Beyond Automation in Tax Compliance Through Artificial Intelligence and Professional Judgment

Jiaying Chen[1]* and Huijie Fan[2]

[1]Cornell University, Ithaca, USA

[2]Hunan Agricultural University, Changsha, China

*Corresponding Author: Jiaying Chen. jc2744@cornell.edu

Abstract

Tax compliance has evolved significantly with the integration of artificial intelligence (AI) technologies, transforming traditional manual processes into sophisticated automated systems. This review examines the intersection of AI automation and professional judgment in tax compliance, exploring how these elements complement rather than replace each other. The paper analyzes various AI applications including machine learning (ML), natural language processing (NLP), robotic process automation (RPA), and blockchain technology in tax administration and compliance functions. While AI demonstrates remarkable capabilities in processing vast amounts of tax data, identifying patterns, and automating routine tasks, professional judgment remains indispensable for interpreting complex tax regulations, assessing unique circumstances, and making ethical decisions. This review synthesizes recent research on intelligent automation systems, predictive analytics for tax risk assessment, and cognitive technologies that support tax professionals. The analysis reveals that optimal tax compliance outcomes emerge from hybrid approaches that leverage AI efficiency alongside human expertise. Key challenges include algorithmic transparency, regulatory adaptation, data quality, and the preservation of professional skepticism in automated environments. The findings suggest that successful tax compliance in the digital era requires reimagining professional roles, developing new competencies, and establishing governance frameworks that ensure responsible AI deployment. This comprehensive examination provides insights into the future of tax compliance where technology augments rather than diminishes the critical role of professional judgment.

Keywords

Artificial intelligence, tax compliance, professional judgment, machine learning, automation, tax administration, human-AI collaboration, robotic process automation, predictive analytics, digital taxation

Introduction

The landscape of tax compliance has undergone profound transformation driven by the rapid advancement and adoption of artificial intelligence (AI) technologies across governmental tax administrations and corporate tax departments. Traditional tax compliance processes, characterized by manual data entry, rule-based calculations, and extensive human review, are increasingly supplemented or replaced by intelligent systems capable of processing enormous volumes of transactions, identifying anomalies, and predicting compliance risks with unprecedented speed and accuracy [1]. This technological revolution reflects broader trends in digital transformation, where organizations leverage computational capabilities to enhance efficiency, reduce errors, and manage the growing complexity of tax obligations in an interconnected global economy. However, the integration of AI into tax compliance raises

fundamental questions about the evolving role of tax professionals and the extent to which automated systems can or should replace human judgment in fiscal matters.

AI encompasses a diverse array of technologies including machine learning (ML), natural language processing (NLP), robotic process automation (RPA), and expert systems, each offering distinct capabilities for tax compliance applications [2]. ML algorithms can analyze historical tax data to identify patterns indicative of errors, fraud, or optimization opportunities, enabling more targeted audits and proactive compliance management. NLP facilitates the interpretation of complex tax regulations, extracting relevant provisions from legislative texts and judicial decisions to support compliance determinations [3]. RPA automates repetitive tasks such as data extraction, form completion, and reconciliation processes, freeing human resources for higher-value analytical work. Blockchain technology promises enhanced transparency and traceability in tax reporting, potentially revolutionizing value-added tax systems and cross-border transactions [4]. The convergence of these technologies creates powerful platforms that fundamentally reshape how tax compliance is conceived, executed, and monitored.

Despite the impressive capabilities of AI systems, tax compliance remains inherently complex, requiring nuanced interpretation of ambiguous regulations, assessment of unique factual circumstances, and consideration of broader policy objectives that extend beyond mechanical rule application [5]. Tax laws frequently contain subjective standards such as reasonableness, substantiality, and primary purpose, which demand professional judgment informed by experience, ethical principles, and understanding of legislative intent. Moreover, tax planning and compliance often involve weighing competing considerations, anticipating regulatory responses, and making decisions under uncertainty where algorithmic approaches may prove insufficient [6]. The relationship between transactions and tax consequences is rarely straightforward, with form versus substance distinctions, economic substance doctrines, and anti-avoidance provisions requiring sophisticated analysis that challenges purely computational approaches.

The integration of AI into tax compliance therefore presents not a simple automation story but rather a complex narrative of human-machine collaboration where technology and professional judgment must work in concert [7]. This relationship parallels developments in other professional domains such as medicine, law, and auditing, where AI serves as a powerful tool that augments rather than replaces human expertise. Tax professionals increasingly function as supervisors and interpreters of AI outputs, validating algorithmic conclusions, investigating flagged anomalies, and exercising judgment in areas where AI capabilities remain limited. This evolution requires new competencies combining traditional tax knowledge with data literacy, technological fluency, and critical thinking skills necessary to effectively leverage AI tools while maintaining appropriate skepticism and professional standards [8].

Tax authorities worldwide have embraced AI technologies to enhance compliance monitoring, risk assessment, and enforcement capabilities, fundamentally altering the relationship between taxpayers and revenue agencies [9]. Predictive analytics enable tax administrations to identify high-risk taxpayers for audit selection, improving resource allocation and increasing detection rates for non-compliance. Real-time reporting systems supported by AI processing provide governments with unprecedented visibility into economic transactions, enabling more responsive policy adjustments and reducing opportunities for evasion.

However, these developments also raise concerns about privacy, due process, and the potential for algorithmic bias in enforcement decisions [10]. The opacity of many AI systems creates

challenges for taxpayers seeking to understand why they were selected for audit or how their risk profiles were calculated, potentially undermining principles of transparency and fairness in tax administration.

The academic and professional literature on AI in tax compliance has expanded rapidly, reflecting both enthusiasm for technological possibilities and concern about implementation challenges. Researchers have documented significant efficiency gains, accuracy improvements, and cost reductions associated with AI adoption in tax functions [11]. Studies have also identified risks including over-reliance on automation, degradation of professional skills, and the potential for AI systems to perpetuate or amplify existing biases in tax administration. The ethical dimensions of algorithmic tax compliance remain underexplored, with questions about accountability, transparency, and the appropriate balance between efficiency and fairness requiring deeper examination. Understanding how to optimally integrate AI capabilities with professional judgment represents a critical challenge for tax policy, practice, and education.

This review paper provides a comprehensive analysis of AI applications in tax compliance and the enduring importance of professional judgment in an increasingly automated environment. The paper examines various AI technologies deployed in tax contexts, analyzes their capabilities and limitations, and explores how human expertise complements computational approaches. By synthesizing recent research and identifying key trends, this review aims to inform practitioners, policymakers, and educators about the evolving nature of tax compliance work and the competencies required for effective practice in the digital age. The following sections present a detailed literature review, discuss specific AI technologies and their applications, examine the critical role of professional judgment and human-AI collaboration, and conclude with recommendations for research and practice that can advance responsible AI integration in tax compliance.

2. Literature Review

The academic literature examining AI applications in tax compliance has proliferated substantially over the past five years, reflecting growing interest in understanding how intelligent technologies transform tax administration and professional practice. Early research in this domain focused primarily on descriptive accounts of specific technologies and their potential applications, but recent scholarship has evolved toward more critical analyses examining implementation challenges, effectiveness assessments, and broader implications for tax systems and professional roles [12]. Researchers have documented significant variations in AI adoption across jurisdictions, with some tax authorities implementing comprehensive digital transformation strategies while others maintain largely traditional approaches. This heterogeneity creates opportunities for comparative studies that illuminate factors influencing successful technology integration and identify best practices applicable across different contexts [13].

Several comprehensive studies have examined ML applications for tax risk assessment and audit selection, demonstrating substantial improvements over conventional statistical methods [14]. These investigations typically employ supervised learning algorithms trained on historical audit data, using features derived from tax returns, financial statements, and third-party information to predict non-compliance likelihood. Classification models such as random forests, gradient boosting machines, and neural networks have shown strong performance in distinguishing compliant from non-compliant taxpayers, with reported accuracy rates often exceeding those achieved through traditional profiling approaches [15]. Research indicates that

ensemble methods combining multiple algorithms generally outperform individual models by leveraging diverse predictive signals and reducing overfitting risks [16]. Feature importance analyses reveal that specific attributes such as discrepancies between reported income and lifestyle indicators, unusual deduction patterns, and historical compliance behavior strongly influence risk predictions.

