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| RESEARCH ARTICLE

The Use of Technology and Data Analytics in Modern Auditing: A Systematic Review

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| ABSTRACT

The auditing profession is undergoing a significant transformation driven by advancements in technology and data analytics. While these innovations promise enhanced audit quality, efficiency, and reliability, their adoption and effectiveness vary across contexts. This systematic review synthesizes empirical evidence from 2020 to 2025 to examine the types, applications, outcomes, and challenges of technology and data analytics in modern auditing. Following PRISMA guidelines, a comprehensive search was conducted across Scopus, Web of Science, IEEE Xplore, and ScienceDirect, yielding 260 records. After screening, 10 studies met the inclusion criteria. Risk of bias was assessed using the ROBINS-I tool, and findings were synthesized narratively due to methodological heterogeneity. The review highlights the transformative impact of technologies such as big data analytics, artificial intelligence, and federated learning on audit quality and efficiency. Key findings include the positive role of client technological readiness in remote auditing, the moderating effect of cybersecurity on audit data analytics, and the challenges of skill gaps and resource constraints in small and medium-sized practices. However, benefits are context-dependent, with emerging markets facing unique regulatory and infrastructural barriers. While technology and data analytics offer substantial benefits for auditing, their successful implementation requires tailored strategies that address contextual, technical, and human factors. Future research should prioritize longitudinal and comparative studies to bridge the gap between experimental promise and practical application.

| KEYWORDS

Auditing, technology, data analytics, artificial intelligence, systematic review, audit quality

| ARTICLE INFORMATION

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1. Introduction

The auditing profession is experiencing unprecedented transformation driven by rapid technological advancements and the proliferation of big data (Salijeni, Samsonova-Taddei et al. 2019). Traditionally, auditing relied heavily on manual procedures, sampling methods, and retrospective analyses, often constrained by time and resource limitations (Bass, Kaplan et al. 2023). However, the emergence of advanced technologies, such as artificial intelligence (AI), machine learning, blockchain, robotic process automation (RPA), and sophisticated data analytics tools, has fundamentally reshaped the landscape of audit practices (Chukwuani 2023). These technological innovations enable auditors to process vast volumes of data efficiently, identify anomalies and risks proactively, and provide enhanced assurance with greater precision and timeliness (Hossain, Johora et al. 2024).

In recent years, regulatory bodies and professional organisations, including the International Auditing and Assurance Standards Board (IAASB) and major accounting firms, have increasingly emphasised the integration of technology into audit methodologies to enhance audit quality, efficiency, and relevance (Crawford, Helliar et al. 2014). Data analytics, in particular, allows auditors to analyse entire data populations rather than limited samples, facilitating deeper insights into financial transactions and operational processes (Liew, Boxall et al. 2022). Similarly, AI and machine learning algorithms are being used to automate routine tasks, support fraud detection, and generate predictive models, while blockchain offers the potential for real-time verification of transactions with immutability and transparency (Bello, Idemudia et al. 2024).

Despite these promising developments, the adoption and effective implementation of technology in auditing remain heterogeneous across contexts and jurisdictions. Challenges such as data integration complexities, lack of technical expertise, regulatory uncertainties, and concerns regarding data privacy and security continue to affect widespread implementation (Austin, Carpenter et al. 2021). Furthermore, existing research on the practical application, effectiveness, and implications of these technologies in audit practices is fragmented, with limited systematic synthesis to inform evidence-based adoption strategies for audit firms and regulators.

Given this background, this systematic review aims to comprehensively examine and synthesise existing empirical evidence on the use of technology and data analytics in modern auditing. By analysing recent studies published between 2020 and 2025, the review seeks to answer the following key questions: What types of technologies and data analytics tools are currently used in auditing? How have these technologies been implemented in audit processes? What outcomes, benefits, and challenges are reported in the literature regarding their use? Addressing these questions will provide valuable insights into the state of technological adoption in auditing and identify gaps to inform future research, policy development, and professional practice.

2. Results

2.1 Studies Selection Process

The study selection process followed the PRISMA guidelines, beginning with the identification of 260 records from four databases: IEEE Xplore (n = 72), Web of Science (n = 48), ScienceDirect (n = 47), and Scopus (n = 93). After removing 164 duplicate records, 96 studies remained for screening. Of these, 31 were excluded due to paywall restrictions, leaving 65 full-text articles assessed for eligibility. Further exclusions were applied, including 23 studies focused on traditional manual auditing and 32 editorial letters, review articles, and case reports. Ultimately, 10 studies met the inclusion criteria and were retained for the systematic review (Figure 1).

