UHASSELT
KNOWLEDGE IN ACTION

Faculty of Business Economics

Master of Management

Master's thesis

A literature review on the application of Machine Learning in auditing

Muhammad Sanaan Zia

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Data Science

SUPERVISOR :
Prof. dr. Mieke JANS

2024
2025

UHASSELT
KNOWLEDGE IN ACTION

www.uhasselt.be
Universiteit Hasselt
Campus Hasselt:
Martelarenlaan 42 | 3500 Hasselt
Campus Diepenbeek:
Agoralaan Gebouw D | 3590 Diepenbeek

Faculty of Business Economics

Master of Management

Master's thesis

A literature review on the application of Machine Learning in auditing

Muhammad Sanaan Zia

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Data Science

SUPERVISOR :

Prof. dr. Mieke JANS

ACKNOWLEDGMENT

First and foremost, I would like to express my deepest gratitude to my supervisor, Dr. Mieke Jans, for her unwavering guidance, insightful feedback, and continuous support throughout the duration of my master's program. Your expertise and encouragement have been invaluable to the completion of this thesis.

I am grateful to my parents, Mr. Ghulam Subhani Zia and Mrs. Shazia Subhani, for their constant encouragement, patience, and belief in my abilities.

I would also like to extend my heartfelt thanks to my friends, Ms. Adrija Bose, Mr. Syed Saad Ali, Mr. Shah Fahad, and Mr. Jalal Momin Afridi, who have provided me with moral support and numerous moments of laughter.

Lastly, I thank my brother, Mr. Muhammad Imran Zia, who has taken on all my responsibilities back home, allowing me the peace of mind and support I needed to begin and pursue this master's journey—without his selfless help, this would not have been possible.

Muhammad Sanaan Zia

June 2025.

Applications of Machine Learning in Auditing

Muhammad Sanaan Zia
Faculty of Business Economics
Hasselt University
Diepenbeek, 3590, Belgium

Abstract. Machine Learning (ML) is transforming the audit profession by enabling automated, data-driven analysis of financial records at scale. This study examines the application of machine learning (ML) in auditing through a semi-systematic literature review of 30 peer-reviewed studies. The review identifies the most frequently applied ML models, common data preprocessing strategies, and key challenges that hinder their adoption in audit contexts. Findings reveal that supervised learning models, particularly Random Forest and Logistic Regression, dominate due to their balance between predictive performance and interpretability. Unsupervised and hybrid models, though less frequently used, show strong potential for detecting previously unseen anomalies and providing deeper insights to auditors. Preprocessing steps, such as addressing data imbalance, missing values, and heterogeneous formats, emerge as critical for both model accuracy and explainability. Adoption barriers span technical, organizational, and human factors, including high implementation costs, data quality issues, resistance to workflow changes, and limited ML expertise within the auditing profession. The study concludes that ML can significantly enhance audit quality, efficiency, and coverage, but successful integration requires selecting appropriate algorithms, ensuring high-quality data, incorporating interpretability tools, aligning with strategic objectives, and fostering a culture receptive to technology-assisted judgment.

Keywords: Machine learning; auditing; artificial intelligence; accounting

---

1 Introduction

The audit profession is experiencing extensive change, which is driven mainly by the torrent of data in modern financial environments and the increasing complexity of fraud detection using traditional methods (Adelakun, 2022). Conventional audits that were reliant on manual sampling and predefined rules are having a tough time coping with the scale and speed of today's financial data; millions of transactions can happen in seconds (Noordin et al., 2022). This change has created a need for advanced technologies like Machine Learning (ML), a category of algorithmic processes capable of recognizing patterns and outliers in high-volume datasets. ML allows automating anomaly detection, decreasing sampling risk, and accommodating the implementation of continuous auditing frameworks. These developments are of high significance in today's financial world (Mathauer & Oranje, 2024).

Regardless of these encouraging results, the real-world integration of ML into auditing remains scattered and unexplored. Practitioners are reluctant to implement ML in auditing due to the perceived lack of transparency in algorithmic decision-making, the high level of technical expertise required, and regulatory uncertainty (Dawood & ALmagtome, 2025; Ivakhnenkov, 2023). Moreover, real-world financial datasets often pose challenges such as inconsistency, incompleteness, and severe class imbalance, which limit their applicability and performance (Iliou et al., 2015). These issues highlight the importance of understanding not just which ML methods are used but also how data is preprocessed to adapt it to audit-specific formats, as well as the challenges holding back their widespread deployment.

We see existing literature focusing on various ML algorithms used in auditing, which include but are not limited to neural networks, support vector machines, and decision trees. There is no complete clarity in how these models have been applied in the context of a real-world audit environment (Baghdasaryan et al., 2022; Zhang et al., 2022a). The focus of most studies remains technical performance rather than practical deployment; this leaves auditors with no clear guidelines for model adoption. Unsupervised learning algorithms such as autoencoders and isolation forests show promise since they do not need labeled data to identify anomalies (Janjua et al., 2024). Conversely, supervised learning algorithms such as decision trees and logistic regression have proven effective at detecting known fraud patterns when labeled data is available (Ashtiani & Raahemi, 2022). Though each has its own pros and cons, it is not clear which (supervised or unsupervised) is better suited for auditing purposes. However, the success of either approach is heavily dependent on high-quality input data, correct feature engineering, model tuning, and the proper use of evaluation metrics, e.g., precision, recall, and F1 score to get the correct balance between false negatives and false positives.

Against the backdrop of the above challenges and opportunities, this thesis addresses the following research questions based on insights drawn from the existing literature:

Q1. Which ML methods are most widely used in auditing applications?

Q2. What data preprocessing techniques are being used on what kinds of data?

Q3. What challenges are hindering the adoption of ML in auditing processes?

To investigate the research questions, this study conducts a semi-systematic literature review, which is explained by (Snyder, 2019), which consists of academic studies with no year of publication limit.

The objectives of this study are:

- Identifying the most used ML models for anomaly detection in audit-related tasks.
- Examining preprocessing strategies like feature engineering and hyperparameter tuning.
- highlighting major hurdles to ML adoption.

While earlier research has examined individual machine learning approaches in auditing, there hasn't been much comparison of supervised, unsupervised, and hybrid models. The majority of the existing literature concentrates on algorithmic performance, often ignoring real-world implementation issues such as data preprocessing, model interpretability, and regulatory limitations. This thesis fills in these gaps through a semi-systematic literature review by providing a cohesive overview that unifies adoption barriers, data preparation methods, and model selection. By synthesizing methodological and organizational perspectives, this research contributes to both academic understanding and practical guidance for deploying ML in auditing contexts.

The remainder of this paper is structured as follows: Section 2 provides a review of the related literature in this domain. Section 3 describes the methodology used in this study. Section 4 illustrates the findings against the objectives of this study. Lastly, Sections 5 and 6 offer a discussion and conclusion of the paper, respectively.