The application of NLP to tax compliance has garnered increasing attention as researchers explore methods for automating the interpretation of tax regulations and extracting relevant information from unstructured documents [17]. Studies demonstrate that modern NLP techniques including transformer-based language models can effectively parse legislative texts, identify applicable provisions for specific transactions, and even generate preliminary compliance assessments. Research has shown that AI systems can be trained to recognize definitional concepts, identify cross-references among statutory provisions, and track regulatory changes over time, potentially reducing the time tax professionals spend on research tasks [18]. However, the literature also acknowledges significant limitations in current NLP capabilities, particularly regarding the interpretation of ambiguous language, resolution of conflicting authorities, and application of subjective standards that characterize many tax provisions [19]. The contextual understanding required for sophisticated tax analysis remains challenging for AI systems, necessitating human oversight and validation of algorithmically generated interpretations.

RPA has received substantial attention in the literature as a technology offering immediate efficiency gains in tax compliance processes [20]. Researchers have documented RPA implementations across various tax functions including data extraction from source documents, tax return preparation, reconciliation procedures, and routine correspondence handling. Studies report significant time savings, error reductions, and cost decreases associated with RPA deployment, with some organizations achieving return on investment within months of implementation [21]. The literature distinguishes between simple RPA applications that follow deterministic rules and more sophisticated cognitive automation that incorporates ML components to handle variations and exceptions. Research suggests that greatest value emerges when RPA is strategically implemented as part of broader process redesign efforts rather than simply automating existing inefficient workflows [22]. The change management challenges associated with RPA adoption have also been examined, with studies highlighting the importance of stakeholder engagement, training, and clear communication about how automation affects professional roles.

Blockchain technology's potential applications in tax administration have stimulated considerable research interest, though practical implementations remain relatively limited [23]. Scholars have explored how distributed ledger technology could facilitate real-time tax reporting, enhance transparency in value-added tax systems, and reduce compliance costs through automated smart contracts that calculate and remit taxes on transactions. Research has analyzed pilot programs in various jurisdictions, identifying technical, regulatory, and adoption challenges that must be addressed for blockchain-based tax systems to achieve widespread use [24]. The literature emphasizes that blockchain's benefits depend critically on network effects and standardization, with value increasing as more participants join the system. Privacy concerns and the tension between transparency requirements and taxpayer confidentiality have emerged as significant issues requiring careful consideration in blockchain-based tax solutions [25].

The literature extensively discusses the class imbalance problem in tax compliance prediction, as non-compliant taxpayers typically represent a small minority of all filers [26]. Studies have explored various techniques for addressing this imbalance including synthetic minority oversampling, cost-sensitive learning, and anomaly detection approaches. Research indicates that standard accuracy metrics can be misleading in highly imbalanced settings, with models potentially achieving high overall accuracy while failing to identify most non-compliance cases [27]. Alternative performance measures such as precision, recall, and area under the receiver operating characteristic curve provide more appropriate assessments of model effectiveness in tax risk prediction contexts. The literature emphasizes the importance of carefully calibrating false positive and false negative rates, as excessive false alarms overwhelm audit resources while missed non-compliance cases result in revenue losses.

Several studies have investigated the explainability challenges associated with complex ML models used in tax compliance, addressing concerns about algorithmic transparency and accountability [28]. Researchers have employed techniques such as local interpretable modelagnostic explanations and Shapley additive explanations to elucidate why specific taxpayers were flagged as high-risk or how particular features influenced predictions. These approaches enable tax authorities to understand and justify audit selection decisions, potentially improving public trust and legal defensibility [29]. The literature suggests that interpretability represents not merely a technical requirement but a fundamental prerequisite for responsible AI deployment in tax administration, where decisions significantly affect individuals and businesses. Some scholars argue that certain inherently opaque models may be inappropriate for tax compliance applications regardless of their predictive accuracy, advocating instead for more transparent approaches that facilitate human understanding and oversight [30].

The role of professional judgment in tax compliance has been extensively examined, with researchers emphasizing its enduring importance despite technological advances [31]. Studies identify multiple dimensions of professional judgment including technical analysis, ethical reasoning, risk assessment, and client counseling, many of which prove resistant to automation. Research demonstrates that experienced tax professionals employ tacit knowledge developed through years of practice, enabling them to recognize patterns, anticipate issues, and devise creative solutions that algorithmic approaches struggle to replicate [32]. The literature also explores how professional judgment operates within organizational and social contexts, influenced by incentives, norms, and relationships that shape compliance decisions. Some scholars have raised concerns that excessive reliance on AI systems might lead to de-skilling of professionals and erosion of judgment capabilities over time, particularly among newer practitioners with limited exposure to non-automated processes [33].

The integration of AI and professional judgment through human-AI collaboration frameworks has emerged as a prominent theme in recent literature [34]. Researchers have examined various collaboration models including AI as tool, AI as assistant, and AI as partner, each characterized by different levels of human involvement and algorithmic autonomy. Studies suggest that optimal outcomes often result from complementary partnerships where AI handles data-intensive analytical tasks while humans focus on interpretation, validation, and decision-making under uncertainty [35]. The literature explores design principles for effective collaboration interfaces, emphasizing the importance of transparency regarding AI capabilities and limitations, provision of contextual explanations for algorithmic outputs, and preservation of human agency in final determinations. Research has also investigated cognitive biases that

may affect human-AI interaction, including automation bias where users uncritically accept AI recommendations and algorithm aversion where users inappropriately dismiss AI outputs [36].

Ethical considerations surrounding AI in tax compliance have received growing attention, encompassing issues of fairness, accountability, privacy, and social justice [37]. Scholars have examined potential sources of algorithmic bias in tax risk models, including biased training data, problematic feature selection, and optimization objectives that may disadvantage certain demographic groups. Research demonstrates that AI systems can perpetuate or amplify existing disparities in tax enforcement, with low-income and minority taxpayers potentially facing disproportionate audit risk if historical enforcement patterns are reflected in training data [38]. The literature discusses various fairness criteria and technical approaches for bias mitigation, though consensus on appropriate standards remains elusive [39]. Privacy concerns related to extensive data collection and analysis required for effective AI systems have also been explored, with researchers examining tensions between compliance enforcement and individual privacy rights.

The organizational and professional implications of AI adoption in tax compliance have been analyzed from multiple perspectives [40]. Studies have investigated how AI affects workforce composition, skill requirements, and career progression in tax departments and professional service firms. Research indicates that routine compliance work becomes increasingly automated while demand grows for professionals with hybrid competencies spanning tax expertise, data analytics, and technology management [41]. The literature explores challenges in developing these competencies through education and training, with some scholars advocating for fundamental curriculum reforms in tax programs to better prepare students for technology-enabled practice [42]. Organizational change management aspects have also been examined, with research highlighting the importance of leadership commitment, clear communication strategies, and inclusive implementation processes that engage affected stakeholders.

The regulatory and policy dimensions of AI in tax compliance have attracted scholarly attention, with researchers examining how legal frameworks must adapt to accommodate intelligent technologies [43]. Studies have analyzed regulatory gaps and ambiguities regarding liability for AI errors, requirements for algorithmic transparency, and standards for acceptable AI use in tax administration. The literature explores tensions between efficiency gains from AI deployment and due process protections for taxpayers, questioning whether algorithmic decision-making systems provide adequate opportunities for challenge and appeal [44]. Comparative analyses of different jurisdictions' approaches to AI regulation in tax contexts reveal diverse strategies ranging from permissive frameworks that encourage innovation to more restrictive regimes emphasizing taxpayer protection and human oversight. Researchers have also examined international coordination challenges, as cross-border tax compliance increasingly involves AI systems operating across multiple jurisdictions with varying regulatory standards [45].