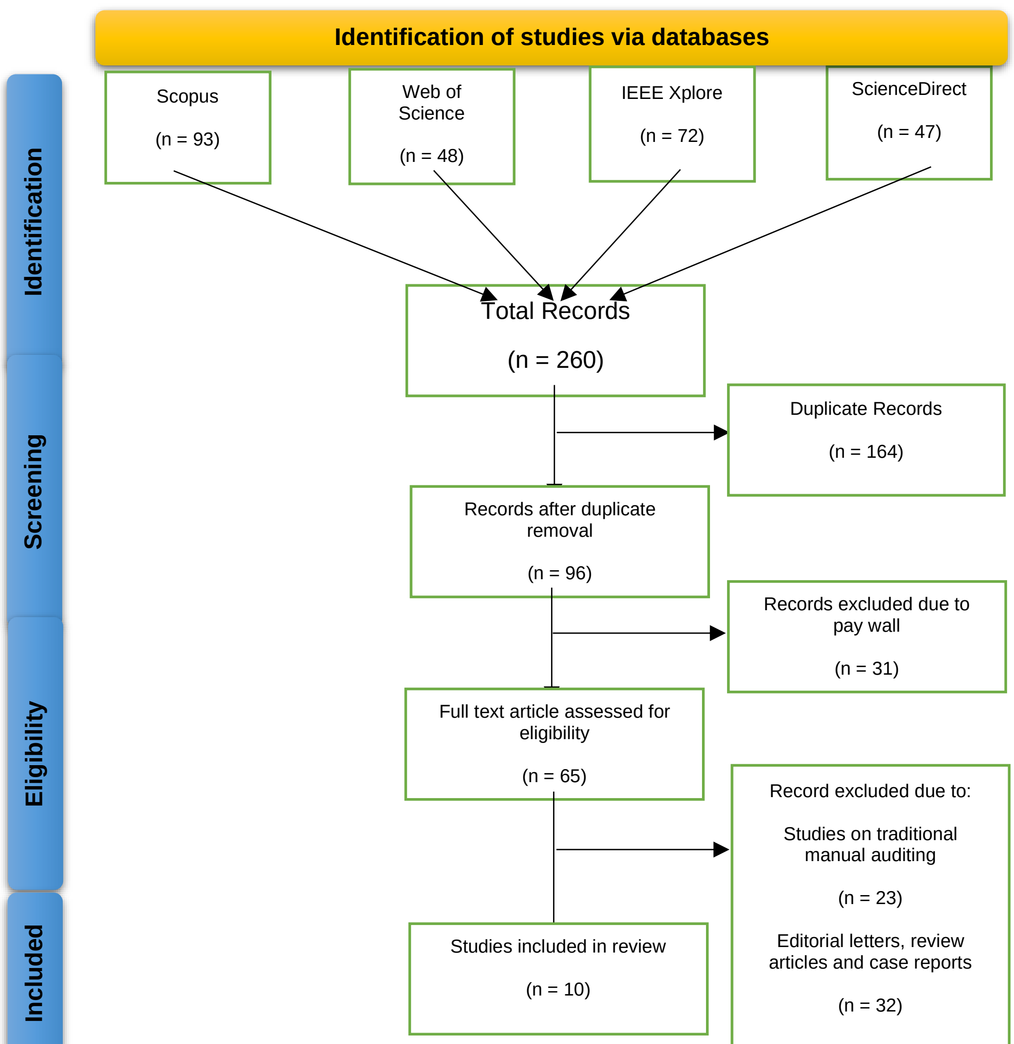

Figure 1: PRISMA Flowchart of Studies Selection Process

2.2 Impact of Big Data and Data Analytics on Audit Quality

The reviewed studies demonstrate a significant positive impact of big data and data analytics (BD&A) on audit quality (AQ). For instance, Al Lawati, Sanad et al. found that big data disclosure enhances audit quality in Omani financial firms, with family board membership positively moderating this relationship, while royal membership negatively moderates it (Al Lawati, Sanad et al. 2024). Similarly, Abdelwahed, Abu-Musa et al. provided empirical evidence from Egypt, showing that BD&A adoption improves audit processes and auditor competence, though its effect on audit fees was insignificant (Abdelwahed, Abu-Musa et al. 2025). These findings highlight the growing importance of BD&A in enhancing audit reliability and effectiveness, particularly in emerging markets. However, the study by Al Lawati, Sanad et al. was limited to financial institutions, suggesting the need for broader sectoral applicability (Al Lawati, Sanad et al. 2024) (Table 1).

