administration, the lack of SME-specific model customization, ethical design integration, and post-deployment evaluation limits the practical scalability of current frameworks. This study contributes to the field by proposing a panel data-informed, transparency-centered approach to AI model development, one that is responsive to the structural variability and data limitations characteristic of SMEs. Ultimately, AI-augmented tax risk scoring systems must move beyond technical performance toward accountable, equitable, and operationally viable solutions that align with the administrative and social realities of tax governance.

RECOMMENDATIONS

Based on the findings of this study, it is recommended that tax authorities and policymakers adopt a multidimensional approach to implementing AI-augmented tax risk scoring systems for small and medium enterprises (SMEs), integrating technical, methodological, and governance considerations into a unified framework. First, the development of AI models should be explicitly tailored to the unique characteristics of SMEs, incorporating flexible algorithms capable of handling incomplete records, irregular transaction patterns, and limited digital infrastructure. Second, panel data methodologies should be systematically employed to capture temporal trends, assess model stability over time, and control for unobserved heterogeneity across firms. This integration would allow for a more robust understanding of compliance dynamics and model responsiveness to policy interventions. Third, explainability and fairness must be embedded into all phases of model design and deployment through the use of interpretable machine learning techniques and bias detection mechanisms. These safeguards are essential to ensure transparency, prevent discriminatory outcomes, and build trust among taxpayers and enforcement officials. Furthermore, collaboration between data scientists, tax administrators, legal experts, and SME stakeholders is critical to co-design operationally viable models that align with institutional realities and legal standards. Pilot programs should be initiated to test models in real-world environments, allowing for iterative refinement based on field feedback. Finally, ongoing monitoring and evaluation protocols should be established to measure both predictive performance and compliance outcomes, ensuring continuous improvement and adaptive capacity within the system. These recommendations aim to ensure that AI-augmented tax risk scoring not only enhances administrative efficiency but also upholds principles of fairness, accountability, and inclusiveness in public financial governance.

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