3. Artificial Intelligence Technologies in Tax Compliance

The deployment of AI technologies in tax compliance encompasses diverse applications ranging from routine process automation to sophisticated analytical capabilities that augment human decision-making. ML algorithms represent one of the most widely implemented AI technologies, offering powerful capabilities for pattern recognition, classification, and prediction in tax contexts [46]. Supervised learning approaches train models on labeled historical data, learning relationships between taxpayer characteristics and compliance outcomes to identify high-risk

cases warranting further investigation. Tax authorities worldwide have implemented ML-based risk scoring systems that analyze hundreds of features from tax returns, third-party information reports, and external databases to generate compliance risk assessments for each taxpayer [47]. These systems enable more efficient audit resource allocation by concentrating examination efforts on cases with highest predicted non-compliance probability, potentially increasing detection rates while reducing burden on compliant taxpayers.

The architecture of ML systems for tax risk assessment typically involves several components including data integration, feature engineering, model training, and prediction deployment [48]. Data integration combines information from multiple sources such as tax returns, payment records, previous audit findings, and external databases containing information about business registrations, property ownership, and financial transactions. Feature engineering transforms raw data into predictive variables through calculations of ratios, trend analysis, and identification of discrepancies or anomalies. Common features include incometo-deduction ratios, year-over-year changes in reported amounts, comparisons between related return items, and deviations from industry norms [49]. Model training employs various algorithms including logistic regression, decision trees, random forests, gradient boosting machines, and neural networks, with performance evaluated using holdout validation sets and cross-validation procedures. Once validated, models generate risk scores for incoming tax returns, which feed into audit selection systems that balance predicted risk against audit capacity and strategic priorities.
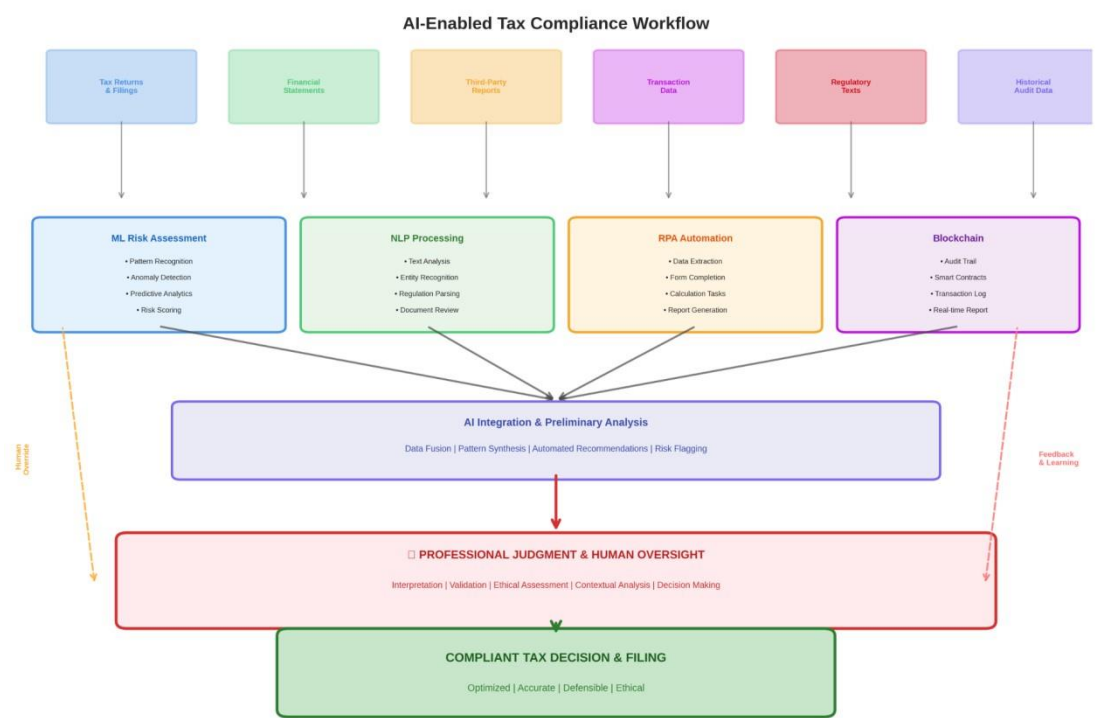

Figure 1: AI-enabled tax compliance workflow showing the integration of data sources, ML risk assessment, RPA automation, NLP regulation interpretation, and human professional judgment in decision-making processes.

Figure 1 illustrates the comprehensive workflow architecture that integrates multiple AI technologies within modern tax compliance systems. The diagram shows how diverse data sources—including tax returns, financial statements, third-party reports, and regulatory databases—feed into specialized AI processing modules. ML algorithms perform risk

assessment by analyzing patterns across taxpayer features to generate compliance risk scores. RPA components automate routine data extraction, form preparation, and reconciliation tasks, reducing manual processing burden. NLP modules interpret regulatory texts, extract relevant provisions, and support compliance determinations for specific transactions. Critically, the workflow maintains human professional judgment as the central decision-making authority, with AI outputs serving as inputs to professional analysis rather than final determinations. The diagram emphasizes oversight mechanisms including validation checkpoints, exception handling procedures, and escalation pathways that ensure complex or ambiguous situations receive appropriate human attention. This architecture reflects the hybrid approach where AI efficiency complements rather than replaces professional expertise.

Deep learning approaches have shown particular promise for analyzing complex, highdimensional tax data and extracting subtle patterns that simpler models might miss [50]. Neural networks with multiple hidden layers can automatically discover hierarchical feature representations, potentially uncovering non-obvious relationships among tax variables that human analysts or traditional statistical methods would overlook. Convolutional neural networks have been applied to analyze spatial patterns in taxpayer data, identifying geographic clusters of non-compliance or unusual reporting patterns across related entities [51]. Recurrent neural networks and their variants prove effective for modeling temporal sequences in taxpayer behavior, detecting gradual shifts in reporting patterns that might indicate increasing non-compliance or sophisticated avoidance strategies. However, the blackbox nature of deep learning models creates challenges for tax administration applications where decisions must be explainable and defensible, leading some authorities to prefer more interpretable approaches despite potential accuracy trade-offs [52].

NLP technologies enable tax systems to process and understand textual information in tax returns, supporting documents, regulations, and judicial decisions [53]. Modern NLP approaches based on transformer architectures such as BERT and GPT have demonstrated remarkable capabilities in understanding context, recognizing entities, and extracting relevant information from unstructured text. In tax compliance contexts, NLP systems can automatically categorize expense descriptions, identify potentially misclassified items, extract key facts from audit documentation, and even generate preliminary analyses of whether specific transactions satisfy statutory requirements. Some tax authorities have implemented NLP-powered chatbots that answer common taxpayer questions, provide guidance on tax obligations, and assist with return preparation, potentially reducing errors and improving voluntary compliance. Research-oriented applications include systems that analyze legislative text to identify definitional elements, trace cross-references, and map relationships among statutory provisions, creating structured knowledge representations that support more sophisticated reasoning about tax consequences. Recent work by Tan et al. demonstrated the effectiveness of knowledge-guided expert mixture architectures for analyzing uncertain tax positions, achieving 90.5% accuracy in classifying tax risk levels while maintaining high citation accuracy through retrieval-augmented generation that grounds analysis in authoritative tax sources [54].

The application of NLP to tax regulation interpretation presents both opportunities and challenges, as tax laws contain specialized terminology, complex syntactic structures, and context-dependent meanings that challenge even advanced language models [55]. While NLP systems can effectively identify relevant statutory provisions and extract key terms, the logical reasoning required to determine how provisions apply to specific fact patterns remains difficult to automate fully. Tax rules often involve multiple interacting provisions, exceptions, special rules, and implicit assumptions that require understanding legislative purpose and policy

objectives beyond surface-level text analysis [56]. Moreover, judicial interpretations and administrative guidance significantly shape how statutory language is applied in practice, requiring AI systems to synthesize information across multiple types of authorities with varying precedential weight. These complexities suggest that NLP in tax compliance currently functions best as a support tool that accelerates human analysis rather than a replacement for professional interpretation.