2 Background

In recent decades, auditing and accounting have experienced profound changes driven by advances in digital technologies. The integration of emerging technologies into accounting and auditing is widely portrayed as both transformative and uneven, with blockchain, artificial intelligence (AI), and advanced analytics at the forefront of this shift. Blockchain's architecture of immutable, consensus-driven ledgers and self-executing smart contracts offers the potential to enhance transparency, trust, and operational efficiency, while AI-driven tools for anomaly detection and risk assessment expand analytical capacity and decision support (Han et al., 2023). In the broader context of Industry 4.0, these innovations intersect with the Internet of Things and big data analytics, automating transactional processes, reshaping professional skill requirements, and redefining the boundaries of financial information systems (Fulop et al., 2022). Advanced analytics, from descriptive to prescriptive forms, promise improved audit quality and more timely insights, yet implementation is constrained by uneven organizational readiness, disparities in technological investment, and uncertainty in regulatory frameworks governing audit evidence and technology-enabled assurance (Barr-Pulliam et al., 2022).

While the potential benefits are substantial, the actual pace and depth of adoption reveal a more complex reality. Practical impact often falls short of the disruption envisioned in early predictions, with barriers including technological limitations, high implementation costs, the persistence of qualitative judgments in auditing, and the challenges of integrating new systems into established governance structures (Oladejo et al., 2024; Seizov & Wulf, 2020). These tensions are evident across both private and public sector contexts, where digital technologies are influencing accountability, performance measurement, and reporting within evolving governance models such as network-based, collaborative, and digitally enabled systems (Grossi & Argento, 2022). The trajectory of change is therefore shaped not solely by technical capability but by the interplay of innovation potential with institutional, cultural, and environmental factors, highlighting that digital transformation in accounting and auditing is as much a socio-organizational process as it is a technological one.

Machine learning (ML) has become a central technology in the digital transformation of auditing, enabling auditors to recognize and apply patterns from financial data, refine algorithms based on feedback, and efficiently detect anomalies in accounting records (Fulop et al., 2022; Han et al., 2023). The progressive digitization of organizational operations and financial records has led to unprecedented increases in volume, velocity, and variety of audit-relevant data, particularly journal entries. These developments have surpassed the processing capabilities of traditional audit approaches. Manual sampling, retrospective rule-based testing, and static audit plans no longer meet the demands of modern audit environments (Z. Zhang & Wang, 2021). In response, both regulators and practitioners are increasingly integrating machine learning (ML) into audit processes to automate anomaly detection, identify potential misstatements, and support risk-based auditing frameworks. Supervised learning algorithms, such as support vector machines and logistic regression, have been used to detect fraud patterns when labeled data is available (Ashtiani & Raahemi, 2022), while random forest models have demonstrated high precision and recall in handling complex financial datasets and identifying non-linear relationships (Liu et al., 2024). Hybrid approaches that combine random forest with neural networks have been suggested to enhance adaptability to evolving fraud tactics (Liu et al., 2024). In contrast, unsupervised methods such as isolation forest and autoencoders are increasingly valued for their ability to detect novel anomalies without requiring labeled data (Janjua et al., 2024).

Ensemble techniques, such as light gradient boosting machines and combinations of random forest models, have achieved strong performance in transactional environments involving payments, transfers, and withdrawals. These models have optimized prediction speed, reduced false positives, and improved AUC scores, making them suitable for large-scale auditing tasks (Sun & Zhang, 2024). However, many evaluations are conducted using benchmark datasets, raising questions about their generalizability to the more complex and diverse datasets encountered in practice. Data preprocessing remains a critical step in adapting financial data for ML applications. Common challenges include incomplete, inconsistent, and imbalanced data, which can bias model performance (Zlobin & Bazylevych, 2025). Structured preprocessing pipelines incorporating feature scaling, stratified sampling, random undersampling, and outlier removal have been shown to improve detection accuracy, as measured by metrics such as ROC-AUC and cross-validation accuracy (Zlobin & Bazylevych, 2025).

The interpretability of ML models presents another challenge for audit adoption. Many algorithms function as “black boxes,” making their compliance with audit documentation standards and regulatory requirements difficult to assess. Explainable AI (XAI) techniques, including Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), have been proposed to address this issue, improving transparency and enabling auditors to understand and validate model outputs (Zhang et al., 2022b). While these advances hold promise, organizational and regulatory factors also influence adoption. Barriers include a shortage of internal expertise, high implementation costs, restrictions on client data access, and the need for auditor training to integrate these tools effectively while maintaining professional judgment and skepticism (Maharani et al., 2024). Emerging regulations, such as the EU AI Act, emphasize transparency, explainability, and auditability, yet the establishment of standardized datasets, governance frameworks, and best practices remains an ongoing priority (Seizov & Wulf, 2020).

Collectively, these developments indicate a paradigm shift in auditing and accounting where technological capability, regulatory adaptation, and human judgment must align to sustain innovation, enhance trust, and meet the evolving needs of stakeholders. ML, blockchain, and advanced analytics are not only reshaping technical practices but also redefining the role of the auditor in a data-driven, interconnected, and highly regulated global environment.

3 Methodology

The goal of this study is to identify the most widely used ML methods in auditing, examine the data preprocessing techniques applied, and explore the main challenges to ML adoption in auditing contexts. To achieve this, the study adopts a semi-structured literature review approach, explained by (Snyder, 2019), to explore the applications of ML in auditing. Given the rapid technological developments and the absence of consolidated academic reviews on ML in audit practice, a semi-systematic approach enables mapping the field's evolution, synthesizing methodologies, and identifying key challenges in an emerging and fragmented literature.

To ensure relevance and scholarly quality, a literature search across two databases was conducted: IEEE Xplore and Springer Link. For the search process, a search query was used based on three search terms: ("Machine" OR "unsupervised" OR "supervised" OR "ensemble") AND ("Learning" OR "methods") AND "Auditing". Initially, a total of 15,801 papers were returned from the search, 325 from IEEE Xplore and 15,476 from Springer Link. In Springer Link, we further use an "Auditing" subject filter to make sure the topics are of a relevant nature. The search included papers until June 2025. The selected literature offers insights into implementation practices, technical challenges, and performance benchmarks associated with ML in auditing contexts.