Table 1: Characteristics of Included Studies

Author(s) (Year)	Country	Study Objective	Study Design	Sample / Data Source	Technology / Tool Used	Application Area	Key Findings / Outcomes	Limitations (if reported)
(Al Lawati, Sanad et al. 2024)	Oman	To investigate the impact of big data disclosure on audit quality in Omani financial firms	Content analysis with OLS and panel data regression	Annual reports of financial companies listed on Muscat Stock Exchange (2014–2020)	Content analysis; OLS regression; panel data regression	Audit quality enhancement through big data disclosure	Big data disclosure enhances audit quality; family membership on board positively moderates this relationship; royal membership negatively moderates it	Only financial institutions included in the sample
(Ali, Elshaer et al. 2024)	Egypt	To examine the impact of remote audit quality (RAQ) on quality of audit work (QAW), and to explore the moderating effects of client technological readiness (CLTR) and auditor technology readiness (ADTR) on this relationship.	Questionnaire survey-based quantitative study	280 external auditors in Egypt	Smart-PLS software	Remote auditing and audit quality assessment	RAQ positively and significantly impacts QAW. CLTR positively moderates (strengthens) the RAQ-QAW relationship, while ADTR negatively moderates (weakens) it.	Not reported
(Eulerich, Masli et al. 2023)	Germany	To examine how internal auditors use Technology-Based Audit Techniques	Mixed-method (Two surveys + Interviews)	Individual auditors and Chief Audit Executives (CAEs)	Technology-Based Audit Techniques (TBATs)	Internal auditing	TBATs usage is associated with completing more audits, identifying more risk	Benefits of TBATs are difficult to quantify in a timely manner; challenges

		(TBATs) and how these impact audit efficiency and effectiveness					factors, giving more recommendations, and reducing audit days; however, TBATs increase internal audit function size due to costs. CAEs find benefits hard to quantify and face skill gaps	in hiring auditors with appropriate skills; no country-specific generalizability reported
(Ditkaew and Suttipun 2023)	Thailand	To examine the impact of audit data analytics (ADA) on audit quality (AQ) and audit review continuity (ARC)	Quantitative survey study with path analysis	452 Certified Public Accountants (CPAs) in Thailand; data collected via mail questionnaires	Audit Data Analytics (ADA); Cybersecurity (as moderator)	Auditing (Audit Quality and Review Continuity)	ADA had a positive impact on AQ and ARC; Cybersecurity moderated the interaction between ADA, AQ, and ARC	Not reported
(Mashiko, Kawamata et al. 2025)	Japan	To propose and evaluate a Data Collaboration (DC) analysis framework for anomaly detection in auditing while preserving data confidentiality and reducing communication overhead	Experimental study evaluating proposed method on synthetic and real datasets	Synthetic dataset and real journal entry data from multiple organizations	DC analysis; Federated Learning (FL); FedAvg; Autoencoder; Dimensionality Reduction	Financial auditing anomaly detection	Proposed DC-based framework outperformed single-organization baselines and FedAvg in non-i.i.d. settings, ensured data confidentiality, and reduced communication rounds needed for federated learning	Not reoprted
(Schreyer, Hemati et al. 2022)	USA	To propose and evaluate a Federated Continual Learning framework for detecting accounting	Empirical evaluation study	Real-world datasets (not specified which firms or countries)	Federated Continual Learning framework using Deep Learning techniques	Financial auditing – detection of accounting anomalies in decentralized digital	Demonstrated that combined federated continual learning strategies can effectively detect anomalies in audit settings	Not reported

		anomalies in decentralised and dynamic audit settings				accounting data	with data distribution shifts over clients and time periods	
(Mhlongo 2021)	South Africa	To investigate the factors that contribute to successes and failures in other areas of audit by small and medium-sized audit practices, focusing on data analytics adoption.	Qualitative	10 internal auditors interviewed	NVivo (for thematic analysis); Fuzzy Set Theory; Grounded Theory	Internal auditing (Small and Medium Practices)	Transformation of internal audit activities in small and medium practices requires greater data analytics development beyond just technical capabilities to reach maturity in data analytics usage.	Study based on small sample size (10 participants); qualitative generalizability not discussed explicitly.
(Abdelwahed, Abu-Musa et al. 2025)	Egypt	To empirically investigate the impact of adopting big data and data analytics (BD&A) on audit quality (AQ)	Quantitative survey using Partial Least Square Structural Equation Modeling (PLS-SEM)	205 responses from audit practitioners working at audit firms in Egypt	Big Data & Data Analytics (BD&A); PLS-SEM for analysis	Audit process, auditor competence, audit fees, and overall audit quality	BD&A has significant positive effects on audit process and auditor competence, an insignificant effect on audit fees, and overall significant direct and indirect impacts on audit quality	Results may be limited to a developing country with a less-regulated audit environment
(Pratama and Komariyah 2023)	Indonesia	To examine the determinants of auditors' acceptance of big data analytics (BDA) technology using UTAUT and trust model	Quantitative survey-based study with Structural Equation Modeling	Responses from 83 government auditors who attended BDA training and had access to BDA technology	Big Data Analytics (BDA) technology; SmartPLS 3 software for SEM analysis	Auditors' acceptance of Big Data Analytics technology	Effort expectancy, performance expectancy, and facilitating condition significantly influence acceptance; social influence and trust do not influence acceptance	Not reported