RPA technologies automate repetitive, rule-based tasks that characterize much routine tax compliance work, offering immediate efficiency gains without requiring sophisticated AI capabilities [57]. RPA software bots mimic human interactions with computer systems, executing workflows such as extracting data from emails and attachments, inputting information into tax software, performing calculations, generating reports, and routing documents for review. Unlike traditional system integration approaches that require programming and API development, RPA operates at the user interface level, making it relatively quick and inexpensive to implement for well-defined processes. In tax departments, RPA commonly automates activities such as sales tax return preparation, estimated tax payment processing, compliance calendar management, and routine correspondence responses [58]. The technology scales easily, with software bots working continuously without fatigue, enabling organizations to handle increased transaction volumes without proportional staffing increases.

The limitations of basic RPA become apparent when processes encounter exceptions, variations, or situations requiring judgment, leading to the development of cognitive automation that combines RPA with ML capabilities [59]. Cognitive RPA can handle greater variability in inputs, learn from examples to improve performance over time, and make simple decisions based on patterns in data. For instance, cognitive systems can classify incoming tax notices, extract relevant information from documents with varying formats, and determine appropriate responses based on historical handling of similar cases. The integration of optical character recognition technology enables automated processing of paper documents and images, while NLP components allow parsing of textual content to extract structured information. These enhanced capabilities expand the scope of automatable tax processes, though significant human involvement remains necessary for complex situations, quality assurance, and exception handling.

Blockchain technology offers potential applications in tax compliance through enhanced transparency, real-time reporting, and automated tax calculation integrated into transaction execution [60]. The core concept involves recording transactions on distributed ledgers that provide tamper-resistant audit trails accessible to relevant parties including tax authorities. Smart contracts deployed on blockchain platforms can automatically calculate applicable taxes on transactions, execute withholding, and remit payments to tax authorities, potentially reducing compliance costs and improving collection efficiency. Pilot implementations have explored blockchain applications for value-added tax systems where tracking goods and services through supply chains presents challenges, for cross-border transactions requiring coordination among multiple tax authorities, and for cryptocurrency taxation where traditional reporting mechanisms prove inadequate [61]. Despite conceptual appeal, blockchain adoption in tax compliance faces obstacles including technical complexity, scalability limitations, privacy concerns, and the need for standardization across diverse stakeholders.

Predictive analytics extends beyond risk assessment to support various forward-looking tax compliance functions including forecasting tax liabilities, modeling the impact of proposed transactions or tax law changes, and optimizing tax positions within legal constraints [62]. Time

series models analyze historical patterns to predict future tax obligations, enabling better cash flow planning and reducing surprises from unexpected tax bills. Scenario analysis tools powered by ML simulate outcomes under different assumptions, helping taxpayers and advisors evaluate alternative structures or timing options. Optimization algorithms can identify tax-efficient approaches to business decisions such as supply chain configuration, transfer pricing policies, or entity structuring, subject to specified constraints and business objectives. These predictive capabilities shift tax compliance from purely reactive historical reporting toward proactive planning and decision support, though they require careful validation to ensure predictions accurately reflect complex tax rules and potential authority responses.

The integration of multiple AI technologies creates comprehensive tax compliance platforms that combine strengths of different approaches while mitigating individual limitations [63]. Modern systems might employ NLP for document analysis and regulation interpretation, ML for risk assessment and prediction, RPA for process automation, and blockchain for transaction recording and reporting. These integrated platforms can support end-to-end compliance workflows from transaction capture through return preparation, payment, audit defense, and dispute resolution. The emergence of cloud-based AI services and application programming interfaces enables smaller organizations to access sophisticated capabilities previously available only to large enterprises with substantial technology investments. However, the complexity of integrated systems raises challenges regarding vendor dependencies, system maintenance, data governance, and the preservation of human expertise necessary to supervise and validate AI outputs effectively.

4. Professional Judgment and Human-AI Collaboration in Tax Compliance

Professional judgment in tax compliance encompasses multiple interrelated dimensions including technical analysis of complex legal provisions, assessment of factual circumstances, evaluation of uncertain positions, and ethical decision-making regarding aggressive versus conservative reporting stances [64]. Tax professionals exercise judgment when interpreting ambiguous statutory language, determining whether specific facts satisfy legal tests such as business purpose or economic substance, evaluating the strength of authority supporting particular positions, and deciding what disclosures provide adequate transparency to tax authorities. These judgments often occur in areas where bright-line rules do not exist, reasonable professionals might disagree, and outcomes depend on subjective factors that resist algorithmic determination. The tacit knowledge developed through experience enables seasoned practitioners to recognize patterns, anticipate likely regulatory responses, and navigate gray areas in ways that novices and AI systems cannot easily replicate [65].

The irreducible role of professional judgment stems partly from inherent characteristics of tax law including intentional ambiguity, reliance on standards rather than rules, and the contextual nature of many legal determinations [66]. Legislators deliberately employ broad concepts such as ordinary and necessary business expenses, reasonable compensation, or arm's length pricing, expecting that specific applications will be determined through professional analysis considering all relevant circumstances. These standards require balancing competing considerations, weighing factors without precise weightings, and ultimately making holistic assessments that integrate legal, factual, economic, and policy dimensions. While AI systems can identify relevant factors and provide data-driven insights regarding some considerations, the synthetic judgment required to reach final conclusions in ambiguous situations remains fundamentally a human cognitive activity rooted in professional training, experience, and ethical commitments.

Comparative Capabilities of AI Systems and Human Professional Judgment

Analysis Across Key Tax Compliance Functions

Tax Compliance Function	AI System Strengths	AI System Limitations	Human Judgment Strengths	Human Judgment Limitations	Optimal Approach
Data Processing & Volume Handling	Processes millions of transactions instantly; consistent accuracy; no fatigue; scalable	Cannot handle truly novel data formats; requires structured inputs	Handles unusual formats; adapts to unexpected situations flexibly	Limited processing capacity; fatigue affects performance; not scalable	AI processes data; humans validate outputs and flag exceptions
Pattern Recognition & Anomaly Detection	Identifies subtle patterns in large datasets; detects outliers; real-time monitoring	May miss context-dependent anomalies; false positives in unusual situations	Recognizes context-specific anomalies; applies experience to edge cases	May miss patterns in massive datasets; subject to cognitive biases	AI flags potential issues; humans investigate and determine significance
Regulation Interpretation	Quickly retrieves relevant provisions; identifies keywords; basic rule application	Struggles with ambiguous language; cannot resolve conflicting authorities	Interprets ambiguous language; weighs conflicting authorities; understands intent	Time-consuming research; potential knowledge gaps; inconsistent recall	AI retrieves provisions; humans interpret and apply to specific facts
Risk Assessment & Scoring	Analyzes multiple factors simultaneously; quantitative scoring; predictive models	Limited contextual understanding; difficulty with qualitative factors	Incorporates qualitative factors; assesses unique circumstances; balances multiple objectives	Cannot simultaneously analyze hundreds of factors; subjective weighting	AI generates risk scores; humans contextualize and make final decisions
Ethical Reasoning & Judgment	Can apply predefined ethical rules; identifies conflicts of interest	Cannot make nuanced ethical judgments; lacks moral reasoning capacity	Makes nuanced ethical judgments; considers broader impacts; moral reasoning	Subject to personal biases; influenced by incentives; inconsistent standards	AI identifies ethical issues; humans make final ethical determinations
Client Counseling & Communication	Handles routine inquiries; provides standardized guidance via chatbots	Cannot build relationships; lacks empathy; misses emotional cues	Builds trust relationships; understands client needs; communicates empathetically	Time-intensive; limited availability; costs scale with volume	AI handles routine queries; humans manage complex relationship-based work
Audit Negotiation & Dispute Resolution	Retrieves precedents; organizes documentation; identifies relevant cases	Cannot engage in nuanced negotiation; lacks persuasive ability	Engages in strategic negotiation; persuades authorities; finds compromise	Requires significant time; not always available; expensive resources	AI organizes evidence; humans conduct negotiations and strategic discussions
Strategic Tax Planning & Novel Situations	Analyzes historical data; optimization algorithms; scenario modeling	Struggles with unprecedented situations; cannot reason by analogy effectively	Handles novel situations; reasons by analogy; devises creative solutions	Analysis may be incomplete; relies on limited experience; time-consuming	AI provides analysis; humans synthesize and devise innovative solutions

Table 1: Comparative capabilities of AI systems and human professional judgment across key tax compliance functions.