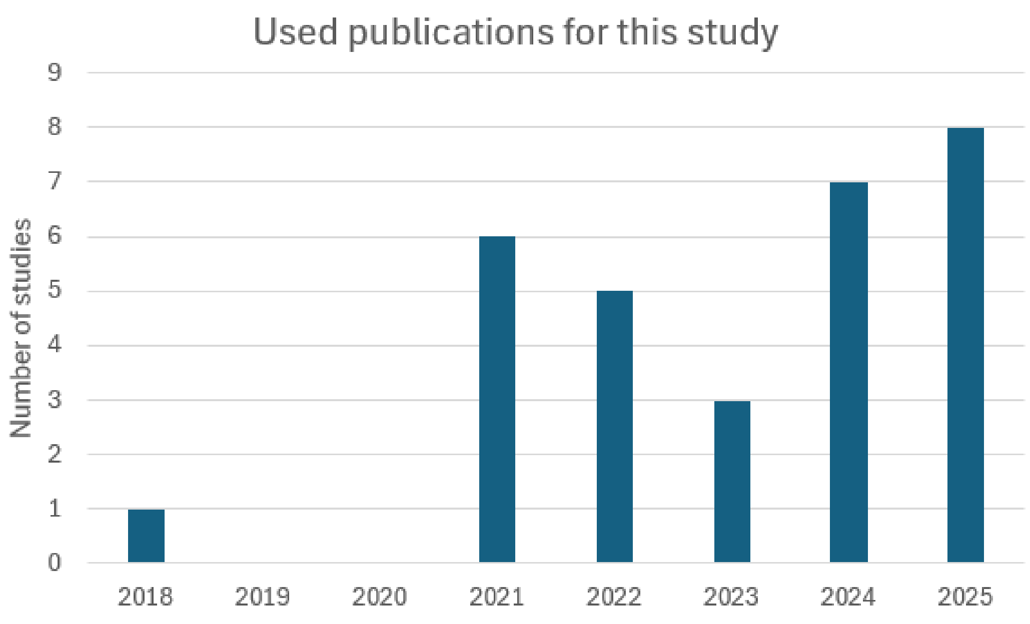

Fig. 1. Distribution of selected publications by year of publication.

3.1 Study Selection Criteria

To ensure quality and relevance, the literature selection followed specific inclusion criteria:

- Focus: ML applications in financial auditing
- Language: English
- Content: Articles presenting technical details on ML algorithms, pre-processing strategies, and practical implications such as interpretability and deployment

Exclusion criteria:

- Books, chapters, magazines
- Non-peer-reviewed sources
- Studies unrelated to auditing or financial data contexts
- Papers lacking technical details on ML usage
- Duplicate studies
- Non-English language articles

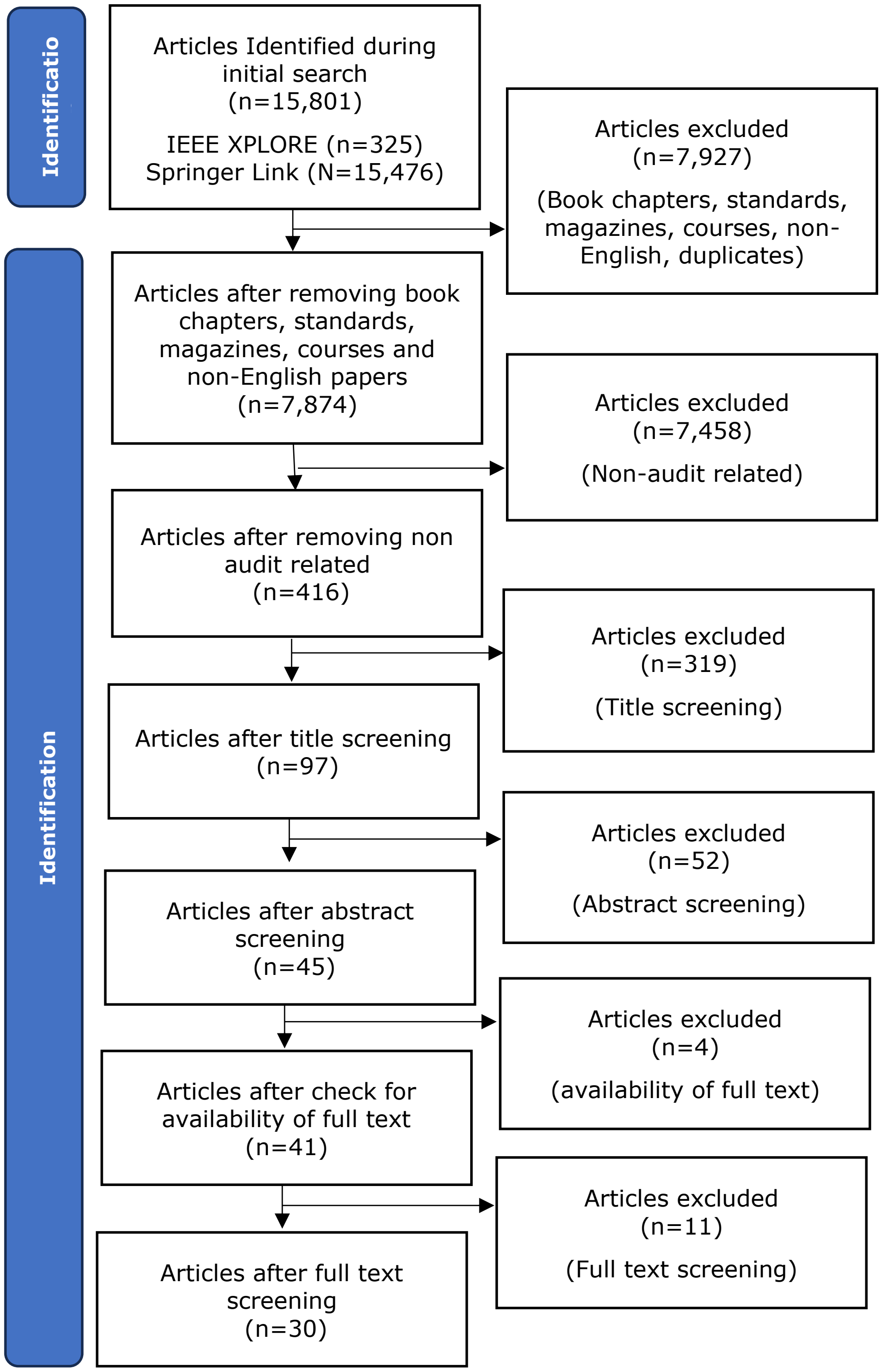

Fig. 1. A flowchart illustrates the screening and selection process of studies included in the literature review.

Literature was identified using academic databases such as IEEE Xplore and SpringerLink. An initial pool of 15,801 records was retrieved. Subject filters were used to remove the non-audit-related papers. The full dataset came down to 30 papers after the last screening step, i.e., full-text screening.

3.2 Data Extraction

A coding scheme was used, based on which each paper was examined. Inductive coding was used to extract important insights from the studies. Inductive coding is analyzing data without predetermined categories, allowing for the discovery of emergent patterns or themes directly from the data (D. R. Thomas, 2006). The data extracted from each paper were based on the following codes:

- Types of ML algorithms employed
- Types of data preprocessing techniques used
- Reported deployment challenges or barriers

4 Findings

In this chapter, the main findings are organized around the research questions defined in Chapter 1. Specific objectives are addressed in each subsection, synthesizing relevant insights from the studies under review.