(Sofyani, Rohman et al. 2025)	Indonesia	To examine the impact of quality of Big Data Analytics (BDA)-based audit systems on audit performance in the public sector, focusing on the mediating role of audit judgment	Quantitative survey-based study	137 government auditors across Indonesia	Big Data Analytics (BDA)-based audit system; SEM-PLS for analysis	Public sector auditing	Audit judgment mediates the relationship between BDA-based audit system quality and audit performance, highlighting its role in optimizing audit technology effectiveness	Not reported

2.3 Role of Technology-Based Audit Techniques (TBATs)

Technology-Based Audit Techniques (TBATs) were found to significantly improve audit efficiency and effectiveness. Eulerich, Masli et al. revealed that TBATs enable auditors to complete more audits, identify more risk factors, and provide more recommendations while reducing audit days (Eulerich, Masli et al. 2023). However, the study also noted challenges, such as difficulties in quantifying TBATs' benefits and skill gaps among auditors. These findings underscore the dual nature of TBATs—offering substantial operational benefits while requiring careful cost-benefit analysis and workforce upskilling (Table 2).

Table 2: Key Contributions and Implications of Included Studies

Author(s) (Year)	Methodology / Analytical Approach	Key Contribution / Innovation	Practical Implications for Auditing Practice	Future Research Suggested
(Al Lawati, Sanad et al. 2024)	Content analysis of annual reports (2014-2020); OLS regression; Panel data regression; Moderation analysis with family and royal board membership	First study to examine the impact of big data disclosure on audit quality in the Omani context; Revealed positive moderation by family membership and negative moderation by royal membership	Highlights the importance for investors, managers, and policymakers to implement regulations mandating big data disclosure in annual reports to enhance audit quality, reliability, and validity of financial reports	Suggests expanding research beyond financial institutions to other sectors for generalisability; further exploration of different board compositions moderating the disclosure-audit quality relationship
(Ali, Elshaer et al. 2024)	Questionnaire survey of 280 external auditors in Egypt; Data analysis using Smart-PLS software	First study examining the moderating roles of CLTR and ADTR on the relationship between RAQ and QAW; Found CLTR strengthens and ADTR weakens RAQ-QAW relationship	Provides guidance for companies, auditing firms, professional bodies, and regulators on the importance of technological readiness in enhancing remote audit effectiveness; Encourages focus on client tech readiness while managing auditor tech readiness to optimize audit quality	Further studies could explore these moderating effects in other emerging markets and advanced economies; Investigate additional technological or organizational factors influencing remote audit quality
(Eulerich, Masli et al. 2023)	Two surveys and interviews of individual auditors and CAEs	Examined how TBATs impact audit efficiency and effectiveness; Found that increased	TBATs can significantly enhance audit efficiency and effectiveness but require careful cost-benefit analysis	Further research on quantifying TBATs' benefits, understanding

		TBAT use is linked to more audits completed, more risk factors identified, more recommendations provided, and fewer audit days, despite higher costs due to larger audit teams	and hiring of skilled auditors to implement effectively	barriers to their adoption, and evaluating their long-term impacts on audit quality and organizational performance
(Ditkaew and Suttipun 2023)	Mail questionnaires collected from 452 CPAs in Thailand; Descriptive analysis, correlation matrix, and path analysis	Demonstrated that ADA positively influences AQ and ARC; introduced cybersecurity as a moderating factor enhancing these relationships; applied Resource Advantage Theory in the auditing context	Encourages auditors and audit firms to integrate Big Data and ADA to enhance AQ and ARC; highlights the importance of cybersecurity considerations in audit analytics applications	Future research can explore the role of cybersecurity in greater depth, assess ADA impacts in different national contexts, and investigate additional moderating variables affecting the ADA-AQ-ARC relationship
(Mashiko, Kawamata et al. 2025)	DC analysis framework with dimensionality reduction and autoencoder for anomaly detection; compared with FedAvg (federated learning baseline); evaluated on synthetic and real journal entry data.	Proposed a novel non-model share FL approach (DC analysis) enabling single-round communication for cross-organization anomaly detection while preserving data confidentiality; outperformed traditional FedAvg in non-i.i.d. conditions.	Enables audit firms to collaboratively build high-performing anomaly detection models without sharing confidential data, reducing communication overhead and enhancing practical feasibility of AI-based audits.	Future studies could explore extension to other audit tasks beyond anomaly detection, real-world implementation across diverse audit firm systems, and integration with regulatory compliance frameworks.
(Schreyer, Hemati et al. 2022)	Federated Continual Learning framework; empirical evaluation using real-world datasets; combined federated continual learning strategies	Proposed a Federated Continual Learning framework enabling auditors to build adaptive audit models from decentralized clients continuously; demonstrated effectiveness in detecting accounting anomalies under data distribution shifts	Enhances auditors' ability to conduct real-time anomaly detection across decentralized and dynamic organizational datasets, improving continuous assurance and audit quality	Future research could explore optimizing federated continual learning strategies for different audit contexts, integrating additional AI models, and assessing scalability in large multi-client environments
(Mhlongo 2021)	Qualitative research using Grounded Theory and Fuzzy Set Theory; Data collected through interviews with 10 internal auditors; Thematic analysis using NVivo.	Identified that small and medium-sized internal audit practices require significant data analytical development beyond technical capabilities to transform their audit activities towards mature use of data analytics.	Highlights the need for capacity building, skill development, and strategic investment in data analytics for internal auditors to add value and reduce organisational risks in the era of digitisation and Industry 4.0.	Suggested future research to further explore specific data analytical tools and capability-building frameworks tailored for small and medium-sized internal audit practices to achieve data analytics maturity.