The relationship between AI capabilities and professional judgment can be conceptualized along a spectrum from routine tasks amenable to full automation to complex judgments requiring exclusively human involvement, with a substantial middle ground where optimal outcomes emerge from human-AI collaboration [67]. At one end, purely mechanical tasks such as data transfer, mathematical calculations, and application of deterministic rules can be reliably automated with minimal human oversight beyond initial setup and periodic validation. At the opposite end, highly contextual judgments involving novel situations, competing policy considerations, ethical dilemmas, or significant uncertainty require human deliberation informed by professional values and experience. The middle ground encompasses analytical tasks where AI provides powerful processing capabilities while humans contribute interpretive insights, contextual understanding, and ultimate decision authority. Effective tax compliance increasingly involves designing workflows that appropriately allocate activities across this spectrum, leveraging AI where it excels while preserving human judgment where it remains indispensable.

Table 1 presents a systematic comparison of AI system capabilities versus human professional judgment across eight key tax compliance functions. For data processing and pattern recognition, AI demonstrates clear superiority through its ability to analyze vast datasets rapidly and identify subtle correlations that human reviewers would miss. In regulation interpretation, capabilities are more balanced: AI excels at retrieval and initial parsing while humans provide essential contextual understanding and resolution of ambiguous provisions. Risk assessment benefits from AI's quantitative rigor combined with human evaluation of qualitative factors and novel circumstances. The table reveals that ethical reasoning, client counseling, audit negotiation, and strategic planning remain predominantly human domains where interpersonal skills, professional values, and situational judgment prove essential. These functions involve navigating competing considerations, building relationships, and exercising discretion that current AI systems cannot replicate. The comparison underscores that optimal tax compliance outcomes emerge from thoughtful allocation of tasks according to comparative

advantages, leveraging AI for data-intensive analytical work while preserving human judgment for complex, contextual, and ethically-laden decisions.

The design of effective human-AI collaboration requires careful attention to interface design, transparency, and the preservation of human agency [68]. AI systems should present information and recommendations in formats that facilitate human understanding and critical evaluation rather than encouraging passive acceptance. Explanations of why specific predictions were made or what factors drove particular risk scores enable professionals to assess whether algorithmic conclusions appear reasonable given their knowledge of the taxpayer and relevant circumstances. Confidence measures indicating the certainty associated with AI outputs help users appropriately calibrate reliance, perhaps conducting additional analysis when confidence is low or accepting recommendations when confidence is high [69]. The ability to override AI conclusions when professional judgment suggests different outcomes remains essential, as does documentation of rationales for overrides to support learning and system improvement.

Research on human-AI interaction reveals cognitive biases that can undermine effective collaboration if not explicitly addressed [70]. Automation bias describes the tendency to favor suggestions from automated systems even when contradictory information exists, potentially leading to uncritical acceptance of erroneous AI outputs. Algorithm aversion represents the opposite tendency, where users reject valid AI recommendations due to general skepticism about algorithmic decision-making or previous negative experiences with automated systems. Both biases can degrade decision quality, suggesting the need for training that promotes appropriate trust calibrated to actual AI reliability and circumstances. Debiasing interventions might include requiring documentation of independent assessments before viewing AI recommendations, presenting AI conclusions probabilistically rather than as definitive determinations, and fostering cultures that value both technological capabilities and human expertise.

The evolution of professional roles in AI-enabled tax compliance environments represents a significant change management challenge requiring rethinking of workforce composition, skill requirements, and career development pathways [71]. As routine tasks become automated, professionals spend greater proportions of their time on complex analysis, client advisory services, and oversight of AI systems. This shift elevates the cognitive demands of tax work while potentially reducing opportunities for junior professionals to develop expertise through repetitive practice on relatively simple tasks. Organizations must consider how to provide meaningful development experiences that build judgment capabilities when traditional learning pathways are disrupted by automation. Approaches might include structured rotation programs exposing professionals to diverse situations, mentoring arrangements pairing experienced and newer practitioners, and simulation-based training that presents realistic scenarios requiring judgment under controlled conditions.

The competencies required for effective practice in AI-enabled tax compliance extend beyond traditional technical tax knowledge to encompass data literacy, technological fluency, and critical thinking skills [72]. Professionals must understand fundamental ML concepts to evaluate whether AI approaches are appropriate for specific applications, interpret model outputs intelligently, and recognize when algorithmic conclusions appear questionable. Data literacy enables assessment of whether available data supports reliable predictions, identification of potential data quality issues affecting AI performance, and understanding of how data characteristics influence model behavior. Critical thinking skills facilitate questioning

of assumptions embedded in AI systems, consideration of alternative explanations for patterns identified by algorithms, and recognition of situations where human judgment should override algorithmic recommendations. Developing these competencies requires educational reforms integrating technology and analytics into tax curricula alongside traditional doctrinal instruction.

Ethical considerations in AI-enabled tax compliance extend beyond technical capabilities to encompass professional responsibilities, client service, and broader societal impacts [73]. Tax professionals must balance efficiency gains from automation against obligations to provide competent, diligent service that exercises independent professional judgment. Over-reliance on AI systems without adequate understanding or validation could constitute negligence if errors go undetected. Professionals must also consider whether AI recommendations align with client interests and professional ethical standards, exercising judgment about appropriate aggressiveness in tax positions rather than automatically following algorithmic suggestions. Broader societal considerations include ensuring that AI deployment does not systematically disadvantage vulnerable populations, preserving procedural fairness in tax administration, and maintaining public trust in tax systems despite increasing technological opacity.

The governance frameworks for AI in tax compliance must address accountability, transparency, quality assurance, and ongoing monitoring to ensure responsible deployment [74]. Organizations should establish clear policies regarding appropriate AI uses, required human oversight, documentation standards, and escalation procedures for problematic situations. Model validation processes should verify that AI systems perform as expected across diverse scenarios, exhibit acceptable error rates, and do not produce systematically biased outcomes. Ongoing monitoring tracks AI performance over time, detecting degradation that might result from concept drift or data quality deterioration. Transparency requirements might mandate disclosure to clients or stakeholders when significant decisions rely on AI systems, explanation of key factors influencing algorithmic outputs, and opportunities to challenge AI-driven determinations. Accountability mechanisms should clearly assign responsibility for AI outcomes, ensuring that automation does not obscure who bears ultimate liability for compliance errors or poor advice.