4.1 Most Employed ML Models in Auditing and Anomaly Detection

Commonly used supervised algorithms included random forest, logistic regression, and Naïve Bayes. They are primarily used for tasks like fraud detection, audit opinion prediction, and risk classification. Reliability and interpretability have been confirmed by researchers (Dawood & ALmagtome, 2025; Thomas & Mathew, 2022; Zhang et al., 2024). To address the inefficiency and manual burden of traditional auditing, a supervised learning approach (random forest) was employed by Thomas & Mathew (2022) and Dawood & ALmagtome (2025). This was chosen due to the availability of labelled data. Auditors also label new cases alongside, thus creating a continuous learning loop where the model prediction is improved as more data is accumulated. This also made it possible to classify in real time, which enabled scalable auditing of large datasets while saving time.

Likewise, to address the problem of detecting financial misstatements in corporate reporting, Bertomeu et al. (2021) leveraged historic labelled data by employing a supervised learning approach; gradient boosted regression trees (GBRT), GBRT was chosen for its ability to handle complex, nonlinear relationships and its ability to automatically perform feature selection through iterative boosting of shallow trees. The model had outperformed logistic regression and helped significantly improve the identification of financial misstatements in corporate reporting.

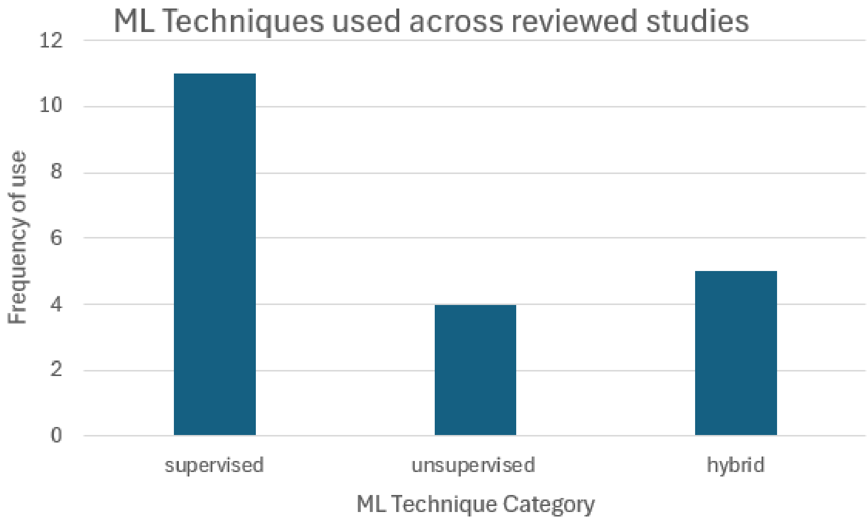

Fig. 2. Illustrates the frequency of ML technique categories across reviewed studies.

On the other hand, unsupervised learning is utilized when labeled data is not available. These models detect patterns or anomalies in data without predefined categories. Clustering algorithms such as fuzzy C-Means (FCM) and K-means are commonly used to identify outliers by grouping together similar data points and highlighting those that deviate from typical patterns. For instance, to improve time-consuming and costly audits of fraudulent financial reporting, Aktas & Cebi (2022) used the FCM clustering algorithm. An unsupervised approach was chosen as the datasets lacked pre-defined risk labels. FCM successfully helped identify these anomalous companies with high classification accuracy. To address the challenge of detecting earnings manipulation in highly imbalanced datasets with limited labeled data, Rahul et al. (2018) employed unsupervised learning methods. Supervised models, while effective on known patterns, risk overlooking novel or previously unseen types of fraud. By using Gaussian anomaly detection, the authors aimed to identify firms exhibiting unusual financial behavior. This approach enabled the creation of a pre-audit shortlisting mechanism that flagged high-risk firms based on their deviation from established norms, thereby enhancing early detection of earnings manipulation.

As the literature review progressed, hybrid learning approaches emerged as a promising solution to get around the respective limitations of supervised and unsupervised models. In particular, Elbrashy et al. (2023) addressed the challenges posed by having a rather small and imbalanced dataset by integrating the clustering capabilities of FCM with the classification strength of supervised algorithms. Unlike traditional binary classifications, this approach allowed the prediction of three audit opinion categories. The "explanatory language" class provided auditors with an in-depth understanding of the intermediate class, which allowed for more informative audit insights. Initially, FCM was used to uncover hidden patterns in the data, which were then used to train supervised classifiers. This dual-layer approach achieved higher accuracy and reduced classification bias, demonstrating how the combined strengths of both paradigms can enhance audit analytics, particularly in data-constrained environments. Models from Ashtiani & Raahemi (2022), and Q. Zhang (2025) further highlight how hybrid systems enhance model performance and adaptability in evolving financial auditing contexts.

Table 1. Machine learning models used in the reviewed studies.

Papers	ML Model Used																									
	Support Vector Machine	Logistic Regression	Naïve Bayes	Random Forest	Decision Tree	Extreme Gradient Boosting	K-Nearest Neighbors	Gradient Boosted Regression Trees	Bayesian Network	Adaptive Boosting	J48	Artificial Neural Network	Linear Discriminant Analysis	Long Short Term Memory	Fuzzy C-Means	Apriori Algorithm	Density-Based Spatial Clustering of Applications with Noise (++)	Isolation Forest	Principal Component Analysis	One-Class Support Vector Machine	Local Outlier Factor	Cluster-Based Local Outlier Factor	Histogram-Based Outlier Score	Copula-Based Outlier Detection	Lightweight Online Detector of Anomalies	One Rule	K-Means Clustering
Elbrashy et al. (2023)	✗	✗	✗												✗												
Ashtiani and Raahemi (2022)														✗		✗											
Thomas and Mathew (2022)				✗																							
Biesner et al. (2022)												✗															
Dawood and Almagtome (2025)				✗																							
Meng and Liu (2025)														✗													
Zhang et al. (2024)		✗		✗	✗																						
Adamyk et al. (2023)												✗															
Zhang (2025)	✗																✗										
Sunny et al. (2022)	✗	✗	✗	✗	✗	✗	✗																				
Kiefer and Pesch (2021)							✗											✗	✗	✗	✗	✗	✗	✗	✗		
Bertomeu et al. (2021)		✗						✗																			
Aktas and Cebi (2022)															✗												
Sharma et al. (2021)		✗	✗	✗					✗	✗	✗																
Ioannou et al. (2021)																✗										✗	✗
Zhang and Wang (2021)												✗															
Nawaiseh and Abbod (2021)		✗			✗								✗														
Rahul et al. (2018)						✗				✗																	