(Abdelwahed, Abu-Musa et al. 2025)	Questionnaire survey (205 responses) among audit practitioners in Egypt; analyzed using PLS-SEM	Empirically investigated the direct and indirect effects of BD&A on AQ; Introduced a model incorporating AP, AF as mediators to explain BD&A's influence on AQ; Provided early evidence from a developing country with a less-regulated audit environment	Demonstrates that BD&A enhances audit processes and auditor competence, thus supporting audit firms in adopting BD&A tools to improve audit quality; Suggests value for audit firms, regulators, and novice auditors in understanding and integrating BD&A effectively	Extend empirical analysis to other developing countries or comparative contexts; Explore additional mediating factors or barriers influencing BD&A's impact on audit quality; Conduct longitudinal studies to assess BD&A effects over time
(Pratama and Komariyah 2023)	SEM using SmartPLS 3 software; based on UTAUT theory and trust model; survey of 83 government auditors	Identified that effort expectancy, performance expectancy, and facilitating conditions significantly influence auditors' acceptance of Big Data Analytics (BDA) technology, while social influence and trust do not; Novel application of UTAUT + trust in government auditing context	Advises government audit agencies to ensure BDA technologies are easy to adopt, demonstrate clear audit quality benefits, and provide strong technical/infrastructure support to enhance acceptance	Future research could explore additional factors influencing BDA acceptance, examine private sector auditors, test alternative technology adoption models, or investigate actual usage behavior and audit outcomes post-implementation
(Sofyani, Rohman et al. 2025)	Quantitative survey of 137 government auditors in Indonesia; data analyzed using SEM-PLS	Identified that audit judgment mediates the relationship between BDA-based audit system quality and audit performance in the public sector, addressing inconsistent findings in prior literature	Highlights the importance of enhancing audit judgment skills to maximize the benefits of Big Data Analytics systems for improved audit performance among government auditors	Further research can explore other potential mediators or moderators influencing the relationship between BDA-based audit systems and audit performance, and validate findings in different sectors or countries

2.4 Remote Auditing and Technological Readiness

The shift toward remote auditing has introduced new dynamics in audit quality. Ali, Elshaer et al. examined the role of technological readiness in RAQ and found that CLTR strengthens the relationship between RAQ and QAW, while ADTR weakens it (Ali, Elshaer et al. 2024). This study emphasizes the need for organizations to prioritize client-side technological preparedness to optimize remote audit outcomes. The practical implications include recommendations for firms and regulators to invest in technology infrastructure and training to support remote auditing practices.

2.5 Audit Data Analytics (ADA) and Cybersecurity

ADA has emerged as a critical tool for enhancing audit quality and continuity. Ditkaew and Suttipun demonstrated that ADA positively influences AQ and ARC in Thailand, with cybersecurity acting as a moderating factor (Ditkaew and Suttipun 2023). This study highlights the importance of integrating cybersecurity measures with ADA to safeguard audit processes and ensure their reliability. The findings suggest that audit firms should adopt ADA while addressing cybersecurity risks to maximize its benefits.

2.6 Federated Learning and Anomaly Detection

Innovative technologies like FL are transforming anomaly detection in auditing. Mashiko, Kawamata et al. proposed a DC analysis framework that outperforms traditional federated learning methods in detecting anomalies while preserving data confidentiality (Mashiko, Kawamata et al. 2025). Similarly, Schreyer, Hemati et al. introduced a Federated Continual Learning framework, enabling auditors to detect accounting anomalies in decentralized and dynamic settings (Schreyer, Hemati et al. 2022). These studies highlight the potential of FL to enhance audit accuracy and efficiency while addressing data privacy concerns.

2.7 Adoption Challenges and Facilitators

The adoption of advanced audit technologies is influenced by various factors. Pratama and Komariyah identified effort expectancy, performance expectancy, and facilitating conditions as key determinants of auditors' acceptance of Big Data Analytics (BDA) technology in Indonesia (Pratama and Komariyah 2023). In contrast, social influence and trust were found to be insignificant. These findings align with Sofyani, Rohman et al., who emphasized the mediating role of audit judgment in linking BDA-based audit systems to audit performance (Sofyani, Rohman et al. 2025). Together, these studies suggest that ease of use, perceived benefits, and institutional support are critical for successful technology adoption in auditing.