Figure 2 presents the conceptual framework governing human-AI collaboration in tax compliance decision-making. The flow begins with data inputs from multiple sources including transaction records, tax returns, regulatory updates, and client information, which feed into AI processing modules that perform risk scoring, anomaly detection, regulatory matching, and preliminary analysis. AI outputs then enter the professional analysis stage where tax professionals evaluate algorithmic conclusions against their contextual knowledge, experience, and understanding of client circumstances. The judgment synthesis phase integrates AI-generated insights with professional assessment to reach compliance determinations, with the framework explicitly marking decision points where human override authority is essential—particularly for ambiguous situations, novel fact patterns, and ethically sensitive matters. Decision implementation feeds back into the system through continuous learning loops that capture outcomes, update model parameters, and refine collaboration protocols. The feedback mechanisms enable both AI system improvement through expanded training data and professional learning through exposure to diverse scenarios and outcomes. This framework emphasizes that effective collaboration requires clear delineation of responsibilities, transparent AI outputs that facilitate human evaluation, and governance structures that maintain accountability throughout the decision process.
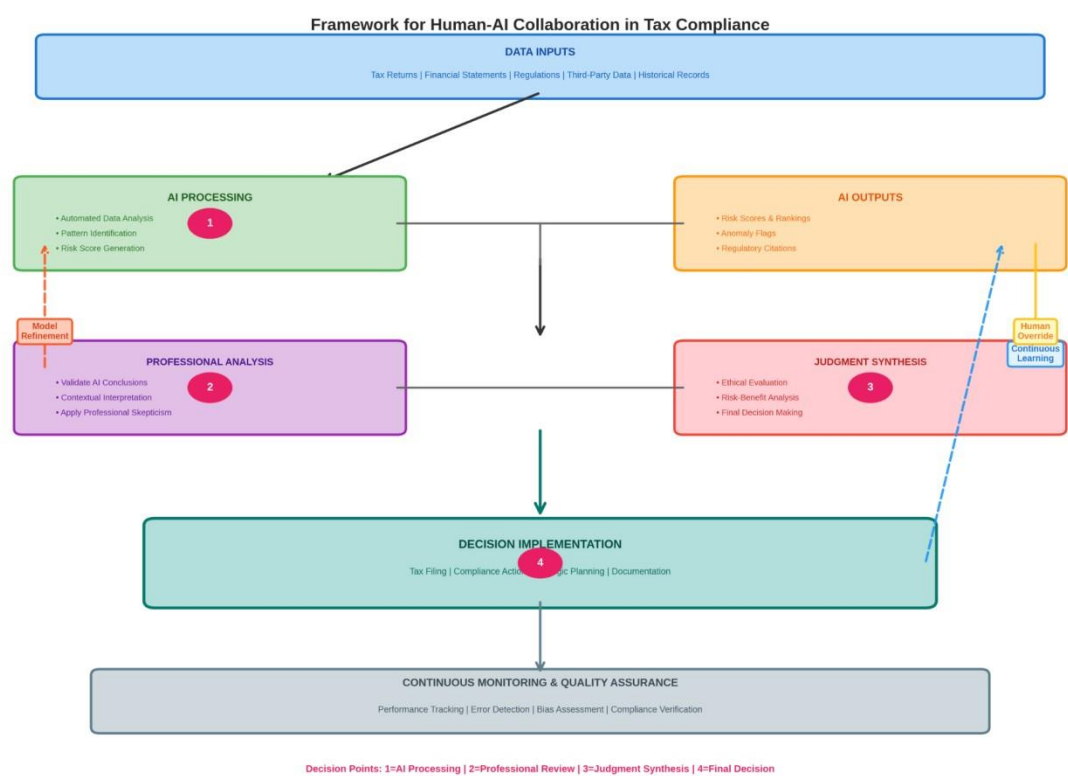
Figure 2: Framework for human-AI collaboration in tax compliance, showing data flow, AI processing, professional analysis, judgment synthesis, and feedback loops.

The future trajectory of AI in tax compliance likely involves continued advancement of technological capabilities alongside persistent recognition that professional judgment remains central to high-quality outcomes. As AI systems become more sophisticated, the boundary between automatable and judgment-intensive activities may shift, with AI handling increasingly complex analytical tasks while humans focus on the most ambiguous, novel, or ethically sensitive situations. However, fundamental characteristics of tax law and compliance suggest that human judgment will remain indispensable for the foreseeable future, with technology serving to augment rather than replace professional expertise. The most successful organizations will be those that thoughtfully integrate AI capabilities with human judgment, creating hybrid approaches that leverage complementary strengths while implementing safeguards against potential pitfalls of either pure automation or technologyresistant traditional practice.

5. Conclusion

The integration of AI technologies into tax compliance represents a transformative development that fundamentally reshapes how tax obligations are identified, analyzed, and fulfilled. This review has examined diverse AI applications including ML for risk assessment, NLP for regulation interpretation, RPA for process automation, and blockchain for enhanced transparency, demonstrating that these technologies offer substantial improvements in efficiency, accuracy, and analytical capability compared to traditional approaches. ML algorithms effectively identify patterns in vast datasets, enabling tax authorities to target audit resources more precisely while helping taxpayers detect errors before filing. NLP systems accelerate research and document analysis, reducing the time professionals spend on routine information retrieval. RPA eliminates repetitive manual tasks, allowing reallocation of human

resources toward higher-value activities requiring expertise and judgment. The empirical evidence clearly establishes that AI technologies deliver significant operational benefits when properly implemented and managed.

Despite these impressive technological capabilities, this review has emphasized that professional judgment remains indispensable in tax compliance for multiple interconnected reasons. Tax law inherently incorporates ambiguity, employs subjective standards, and requires contextual analysis that resists purely algorithmic determination. Many compliance decisions involve weighing competing considerations without clear optimization criteria, anticipating regulatory responses to novel structures, and making ethical choices between aggressive and conservative reporting positions. These activities demand tacit knowledge developed through experience, capacity for reasoning by analogy across disparate situations, and commitment to professional values that cannot be reduced to computational procedures. The complexity of modern tax systems, the continuous evolution of both law and taxpayer circumstances, and the irreducibly human dimensions of judgment suggest that technology will augment rather than replace professional expertise for the foreseeable future.

The optimal approach to tax compliance in the digital age involves thoughtful human-AI collaboration that leverages the complementary strengths of computational and human capabilities. AI excels at processing enormous volumes of data, identifying patterns, performing consistent calculations, and executing routine tasks without fatigue or distraction. Human professionals contribute contextual understanding, interpretive skills, ethical reasoning, and the capacity to handle novel situations that fall outside algorithmic training data. Effective collaboration requires careful workflow design that appropriately allocates activities between human and machine, interface design that facilitates critical evaluation of AI outputs, and governance frameworks that ensure accountability and quality. Organizations that successfully integrate AI tools with professional judgment, rather than viewing technology and expertise as alternatives, will achieve superior compliance outcomes while managing the risks associated with either excessive automation or inefficient resistance to beneficial technological adoption.

The competency requirements for tax professionals have evolved substantially in AI-enabled environments, extending beyond traditional technical knowledge to encompass data literacy, technological fluency, and sophisticated judgment capabilities. Professionals must understand how AI systems function sufficiently to evaluate their appropriateness for specific applications, interpret outputs intelligently, and recognize limitations that require human intervention. The shift toward more cognitively demanding work as routine tasks become automated elevates the importance of critical thinking, communication skills, and ability to exercise judgment under uncertainty. Educational institutions and professional development programs must adapt curricula and training approaches to prepare practitioners for these transformed roles, integrating technological and analytical instruction alongside traditional doctrinal teaching.

The ethical and governance challenges surrounding AI in tax compliance require ongoing attention from practitioners, organizations, and policymakers. Questions about algorithmic transparency, fairness, accountability, and appropriate human oversight demand careful consideration and the development of standards that balance efficiency gains against procedural protections and professional responsibilities. The potential for algorithmic bias, privacy concerns related to extensive data collection, and risks of de-skilling through excessive automation warrant proactive management rather than reactive responses after problems emerge. Professional organizations, regulatory bodies, and industry groups should collaborate

to establish best practices, ethical guidelines, and governance frameworks that promote responsible AI deployment while preserving core values of tax professionalism.

The regulatory environment surrounding AI in tax compliance continues evolving as authorities grapple with how to accommodate technological innovations within existing legal frameworks while protecting taxpayer rights and ensuring system integrity. Tax administrations face tensions between leveraging AI capabilities to enhance compliance and maintaining due process, transparency, and fairness in dealings with taxpayers. The development of standards for algorithmic decision-making in tax contexts, requirements for explainability and human oversight, and mechanisms for challenging AI-driven determinations represent important areas requiring policy attention. International coordination may prove necessary as cross-border tax issues increasingly involve AI systems operating across multiple jurisdictions with potentially divergent regulatory approaches.