4.2 Preprocessing Strategies

The correct preprocessing strategy is very important for optimal model performance as it can greatly increase the model prediction accuracy (Ahsan et al., 2021). To ensure optimal model performance, a variety of data preprocessing techniques tailored to financial datasets were implemented in the reviewed studies. A foundational step was data cleaning, which addressed missing values, duplicate transactions, and erroneous entries (e.g., negative stock prices or incorrect timestamps) (Ashtiani & Raahemi, 2022; Meng & Liu, 2025), next came feature engineering, the process of transforming raw data into meaningful features that improve a machine learning model's performance. Feature engineering introduced variables such as transaction frequency, stock price volatility, and historical trends to enrich the model input, which helps better capture the hidden patterns. (Wang & Meng, 2025). Normalization and scaling bring all numeric features to a similar scale and mitigate skewness; these were primarily done through Min-Max scaling, z-score, and log transformation (Aktas & Cebi, 2022; Sunny et al., 2022). To remove outliers, interquartile range filtering was utilized (Adamyk et al., 2023; Z. Zhang et al., 2024), whereas principal component analysis, genetic algorithms, and Particle Swarm Optimization (PSO) were employed for dimensionality reduction and feature selection (Zhang et al., 2024). These help eliminate irrelevant and redundant features. Handling imbalanced datasets, data sets where the number of observations in each class are not evenly distributed, this was done with strategies like SMOTE (Kiefer & Pesch, 2021; Zhang et al., 2024), Monte Carlo-based sampling (Rahul et al., 2018), and class balancing in WEKA (Sharma et al., 2021) was also a key focus. Moreover, categorical encoding, discretization, and nominal conversion were applied to transform variables for better model interpretation and compatibility (Ioannou et al., 2021), for compatibility; some models handle categorical values better e.g. Naives Bayes, while some work better with numerical e.g. logistic regression, For interpretability; discretization groups together continuous variables into meaningful ranges (e.g., "low," "medium," "high risk").

To preprocess textual data, the study tokenized paragraph texts using BERT's WordPiece tokenizer to split text into subword units for better handling of rare or complex terms, truncated inputs to the 512-token limit to fit the BERT architecture's maximum sequence length since longer text cannot be processed in one pass, and averaged all word-level outputs via mean pooling to create fixed-length sentence vectors, which were then compared using cosine similarity to measure how closely a paragraph matched a given requirement (Biesner et al., 2022). Overall, the preprocessing techniques varied based on the nature of the data (Table 2.), whether numerical, categorical, or textual; they were crucial in reducing noise, addressing class imbalance, and improving the accuracy and interpretability of machine learning models.

Table 2. Common Preprocessing Techniques Used in Reviewed Audit-Focused ML Studies

Preprocessing Technique	Studies Using It	Type of Data	Reported Benefits
Data Cleaning	Ashtiani & Raahemi (2022), Meng & Liu (2025)	Numerical	Removes inconsistencies and errors
Feature Engineering	Wang & Meng (2025)	Numerical	Enhances input features for model learning
Normalization & Scaling	Sunny et al. (2022), Aktas & Cebi (2022)	Numerical	Standardizes data; mitigates skewness
Outlier Removal	Zhang et al. (2024), Adamyk et al. (2023)	Numerical	Eliminates noise and improves reliability
Feature Selection	Zhang et al. (2024)	Numerical	Removes irrelevant/redundant features; improves efficiency

Class Balancing	Kiefer & Pesch (2021), Rahul et al. (2018), Sharma et al. (2021)	Numerical	Addresses class imbalance; improves fairness
Categorical Encoding	Ioannou et al. (2021)	Categorical	Converts categories into numeric form for model compatibility
Discretization	Ioannou et al. (2021)	Numerical → Categorical	Groups continuous variables into meaningful ranges for interpretability
Nominal Conversion	Ioannou et al. (2021)	Numerical → Categorical	Ensures numbers are treated as labels, avoiding false ordering assumptions
Text Tokenization (WordPiece)	Biesner et al. (2022)	Textual	Handles rare/complex terms via subword segmentation
Text Truncation (512-token limit)	Biesner et al. (2022)	Textual	Fits text into BERT's maximum sequence length
Mean Pooling for Embeddings	Biesner et al. (2022)	Textual	Produces fixed-length vectors for comparison
Cosine Similarity	Biesner et al. (2022)	Textual	Measures semantic similarity between text pairs

4.3 Challenges in Adoption

The reviewed studies revealed several technical, organizational, and human-centered challenges that hindered the adoption of ML in auditing.

Technical Challenges:

A common concern is the high cost of adoption and maintenance, especially for smaller audit firms that lack the financial resources to invest in infrastructure, staff training, or ML-compatible systems (Grácio et al., 2024; Maharani et al., 2024). Another widespread challenge is posed by data availability and data quality (Dempsey & van Dyk, 2024; Maharani et al., 2024). Clients often submit incomplete, inaccurate, or poorly structured datasets mainly due to outdated IT systems or privacy constraints. This limits the reliability and predictive performance of the model. Auditors frequently report limited access to clients' data due to confidentiality, legal restrictions, or resistance to technological change, which negatively impacts both model training and audit quality (Maharani et al., 2024). Another concern is that managers frequently view ML models as "black boxes" making it difficult to trust their decisions, especially in high-stakes environments like auditing (Adamyk et al., 2023).

Organizational Challenges

Organizational resistance to change was widely reported, often driven by clients' reluctance to modify workflows, share extensive datasets, or pay higher audit fees associated with ML and big data adoption (Maharani et al., 2024). Lack of leadership's understanding of ML, and employees' fear of job loss, also contribute to the low morale and hesitation in adopting ML systems (Nkobane, 2025; Smith et al., 2025). Audit firms also face resource allocation issues, where the substantial investment required for hardware, software, and maintenance competes with other operational demands (Dempsey & van Dyk, 2024; Grácio et al., 2024; Maharani et al., 2024).

Human-Centered Challenges

A shortage of professionals with technical expertise in ML and AI remains a significant barrier, particularly among traditionally trained auditors (Nogueira et al., 2024; Smith et al., 2025). This skills gap means firms must either invest heavily in training or hire external specialists (Maharani et al., 2024). Ethical concerns such as algorithmic bias, privacy risks, and overreliance on automated outputs also emerged as a key challenge, reinforcing that human judgment and professional skepticism remain essential in auditing (Estep et al., 2024; Maharani et al., 2024). Both auditors and clients frequently express reluctance to rely on automated systems, citing fears of job loss and doubts about fairness.

5 Discussion

This section interprets the result from section 4 in light of the research questions. Each theme is examined with reference to the reviewed study and existing theory, and it will offer insights that are relevant to both researchers and practitioners who aim to implement these methods in real-world settings.

5.1 ML models in auditing

From Fig.2. in the findings section, it could be observed that supervised models were most frequently (11/18 papers) used in the reviewed studies that discussed ML models, particularly random forest and logistic regression. This finding aligns with earlier studies that suggested models balancing performance along with interpretability are preferred in domains such as financial auditing (Seizov & Wulf, 2020). Auditors and regulators value models whose decision logic can be traced back and explained easily. Each variable in logistic regression is given a coefficient, whose magnitude indicates the degree of its influence and whose sign indicates whether the variable increases or decreases the likelihood of the outcome. This makes it possible to clearly interpret how each variable affects the prediction. Similarly, random forest, although more complex than logistic regression, can capture complex relations without a black box nature; the subset of trees that vote for a decision can be viewed and traced back if needed. In practice, both random forest and logistic regression offer additional advantages as well; once trained on datasets, they can produce predictions in real time, enabling continuous auditing. They are also relatively easy to retrain when new labelled cases become available, and they also have lower computational requirements than deep learning models (Dawood & ALmagtome, 2025). Other supervised models, such as GBRT/XGBOOST, can be harder to interpret due to the many iterations of boosting, where each is making only a small adjustment (Bertomeu et al., 2021). Similarly, a neural network distributes decision-making across many layers and weights, which makes it almost impossible to trace back a decision without the use of complex interpretability tools.