2.8 Internal Auditing in Small and Medium Practices

Mhlongo explored data analytics adoption in small and medium-sized audit practices, revealing that these firms require more than technical capabilities to achieve maturity in data analytics usage (Mhlongo 2021). The study underscores the need for strategic investments in skills development and capacity building to enable smaller practices to leverage data analytics effectively. These insights are particularly relevant for policymakers and professional bodies aiming to support the digital transformation of smaller audit firms.

2.9 Summary of Key Findings

The reviewed studies collectively illustrate the transformative role of technology and data analytics in modern auditing. From enhancing audit quality through BD&A and TBATs to enabling remote auditing and innovative anomaly detection methods, these technologies offer significant benefits. However, challenges such as skill gaps, cybersecurity risks, and adoption barriers must be addressed to fully realize their potential. Tables 1 and 2 provide a comprehensive overview of the characteristics, contributions, and implications of these studies, highlighting the diverse methodologies and contexts explored.

2.10 Risk of Bias Summary

The ROBINS-I assessment revealed varying degrees of bias across the included studies. Experimental studies, such as those by Mashiko et al. and Schreyer et al., demonstrated the lowest risk due to controlled methodologies and objective outcome measures (Schreyer, Hemati et al. 2022, Mashiko, Kawamata et al. 2025). Conversely, Mhlongo exhibited high bias because of its small qualitative sample (n=10) and subjective thematic analysis (Mhlongo 2021), while Ali et al. faced moderate bias from self-reported remote audit quality data, which risks perceptual distortion (Ali, Elshaer et al. 2024). Surveys relying on self-reported technology adoption (Pratama and Komariyah 2023, Abdelwahed, Abu-Musa et al. 2025, Sofyani, Rohman et al. 2025) were prone to confounding and measurement bias, though their low attrition and full reporting mitigated selective reporting risks. Similarly, Ditkaew & Suttipun and Al Lawati et al. had moderate bias due to single-country samples and mail survey limitations (Ditkaew and Suttipun 2023, Al Lawati, Sanad et al. 2024), whereas Eulerich et al. (2023) achieved low bias despite survey non-response, owing to its mixed-method rigor (Eulerich, Masli et al. 2023) (Table 3).

Table 3: Risk of Bias Assessment Using ROBINS-I Tool

Author(s) (Year)	Confounding	Selection	Intervention Measurement	Missing Data	Outcome Measurement	Selective Reporting	Overall Bias
(Al Lawati, Sanad et al. 2024)	Moderate	Moderate	Low	Low	Low	Low	**Moderate**
(Ali, Elshaer et al. 2024)	High	Moderate	Moderate	Low	Moderate	Low	**Moderate**
(Eulerich, Masli et al. 2023)	Low	Low	Low	Moderate	Low	Low	**Low**
(Ditkaew and Suttipun 2023)	Moderate	Moderate	Moderate	Moderate	Moderate	Low	**Moderate**
(Mashiko, Kawamata et al. 2025)	Low	Low	Low	Low	Low	Low	**Low**

(Schreyer, Hemati et al. 2022)	Low	Low	Low	Low	Low	Low	**Low**
(Mhlongo 2021)	High	High	High	Low	High	Low	**High**
(Abdelwahed, Abu-Musa et al. 2025)	Moderate	Moderate	Moderate	Low	Moderate	Low	**Moderate**
(Pratama and Komariyah 2023)	Moderate	Moderate	Moderate	Low	Moderate	Low	**Moderate**
(Sofyani, Rohman et al. 2025)	Moderate	Moderate	Moderate	Low	Moderate	Low	**Moderate**

3. Discussion

The findings of this systematic review underscore the transformative role of technology and data analytics in modern auditing, while also highlighting critical challenges and variations in implementation across different contexts. The reviewed studies collectively demonstrate that advanced technologies such as BDA, AI, and FL significantly enhance audit quality, efficiency, and reliability. For instance, Al Lawati, Sanad et al. and Abdelwahed, Abu-Musa et al. provide robust evidence that BDA adoption improves audit processes and auditor competence, particularly in emerging markets (Al Lawati, Sanad et al. 2024, Abdelwahed, Abu-Musa et al. 2025). These findings align with prior research by Alles, who argued that data analytics enables auditors to identify anomalies and risks more effectively than traditional methods (Alles 2015). However, the impact of BDA on audit fees remains inconclusive, as noted by Abdelwahed et al., suggesting that cost-benefit trade-offs warrant further exploration (Abdelwahed, Abu-Musa et al. 2025). This contrasts with the optimistic projections of earlier literature (Brown-Liburd, Issa et al. 2015), which assumed widespread BDA adoption would uniformly reduce costs. The moderating effects of organizational factors, such as board composition (Al Lawati, Sanad et al. 2024), further complicate this relationship, indicating that technological benefits are context-dependent.