Future research should explore several underexamined areas to advance understanding of AI's role in tax compliance and inform practice improvements. Longitudinal studies tracking the actual impacts of AI adoption on compliance quality, professional development, and organizational performance would provide valuable insights beyond short-term efficiency metrics. Investigation of how professionals can most effectively develop and maintain judgment capabilities in highly automated environments could inform educational and training approaches. Deeper examination of ethical dimensions including fairness, accountability, and appropriate skepticism toward algorithmic outputs would contribute to responsible AI deployment. Comparative analyses across jurisdictions and organizational contexts could identify factors associated with successful technology integration and illuminate challenges requiring attention.

The transformation of tax compliance through AI technologies appears irreversible, driven by inexorable trends toward digitalization, data abundance, and computational capability that enable increasingly sophisticated automated systems. However, the vision of fully autonomous tax compliance remains distant and perhaps undesirable, given the inherent complexity of tax law, the contextual nature of many compliance determinations, and the essential role of professional judgment in ensuring quality outcomes. The future of tax compliance lies not in choosing between human expertise and technological capability but in thoughtfully combining these complementary resources. Success requires acknowledging both the power and limitations of AI, preserving space for professional judgment while embracing beneficial automation, and maintaining vigilance against risks of either naive techno-optimism or reflexive resistance to change. Organizations and professionals that navigate this balance effectively will deliver superior compliance outcomes while advancing the broader goals of fair, efficient, and trustworthy tax systems.

References

[1] Utama, M. S., Solimun, & Fernandes, A. A. R. (2024). Constructing a Broad View of Tax Compliance Intentions Based on Big Data. In Machine Learning Approaches in Financial Analytics (pp. 279305). Cham: Springer Nature Switzerland.

[2] Battiston, P., Gamba, S., & Santoro, A. (2020). Optimizing tax administration policies with machine learning. University of Milan Bicocca Department of Economics, Management and Statistics Working Paper, (436).

[3] Lin, H., & Liu, W. (2025). Symmetry-Aware Causal-Inference-Driven Web Performance Modeling: A Structure-Aware Framework for Predictive Analysis and Actionable Optimization. Symmetry, 17(12), 2058.

[4] Lin, R., Wang, L., Li, B., Lu, Y., Qi, Z., & Xie, L. (2023). Organizational governance in the smart era: the implications of blockchain. Nankai Business Review International, 14(2), 197-229.

[5] Puthukulam, G., Ravikumar, A., Sharma, R. V. K., & Meesaala, K. M. (2021). Auditors' perception on the impact of artificial intelligence on professional skepticism and judgment in oman. Universal Journal of Accounting and Finance, 9(5), 1184-1190.

[6] Chyz JA, Gaertner FB, Kausar A, et al. Overconfidence and corporate tax policy. Review of Accounting Studies. 2019;24(3):1114-1145.

[7] Janský, P., Knobel, A., Meinzer, M., Palanská, T., & Palanský, M. (2020). Country-by-country reporting and other financial transparency measures affecting the European Union. Institute of Economic Studies, Faculty of Social Sciences, Charles University in Prague.

[8] Drašček, M., Andolšek, D. M., & Buhovac, A. R. (2023). Ethical Decision-making in Management: Perspectives of the Philosopher, the Sociologist and the Manager. Routledge.

[9] Karnosh, K. E. (2020). The application of international tax treaties to digital services taxes. Chi. J. Int'l L., 21, 513.

[10] Floridi, L., & Cowls, J. (2022). A unified framework of five principles for AI in society. Machine learning and the city: Applications in architecture and urban design, 535-545.

[11] Hassan, A. O. (2024). Rethinking Automation of Tax Administration in Nigeria: Successes and Limitations. FUOYE JOURNAL OF PUBLIC ADMINISTRATION AND MANAGEMENT (FJPAM), 2(1), 266-266.

[12] Vanhoeyveld, J., Martens, D., & Peeters, B. (2020). Value-added tax fraud detection with scalable anomaly detection techniques. Applied Soft Computing, 86, 105895.

[13] Ftouhi, K., & Ghardallou, W. (2020). International tax planning techniques: a review of the literature. Journal of Applied Accounting Research, 21(2), 329-343.

[14] Rathi, A., Sharma, S., Lodha, G., & Srivastava, M. (2021). A study on application of artificial intelligence and machine learning in indian taxation system. Psychology and Education Journal, 58(2), 1226-1233.

[15] Hariharan, R., & Kumar, R. S. (Eds.). (2025). Recent Research in Management, Accounting and Economics (RRMAE). Taylor & Francis Group.

[16] Mai, N. T., Fang, Q., & Cao, W. (2025). Measuring Student Trust and Over-Reliance on AI Tutors: Implications for STEM Learning Outcomes. International Journal of Social Sciences and English Literature, 9(12), 11-17.

[17] Hendieh, J. (2025). The new auditor: what does the future hold?. International Journal of Critical Accounting, 14(3), 290-311.

[18] JBajada, C. (2022). The Routledge Companion to Global Value Chains.

[19] Jans, M. (2019). Auditor choices during event log building for process mining. Journal of Emerging Technologies in Accounting, 16(2), 59-67.

[20] Sunyaev, A. (2020). Distributed ledger technology. In internet Computing (pp. 265-299). Springer, Cham.

[21] BIRU, D. (2024). EFECTS OF TAX AUDIT ON REVENUE COLLECTION IN ADDIS ABABA: THE CASE OF ADDIS ABABA No 2 MEDIUM TAX PAYERS BRANCH OFFICE.

[22] Saeeda, U., Janb, S. U., Ahmadb, J., Shaha, S. A., Alshehric, M. S., Ghadid, Y. Y., ... & Buchananb, W. J. (2023). Generative adversarial networks-enabled anomaly detection systems: A survey.

[23] Rodrigues, M. J. S. (2020). Power and trust as determinants of tax compliance. The slippery slope framework applied to Portugal and Switzerland (Master's thesis, Universidade de Lisboa (Portugal)).

[24] Murad, A., & Siddiqui, D. A. (2024). How Tax Complacency, Knowledge, and Penalty Affects Tax Compliance in the Informal Sector of Pakistan: The Mediatory Role of Tax Attitude, Volunteer, and Taxpayer Trust, Complemented by Tax Morale, and Tax Patriotism. Knowledge, and Penalty Affects

Tax Compliance in the Informal Sector of Pakistan: The Mediatory Role of Tax Attitude, Volunteer, and Taxpayer Trust, Complemented by Tax Morale, and Tax Patriotism (June 12, 2024).

[25] Pflueger, D., Kornberger, M., & Mouritsen, J. (2024). What is blockchain accounting? A critical examination in relation to organizing, governance, and trust. European Accounting Review, 33(4), 1139-1164.

[26] Brugnone, N. (2023). A Methodology for Modeling Emergence in Complex Systems. Michigan State University.

[27] Haesevoets, T., De Cremer, D., Dierckx, K., & Van Hiel, A. (2021). Human-machine collaboration in managerial decision making. Computers in Human Behavior, 119, 106730.

[28] Wang, Y., Ding, G., Zeng, Z., & Yang, S. (2025). Causal-Aware Multimodal Transformer for Supply Chain Demand Forecasting: Integrating Text, Time Series, and Satellite Imagery. IEEE Access.

[29] Tsantekidis, A., Passalis, N., & Tefas, A. (2020, September). Improving deep reinforcement learning for financial trading using neural network distillation. In 2020 IEEE 30th International Workshop on Machine Learning for Signal Processing (MLSP) (pp. 1-6). IEEE.

[30] Ying, H., Chen, L., & Zhao, X. (2021). Application of text mining in identifying the factors of supply chain financing risk management. Industrial Management & Data Systems, 121(2), 498-518.

[31] Sidhu, B. K., Singh, K., & Sharma, N. (2022). A machine learning approach to software model refactoring. International Journal of Computers and Applications, 44(2), 166-177.

[32] McKinney SM, Sieniek M, Godbole V, et al. International evaluation of an AI system for breast cancer screening. Nature. 2020;577(7788):89-94.