Although unsupervised models play a crucial role in discovering hidden patterns and detecting unknown fraud schemes, it could be argued that their application in auditing remains limited, as their outputs are often challenging to interpret and difficult to validate without labeled datasets. These tools are mainly used in situations where labelled datasets are not available, and hence supervised models cannot perform. As a result, it makes them more of a specialist tool rather than a mainstream solution. Among the many unsupervised tools, FCM and apriori appeared to be the most frequently used. For example, Aktas & Cebi, (2022) specifically used FCM as it allows soft clustering. Soft clustering is when a model assigns an observation a degree of belonging to each cluster (Bezdek et al., 1984). This gives auditors more nuanced insight, as transactions might exhibit characteristics of multiple groups rather than forcing a strict yes/no classification. In contrast, K-Means, which was also used in another reviewed study (Ioannou et al., 2021)Hard clustering is simply a hard-clustering method; hard clustering is when a model groups observations into a single category. This approach is more efficient from a computational point of view. It also performs well with large datasets where processing speed is critical. Compared to other unsupervised methods found in the reviewed studies, such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN), FCM performs more reliably on high-dimensional audit datasets. DBSCAN relies on distance measurements, which become less meaningful in high-dimensional spaces because data points can appear similarly far apart.

During the literature review, hybrid models emerged as a practical way to overcome the individual limitations of supervised and unsupervised ML models. Hybrid models combined the exploratory power of unsupervised learning while maintaining the explainability of supervised models. Hybrid models have no fixed formula; rather, they are tailored to the problem context. For instance, Elbrashy et al. (2023) addressed a small and imbalanced data set first by applying FCM, which made clusters to discover hidden groupings or patterns. These clustered outputs were subsequently used as input features for supervised classifiers. This approach enabled the prediction of three distinct audit opinion categories, including an intermediate "explanatory" class. This explanatory class provided auditors with richer interpretive insights by capturing cases that did not fit neatly into purely positive or negative classifications. Similarly, Kiefer & Pesch (2021) handled an imbalanced data set with no labels by designing a hybrid framework. First, an ensemble of nine diverse unsupervised algorithms was used to detect unusual transactions; these transactions would be flagged once the majority of the algorithms had agreed on it being an unusual transaction. Then, a supervised XGBoost model was trained to replicate these clustering-based decisions, enabling the use of interpretability tools such as LIME to generate clear, case-level explanations for the model's predictions. Both these examples exhibit how hybrid models can overcome the limitations of both supervised and unsupervised models. Such models are of high value in today's auditing world, where both interpretability and flexibility are non-negotiable.

5.2 Pre-processing strategies

After reviewing the studies, it could be concluded that preprocessing was not just an auxiliary step, but rather a critical step that could determine the success of the model, as most of the time, the financial datasets were incomplete, imbalanced, and heterogeneous. These datasets contain numeric features that require pre-processing. Strategies like normalization, scaling, and outlier removal address distortions, adjust feature ranges, and ensure that variables meet the assumptions of ML algorithms, whereas dimensionality reduction improves the efficiency of the model without losing predictive power. This is a crucial consideration when working with large-scale transactional data. Addressing class imbalance through methods like SMOTE and Monte Carlo sampling mitigates the common bias toward the majority "normal" class, which is especially relevant given the rarity of fraudulent transactions in real-world audit datasets. Notably, a shift was observed in recent studies toward integrating qualitative audit evidence into ML pipelines; for instance, Biesner et al. (2022) applied advanced text pre-processing to incorporate narrative explanations from reports. This development suggests that ML in auditing is moving beyond purely quantitative anomaly detection to a more holistic approach, where both structured and unstructured evidence inform judgments. Such integration not only broadens the detection scope but also poses new challenges for model interpretability and data governance, highlighting areas where future frameworks must evolve to balance analytical power with audit transparency.

These strategies go beyond only addressing technical aspects; they also support regulatory and ethical issues by enhancing model interpretability and traceability. In sensitive domains such as financial auditing, where decisions must be explainable, preprocessing is as much about trustworthy predictions as it is about maximizing model performance.

5.3 Challenges in adoption

Three primary categories of challenges identified in the reviewed studies were technical, organizational, and human-centered. These are similar to those found in other digital transformation contexts but are amplified in auditing due to regulatory scrutiny and the profession's dependence on expert judgment.

Technical challenges, such as low data quality, can significantly raise the technical burden and associated expenses, as they require extensive preprocessing before being able to be used effectively. When combined with the already high implementation costs of ML systems, these issues disproportionately impact smaller audit firms, creating a widening adoption gap between larger firms that have greater resources. Although shared cloud-based platforms and industry-wide data quality standards could possibly reduce both costs and complexity, the effectiveness of these solutions depends on collective industry effort and the establishment of governance mechanisms to ensure consistent application. Furthermore, trust in ML outputs is undermined by the "black box" nature of certain models, particularly neural networks. The use of explainable AI techniques can mitigate this by providing transparent justifications for model decisions. Ultimately, overcoming these technical barriers is not merely a matter of implementing better tools. Rather, it requires coordinated efforts that align technological solutions with the auditing profession’s need for transparency, regulatory compliance, and equitable access to innovation across firms of all sizes.

Technical challenges, such as low data quality, can increase technical burden and costs as they require extensive preprocessing; this, along with high implementation costs of ML, can affect smaller firms more compared to larger firms, thus creating an adoption gap between large and small audit firms. Shared cloud-based platforms and industry-wide data quality standards could help reduce the gap by reducing high implementation costs and technical burdens. Trust in these systems is also undermined due to the “black box” nature of some models, especially neural networks. This can be mitigated by using explainable AI, a system that helps interpret why a decision was reached.

From an organizational point of view, resistance to workflow changes, limited leadership understanding of ML, and resource allocation trade-offs between investing in ML projects and other functional priorities indicate that these obstacles are as much cultural as technical. To build momentum and counter resistance against ML in auditing, firms should employ structured change management programs, involve end users early during the development process, and showcase proven wins. ML initiatives may be neglected in favor of urgent operational tasks if senior leadership isn’t supporting them. In order to secure sustained commitment, it is necessary to align these projects with the organization’s strategic KPIs and clearly position them as essential to enhance audit quality, thereby demonstrating their direct contribution to long-term organizational objectives. As a result, there is a cultural change where employees start to see ML tools as necessary for professional standards, rather than as optional or disruptive add-ons.