Remote auditing, another key theme, has gained prominence due to global digitization trends, but its success hinges on technological readiness. Ali, Elshaer et al. (2024) found that CLTR strengthens the link between RAQ and audit outcomes, while ADTR surprisingly weakens it (Ali, Elshaer et al. 2024). This counterintuitive finding challenges assumptions in existing literature (Cao, Chychyla et al. 2015), which posited that auditor proficiency would dominate remote audit efficacy. A plausible explanation, as inferred from Ali et al., is that clients with superior tech infrastructure reduce auditors' workload, whereas over-reliance on auditor tools may introduce complexity (Ali, Elshaer et al. 2024). This nuance underscores the need for balanced investments in both client and auditor technologies, a gap not fully addressed in earlier frameworks like the TAM applied by Pratama and Komariyah (Pratama and Komariyah 2023). Their study, focusing on Indonesian government auditors, revealed that effort expectancy and facilitating conditions—not social influence—drive BDA acceptance, reinforcing Venkatesh et al.'s UTAUT model while contradicting its social influence component (Venkatesh, Morris et al. 2003). This discrepancy may reflect cultural differences in technology adoption, a factor underexplored in generic audit-tech literature.

The integration of AI and machine learning in auditing, particularly through FL, represents a paradigm shift in anomaly detection and data privacy. Mashiko, Kawamata et al. and Schreyer, Hemati et al. demonstrated that FL frameworks outperform traditional methods in detecting accounting anomalies while preserving data confidentiality (Schreyer, Hemati et al. 2022, Mashiko, Kawamata et al. 2025). These advancements address long-standing concerns about data security in multi-party audits (Kokina, Mancha et al. 2017), yet they also reveal new challenges. For example, Eulerich, Masli et al. noted that TBATs increase internal audit function costs due to skill gaps and scalability issues (Eulerich, Masli et al. 2023), echoing warnings by Issa et al. about the "digital divide" in audit firms (Issa, Sun et al. 2016). The mixed-method findings of Eulerich et al.—where TBATs improved audit outputs but raised operational costs—suggest that efficiency gains are not automatic but require strategic resource allocation (Eulerich, Masli et al. 2023). This aligns with Mhlongo's qualitative work (Mhlongo 2021), which emphasized that small and medium audit practices struggle with data analytics adoption due to limited resources, a theme absent in studies of larger firms (Zhang, Yang et al. 2015). Such disparities highlight the need for tailored adoption roadmaps, as one-size-fits-all approaches risk exacerbating inequities in audit quality.

The role of cybersecurity as a moderator in audit analytics, as explored by Ditkaew and Suttipun, introduces another layer of complexity (Ditkaew and Suttipun 2023). Their study of Thai auditors found that cybersecurity measures strengthen the positive effects of ADA on audit quality and continuity, a finding consistent with global trends (Syam, Djaddang et al. 2025). However, the study's single-country focus limits generalizability, a recurring issue in audit-tech research. Similarly, Sofyani, Rohman et al. identified audit judgment as a mediator between BDA systems and performance in Indonesia's public sector, challenging the techdeterministic view that tools alone guarantee better outcomes (Sofyani, Rohman et al. 2025). This resonates with Knechel and Salterio's assertion that human judgment remains irreplaceable, even in data-driven audits (Knechel and Salterio 2016). The interplay between technology and auditor expertise, as illustrated by these studies, suggests that future frameworks must integrate both technical and cognitive dimensions—a synthesis lacking in earlier models like the "audit data analytics maturity" framework (Alles 2015).

Geographical and sectoral disparities further complicate the adoption and efficacy of audit technologies. Studies from emerging markets (e.g., Egypt, Oman, Thailand) consistently reported moderating factors—such as regulatory environments and board structures—that are less salient in developed economies. For instance, Abdelwahed et al. observed that Egypt's less-regulated audit environment dampens the fee impact of BDA (Abdelwahed, Abu-Musa et al. 2025), a phenomenon not observed in studies from the EU or US ((Brown-Liburd, Issa et al. 2015). This aligns with institutional theory (Scott, 2014), which posits that local norms shape technology assimilation. Conversely, experimental studies like Mashiko et al. and Schreyer et al., which prioritized methodological rigor over contextual diversity, achieved low bias but may lack real-world applicability (Schreyer, Hemati et al. 2022, Mashiko, Kawamata et al. 2025). This tension between internal validity and generalizability is a persistent issue in audit-tech research, as noted by Power in his critique of "tool-centric" auditing studies (Power 2015).