[33] Mehrabi N, Morstatter F, Saxena N, et al. A survey on bias and fairness in machine learning. ACM Computing Surveys. 2021;54(6):1-35.

[34] Muñoz-Izquierdo, N., Laitinen, E. K., Camacho-Miñano, M. D. M., & Pascual-Ezama, D. (2020). Does audit report information improve financial distress prediction over Altman's traditional Z-Score model?. Journal of international financial management & accounting, 31(1), 65-97.

[35] Yaser Saleh, Q., Barakat AL-Nimer, M., & Abbadi, S. S. (2023). The quality of cost accounting systems in manufacturing firms: A literature review. Cogent Business & Management, 10(1), 2209980.

[36] Yang, S., Ding, G., Chen, Z., & Yang, J. (2025). GART: Graph Neural Network-based Adaptive and Robust Task Scheduler for Heterogeneous Distributed Computing. IEEE Access.

[37] Junquera-Varela, R. F., Lucas-Mas, C. Ó., Krsul, I., Calderon, V., & Arce, P. (2022). Digital transformation of tax and customs administrations. Chicago: World Bank.

[38] Hanrahan, D. (2021). Digitalization as a determinant of tax revenues in OECD countries: A static and dynamic panel data analysis. Athens journal of business & economics, 7(4), 321-348.

[39] Adoboe-Mensah, N., Salia, H., & Addo, E. B. (2023). Using the Beneish m-score model to detect financial statement fraud in the microfinance industry in Ghana. International Journal of Economics and Financial Issues, 13(4), 47-57.

[40] Kokina, J., & Bradford, M. (2025). Robotic Process Automation Governance in Accounting Information Systems Research: A Multivocal Literature Review and Future Research Agenda. Journal of Information Systems, 1-23.

[41] Faisal, M. F., Saqlain, M. N. U., Bhuiyan, M. A. S., Miraz, M. H., & Patwary, M. J. (2021, December). Credit approval system using machine learning: Challenges and future directions. In 2021 International Conference on Computing, Networking, Telecommunications & Engineering Sciences Applications (CoNTESA) (pp. 76-82). IEEE.

[42] Zhang, Z. (2021, September). Research on the application of artificial intelligence technology in audit under the background of big data. In Journal of Physics: Conference Series (Vol. 2033, No. 1, p. 012150). IOP Publishing.

[43] da Silva, H. J. T., & Marques, P. V. (2021). Heterogeneity in the productivity of sugar-energy mills in Brazil. International Food and Agribusiness Management Review, 24(3), 371-396.

[44] Lootah, R. E. A. (2024). The impact of blockchain technology on financial reporting practices in UAE. International Journal of Digital Accounting and Fintech Sustainability, 1(1), 2-12.

[45] Kaminski, H. L. (2020). An Analysis of the Technological, Organizational, and Environmental Factors Influencing the Adoption of Lean Accounting in US Lean Manufacturing Firms. Anderson University, Indiana.

[46] Schaap, G., Bosse, T., & Hendriks Vettehen, P. (2024). The ABC of algorithmic aversion: Not agent, but benefits and control determine the acceptance of automated decision-making. AI & society, 39(4), 1947-1960.

[47] Tan, N. L. (2023). The bibliometric overview of research on healthcare information systems using big data analytics.

[48] Magerakis, E. (2024). Corporate tax avoidance under economic policy uncertainty. Does the quality of institutional governance matter?.

[49] Rudin C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence. 2019;1(5):206-215.

[50] Kurdi, G. (2022). Toward an Electronic Resource for Systematic Reviews in Computer Science.

[51] Schmitz J, Leoni G. Accounting and auditing at the time of blockchain technology: A research agenda. Australian Accounting Review. 2019;29(2):331-342.

[52] Ward, C. (2024, September). Getting to grips with heterogeneity in the informal economy.

[53] Lauletta, M., & Montano Campos, F. (2024). Is the forgiveness of a tax amnesty divine? Evidence from Argentina. International Tax and Public Finance, 31(5), 1229-1248.

[54] Tan, Y., Wu, B., Cao, J., & Jiang, B. (2025). LLaMA-UTP: Knowledge-Guided Expert Mixture for Analyzing Uncertain Tax Positions. IEEE Access.

[55] Zhou, D., Zhou, H., Bai, M., & Qin, Y. (2022). The COVID-19 outbreak and corporate cash-holding levels: Evidence from China. Frontiers in psychology, 13, 942210.

[56] Bartolacci, F., Caputo, A., Fradeani, A., & Soverchia, M. (2021). Twenty years of XBRL: what we know and where we are going. Meditari Accountancy Research, 29(5), 1113-1145.

[57] McKinlay, V., & Smith, J. A. (2024). The impact of advancing technologies on the requirement for a human workforce in accounting. In Research Handbook on Accounting and Information Systems (pp. 288-308). Edward Elgar Publishing.

[58] Zhang, Q., & She, J. (2024). Digital transformation and corporate tax avoidance: An analysis based on multiple perspectives and mechanisms. PloS one, 19(9), e0310241.

[59] Malo-Alain, A., Aldoseri, M., & Melegy, M. (2021). Measuring the effect of international financial reporting standards on quality of accounting performance and efficiency of investment decisions. Accounting, 7(1), 249-256.

[60] Weerawarna, R., Miah, S. J., & Shao, X. (2023). Emerging advances of blockchain technology in finance: a content analysis. Personal and Ubiquitous Computing, 27(4), 1495-1508.

[61] Varma, A., Piedepalumbo, P., & Mancini, D. (2021). Big data and accounting: A bibliometric study. The International Journal of Digital Accounting Research, 21(27), 203-238.

[62] Clatworthy, M. A., Lara, J. M. G., & Lee, E. (Eds.). (2025). Accounting and Auditing in China. Routledge.

[63] Oguntibeju, O., Adonis, M., & Alade, J. (2024). Systematic review of real-time analytics and artificial intelligence frameworks for financial fraud detection. International Journal of Advanced Research in Computer and Communication Engineering, 13(9).

[64] Lawal, S. (2021). Determinants of aggressive corporate tax planning practices of listed manufacturing companies in Nigeria (Master's thesis, Kwara State University (Nigeria)).

[65] Al-Hadi, A., Taylor, G., & Richardson, G. (2022). Are corruption and corporate tax avoidance in the United States related?. Review of Accounting Studies, 27(1), 344-389.

[66] Song, L., Zhang, J., Ma, D., Fan, Y., Lai, R., Tian, W., ... & Xu, H. (2022). A bibliometric and knowledgemap analysis of macrophage polarization in atherosclerosis from 2001 to 2021. Frontiers in immunology, 13, 910444.

[67] Grenier, J. H., Robertson, J. C., Simon, C. A., & Vinson, J. M. (2025). PCAOB Inspections and Auditor Liability. Auditing: A Journal of Practice & Theory, 44(2), 131-148.

[68] Agrawal, A., Gans, J., & Goldfarb, A. (Eds.). (2019). The economics of artificial intelligence: An agenda. University of Chicago Press.

[69] Parvez, M. O. (2021). Use of machine learning technology for tourist and organizational services: high-tech innovation in the hospitality industry. Journal of Tourism Futures, 7(2), 240-244.

[70] Myllymäki, D. (2021). Beyond the 'e-'in e-HRM: integrating a sociomaterial perspective. The International Journal of Human Resource Management, 32(12), 2563-2591.

[71] Davenport, T. H., Brynjolfsson, E., McAfee, A., & Wilson, H. J. (2019). Artificial intelligence: The insights you need from Harvard Business Review. Harvard Business Press.

[72] Walker, D. I. (2022). Tax complexity and technology. Ind. LJ, 97, 1095.

[73] Shah, I. H. (2025). Assessing the Influence of Artificial Intelligence on Corporate Tax Compliance and Financial Reporting.

[74] Laapotti, T., & Raappana, M. (2022). Algorithms and organizing. Human Communication Research, 48(3), 491-515.