Human-centered challenges, particularly the lack of skilled ML practitioners, highlight the importance of organized corporate training programs as well as targeted professional development for audit personnel. As auditing practices are evolving with the introduction of ML, providing auditors with a foundational understanding of core ML concepts and applications through internal workshops or continuous learning modules can help close the skill gap. Incorporating fundamental machine learning concepts into auditing curricula would also help future professionals build baseline competencies prior to starting their professional careers. Ethical issues like bias and overreliance on automation continue to be powerful deterrents as they have the potential to compromise the fairness and legitimacy of audit results. These risks are especially important in auditing, as decisions must be transparent due to regulatory compliance.

Even though this study provides a comprehensive review of machine learning applications in auditing and addresses key methodological and practical considerations, there are still several limitations that should be acknowledged when interpreting the findings. The literature review was limited to two databases, Springer Link and IEEE Xplore. While these may not have captured every relevant publication, these databases were chosen as they index the most influential journals and have the highest coverage of peer-reviewed literature related to both auditing and ML. The inclusion criteria of this paper focused primarily on peer-reviewed journal articles and conference papers. Although this may have excluded potentially valuable perspectives from industry reports, grey literature, or unpublished work, this decision was intended to ensure that the findings are based on research that has gone through rigorous academic review. The differences in study designs, datasets, and evaluation metrics across the reviewed literature may have limited direct comparability of results. To mitigate this issue, the study emphasized qualitative synthesis over direct numerical comparison. By describing the application context, dataset characteristics, and reported performance trends for each study. This approach allowed meaningful insights to be drawn despite methodological differences and ensured that the diversity of studies contributed to a broader perspective on how ML is applied across varied auditing contexts. Finally, the rapidly evolving nature of ML in auditing means that some emerging developments may not have been reflected at the time of review, but the methodological focus on recent, peer-reviewed sources increases the likelihood that the key trends and challenges identified remain relevant.

6 Conclusion

This thesis has examined the applications of machine learning (ML) in auditing. A semi-systematic literature review of 30 peer-reviewed studies was conducted, which identified the most frequently applied ML models, the data preprocessing strategies used in audit contexts, and the key challenges that hindered their adoption.

The findings reveal that supervised learning models, particularly Random Forest and Logistic Regression, dominate current applications due to their balance between predictive performance and interpretability. Unsupervised and hybrid models, though less commonly used, hold strong potential for detecting previously unseen anomalies and providing auditors with deeper, more nuanced insights. The review also highlights the pivotal role of preprocessing. Addressing issues such as data imbalance, missing values, and heterogeneous formats not only enhances model accuracy but also improves explainability, which is an essential requirement in regulated domains such as auditing.

Adoption challenges include technical, organizational, and human-centered dimensions. These include high implementation costs, data quality and availability issues, resistance to workflow changes, limited leadership understanding, and a shortage of ML-skilled professionals within the auditing profession. Addressing these barriers will require a combination of technical solutions, such as explainable AI and shared audit data platforms, along with organizational strategies, including change management programs and targeted training initiatives.

Ultimately, the study confirms that ML can significantly enhance audit quality, efficiency, and coverage. However, successful deployment will require not only selecting appropriate algorithms but also ensuring high-quality input data, integrating interpretability tools, aligning projects with strategic objectives, and cultivating a culture that embraces technology-assisted judgment.

Future research could be strengthened by incorporating an empirical validation component, where selected models are applied to publicly available or anonymized audit datasets. This would allow direct model comparisons and reinforce the study’s conclusions by testing how the reviewed findings hold up in practice. Expanding the literature search beyond Springer Link and IEEE Xplore to include databases such as Scopus or Web of Science would also capture a broader range of relevant studies and reduce selection bias. Together, these steps would not only validate insights from the literature but also enhance the comparability and generalizability of results.

Beyond these study-specific improvements, future work in the field could move past model performance benchmarking to examine how ML reshapes the audit process and profession as a whole. This includes investigating the organizational changes needed for large-scale ML integration, understanding the interplay between regulatory frameworks and algorithmic auditing, and developing sector-wide shared audit data platforms to support collaborative model training. Further research could also explore hybrid human–AI decision models that combine computational efficiency with professional judgment, as well as behavioral studies on how auditors interpret, trust, and act on ML-generated insights.

References

1. Adamyk, O., Benson, V., Adamyk, B., Al-Khateeb, H., & Chinnaswamy, A. (2023). Does Artificial Intelligence Help Reduce Audit Risks? *2023 13th International Conference on Advanced Computer Information Technologies (ACIT)*, 294–298. https://doi.org/10.1109/ACIT58437.2023.10275661
2. Adelakun, B. O. (2022). THE IMPACT OF AI ON INTERNAL AUDITING: TRANSFORMING PRACTICES AND ENSURING COMPLIANCE. *Finance & Accounting Research Journal*, *4*(6), 350–370. https://doi.org/10.51594/farj.v4i6.1316
3. Ahsan, M., Mahmud, M., Saha, P., Gupta, K., & Siddique, Z. (2021). Effect of Data Scaling Methods on Machine Learning Algorithms and Model Performance. *Technologies*, *9*(3), 52. https://doi.org/10.3390/technologies9030052
4. Aktas, N., & Cebi, S. (2022). Fraud Detection Using Fuzzy C Means. In C. Kahraman, S. Cebi, S. Cevik Onar, B. Oztaysi, A. C. Tolga, & I. U. Sari (Eds.), *Intelligent and Fuzzy Techniques for Emerging Conditions and Digital Transformation* (pp. 90–96). Springer International Publishing. https://doi.org/10.1007/978-3-030-85626-7_11
5. Ashtiani, M. N., & Raahemi, B. (2022). Intelligent Fraud Detection in Financial Statements Using Machine Learning and Data Mining: A Systematic Literature Review. *IEEE Access*, *10*, 72504–72525. https://doi.org/10.1109/ACCESS.2021.3096799
6. Baghdasaryan, V., Davtyan, H., Sarikyan, A., & Navasardyan, Z. (2022). Improving Tax Audit Efficiency Using Machine Learning: The Role of Taxpayer’s Network Data in Fraud Detection. *Applied Artificial Intelligence*, *36*(1). https://doi.org/10.1080/08839514.2021.2012002
7. Barr-Pulliam, D., Brown-Liburd, H. L., & Munoko, I. (2022). The effects of person-specific, task, and environmental factors on digital transformation and innovation in auditing: A review of the literature. *JOURNAL OF INTERNATIONAL FINANCIAL MANAGEMENT & ACCOUNTING*, *33*(2), 337–374. https://doi.org/10.1111/jifm.12148
8. Bertomeu, J., Cheynel, E., Floyd, E., & Pan, W. (2021). Using machine learning to detect misstatements. *Review of Accounting Studies*, *26*(2), 468–519. https://doi.org/10.1007/s11142-020-09563-8