3.1 Limitations

Despite its comprehensive scope, this review has limitations. First, the predominance of survey-based studies (Ditkaew and Suttipun 2023, Ali, Elshaer et al. 2024) introduces self-reporting biases, and their single-country designs limit cross-regional insights. Second, the exclusion of non-English studies may overlook regional innovations. Third, rapid technological advancements mean some findings (e.g., federated learning applications) may soon become outdated. Finally, the review's focus on academic literature neglects practitioner reports, which often provide earlier evidence of real-world challenges..

4. Materials and Methods

4.1 Study Design

This systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, replicability, and methodological rigour (Page, McKenzie et al. 2021).

4.2 Eligibility Criteria

Studies were included or excluded based on predefined criteria summarised in Table 4. Studies published from 2020 to 2025 were included to ensure that the review captures the most recent advancements and contemporary applications of technology and data analytics in auditing, reflecting current practices, innovations, and research trends relevant to the rapidly evolving auditing landscape. Studies employing quantitative, qualitative, or mixed-methods designs were eligible. Only peer-reviewed journal articles published in English were included to maintain quality and relevance. Conversely, studies were excluded if they were editorials, letters to the editor, commentaries, opinion pieces, conference abstracts without full papers, theses, dissertations, or studies unrelated to auditing practices.

Table 4. Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Population	Auditors, audit firms, or organisations implementing technology/data analytics in auditing	Studies focusing on non-audit domains such as taxation, general accounting software, or unrelated information systems
Intervention/Exposure	Use of technology, data analytics, AI, blockchain, RPA, or advanced IT tools in auditing processes	Studies on traditional manual auditing without technology integration
Outcome	Implementation outcomes, effectiveness, performance, perceptions, or challenges of technology use in auditing	Studies without clear outcomes or descriptive articles lacking analysis of use in auditing
Study Design	Quantitative, qualitative, or mixed-methods original studies	Editorials, reviews, commentaries, letters, conference abstracts, theses, dissertations
Language	English	Non-English publications
Publication Year	2020-2025	Published before 2020

4.3 Information Sources and Search Strategy

A comprehensive literature search was conducted across multiple electronic databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect, to identify relevant studies. The search strategy combined keywords and Medical Subject Headings (MeSH) such as "technology", "data analytics", "audit", "auditing", "blockchain", "artificial intelligence", and "machine learning" using Boolean operators AND and OR to maximise retrieval. The final search was performed on July 13, 2025. Additionally, reference lists of included articles were manually screened to identify any relevant studies missed in the electronic search.

4.4 Study Selection

All retrieved records were exported to EndNote for duplicate removal, followed by import into Rayyan for blinded screening. Two reviewers independently screened titles and abstracts against inclusion criteria. Full-text screening was then conducted for potentially eligible studies. Disagreements between reviewers were resolved through discussion and consensus, and if unresolved, a third reviewer adjudicated.

4.5 Data Extraction

Data were extracted independently by two reviewers using a predesigned extraction form in Microsoft Excel. Extracted data included study characteristics (author, year, country), study objectives, study design, sample and data sources, technology or tool used, application area, key findings or outcomes, and limitations reported. Discrepancies in data extraction were discussed and resolved by consensus to ensure accuracy.

4.6 Risk of Bias Assessment

The risk of bias in included studies was assessed using the ROBINS-I (Risk Of Bias In Non-randomised Studies - of Interventions) tool (Sterne, Hernán et al. 2016), as the review primarily included non-randomised observational and implementation studies. ROBINS-I evaluates seven domains of bias, including confounding, selection of participants, classification of interventions, deviations from intended interventions, missing data, measurement of outcomes, and selection of reported results. Two reviewers independently assessed each study, and any discrepancies were resolved through discussion. The ROBINS-I tool was chosen due to its suitability in evaluating methodological quality and internal validity of non-randomised studies addressing real-world implementation questions relevant to auditing practice.

4.7 Data Synthesis

Due to the heterogeneity of study designs, populations, interventions, and outcomes, and the qualitative or descriptive nature of most included studies, a meta-analysis was not conducted. Instead, a narrative synthesis approach was employed to systematically summarise findings across studies, structured by themes such as types of technologies used, implementation contexts, and reported outcomes or challenges. This approach enabled meaningful integration and interpretation of diverse evidence that could not be statistically pooled due to methodological and outcome variability.

4.8 Reporting

The results of the study selection process are reported using the PRISMA flow diagram. Findings are presented in tables and narrative summaries in the results section, structured according to the review objectives.

5. Conclusions

Technology and data analytics are reshaping auditing, but their benefits are neither uniform nor automatic. While tools like BDA and FL enhance audit quality and efficiency, their success depends on contextual factors—from client readiness to regulatory frameworks—that transcend technical specifications. The findings caution against techno-optimism, urging auditors to balance innovation with human judgment, adaptability, and equity considerations. Future research should prioritize longitudinal and comparative designs to capture evolving practices and bridge the gap between experimental promise and practical implementation. Until then, auditors must navigate this transformative era with both enthusiasm and critical reflection.

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