9. Bezdek, J. C., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy *c*-means clustering algorithm. *Computers & Geosciences*, *10*(2), 191–203. https://doi.org/10.1016/0098-3004(84)90020-7
10. Biesner, D., Pielka, M., Ramamurthy, R., Dilmaghani, T., Kliem, B., Loitz, R., & Sifa, R. (2022). Zero-Shot Text Matching for Automated Auditing using Sentence Transformers. *2022 21st IEEE International Conference on Machine Learning and Applications (ICMLA)*, 1637–1642. https://doi.org/10.1109/ICMLA55696.2022.00251
11. Dawood, A. N., & ALmagtome, A. (2025). Impact of AI on Auditing: Transforming Assurance Services in the Digital Age. *2025 International Conference on Frontier Technologies and Solutions (ICFTS)*, 1–8. https://doi.org/10.1109/ICFTS62006.2025.11031604
12. Dempsey, K., & van Dyk, V. (2024). The Role of Data Analytics in Enhancing External Audit Quality. In T. Moloi & B. George (Eds.), *Towards Digitally Transforming Accounting and Business Processes* (pp. 399–423). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-46177-4_22
13. Elbrashy, A. M., Abdulaziz, A. M. N., & Ibraheem, M. R. (2023). Using Machine Learning Techniques in Predicting Auditor Opinion: Empirical Study. In D. Magdi, A. A. El-Fetouh, M. Mamdouh, & A. Joshi (Eds.), *Green Sustainability: Towards Innovative Digital Transformation* (pp. 233–247). Springer Nature. https://doi.org/10.1007/978-981-99-4764-5_15
14. Estep, C., Griffith, E. E., & MacKenzie, N. L. (2024). How do financial executives respond to the use of artificial intelligence in financial reporting and auditing? *Review of Accounting Studies*, *29*(3), 2798–2831. https://doi.org/10.1007/s11142-023-09771-y
15. Fulop, M. T., Topor, D. I., Ionescu, C. A., Capusneanu, S., Breaz, T. O., & Stanescu, S. G. (2022). Fintech Accounting and Industry 4.0: Future-Proofing or Threats to the Accounting Profession? *JOURNAL OF BUSINESS ECONOMICS AND MANAGEMENT*, *23*(5), 997–1015. https://doi.org/10.3846/jbem.2022.17695
16. Grácio, L., Eugénio, T., & Azevedo, G. (2024). The Impact of Artificial Intelligence on Accounting—The View of Certified Accountants. In G. Azevedo, E. Vieira, R. Marques, & L. Almeida (Eds.), *The Challenges of Era 5.0 in Accounting and Finance Innovation* (pp. 236–256). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-77531-4_15
17. Grossi, G., & Argento, D. (2022). The fate of accounting for public governance development. *ACCOUNTING AUDITING & ACCOUNTABILITY JOURNAL*, *35*(9), 272–303. https://doi.org/10.1108/AAAJ-11-2020-5001
18. Han, H., Shiwakoti, R. K., Jarvis, R., Mordi, C., & Botchie, D. (2023). Accounting and auditing with blockchain technology and artificial Intelligence: A literature review. *INTERNATIONAL JOURNAL OF ACCOUNTING INFORMATION SYSTEMS*, *48*, 100598. https://doi.org/10.1016/j.accinf.2022.100598
19. Iliou, T., Anagnostopoulos, C.-N., Nerantzaki, M., & Anastassopoulos, G. (2015). A Novel Machine Learning Data Preprocessing Method for Enhancing Classification Algorithms

Performance. *Proceedings of the 16th International Conference on Engineering Applications of Neural Networks (INNS)*, 1–5. https://doi.org/10.1145/2797143.2797155

20. Ioannou, A., Bourlis, D., Valsamidis, S., & Mandilas, A. (2021). A Framework for Information Mining from Audit Data. In A. Horobet, L. Belascu, P. Polychronidou, & A. Karasavvoglou (Eds.), *Global, Regional and Local Perspectives on the Economies of Southeastern Europe* (pp. 223–242). Springer International Publishing. https://doi.org/10.1007/978-3-030-57953-1_14

21. Ivakhnenkov, S. (2023). Artificial intelligence application in auditing. *Scientific Papers NaUKMA. Economics*, *8*(1), 54–60. https://doi.org/10.18523/2519-4739.2023.8.1.54-60

22. Janjua, A. N., Abdulraheem, A., & Tariq, Z. (2024, February 12). *Big Data Analysis Using Unsupervised Machine Learning: K-means Clustering and Isolation Forest Models for Efficient Anomaly Detection and Removal in Complex Lithologies*. International Petroleum Technology Conference. https://doi.org/10.2523/IPTC-23580-EA

23. Kiefer, S., & Pesch, G. (2021). Unsupervised Anomaly Detection for Financial Auditing with Model-Agnostic Explanations. In S. Edelkamp, R. Möller, & E. Rueckert (Eds.), *KI 2021: Advances in Artificial Intelligence* (pp. 291–308). Springer International Publishing. https://doi.org/10.1007/978-3-030-87626-5_22

24. Liu, X., Ren, Y., Qi, G., Li, Y., & Fan, R. (2024). Artificial Intelligence Digital Audit System Under Machine Learning Technology. *2024 3rd International Conference on Artificial Intelligence and Autonomous Robot Systems (AIARS)*, 739–743. https://doi.org/10.1109/AIARS63200.2024.00139

25. Maharani, K. D., Muljo, H. H., & Atalla, F. D. (2024). The Future Prospects of Big Data and Machine Learning Implementation in Financial Auditing. *2024 3rd International Conference on Creative Communication and Innovative Technology (ICCIT)*, 1–8. https://doi.org/10.1109/ICCIT62134.2024.10701139

26. Mathauer, I., & Oranje, M. (2024). Machine learning in health financing: Benefits, risks and regulatory needs. *Bulletin of the World Health Organization*, *102*(03), 216–224. https://doi.org/10.2471/blt.23.290333

27. Meng, Q., & Liu, Q. (2025). Corporation Financial Risk Prevention and Control using Long Short-Term Memory Networks. *2025 4th International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)*, 1–6. https://doi.org/10.1109/ICDCECE65353.2025.11035721

28. Nkobane, J. G. (2025). Benefits and Challenges of Utilizing Automation and Artificial Intelligence in Auditing Firms in South Africa. In T. Moloi (Ed.), *Impacting Society Positively Through Technology in Accounting and Business Processes* (pp. 667–682). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-84885-8_36

29. Nogueira, J., Ribeiro, D., & Marques, R. P. (2024). Factors Influencing Statutory Auditors' Perception of the Role of Artificial Intelligence in Auditing. In Á. Rocha, H. Adeli, G. Dzemyda, F. Moreira, & A. Poniszewska-Marańda (Eds.), *Good Practices and New Perspectives in*

Information Systems and Technologies (pp. 306–316). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-60328-0_31

30. Noordin, N. A., Hussainey, K., & Hayek, A. F. (2022). The Use of Artificial Intelligence and Audit Quality: An Analysis from the Perspectives of External Auditors in the UAE. *Journal of Risk and Financial Management*, *15*(8), 339. https://doi.org/10.3390/jrfm15080339
31. Oladejo, M. T., Botes, V., Low, M., & Reeves, S. (2024). Blockchain technology disruptions: Exploring accounting and auditing academics and practitioners' perception. *Accounting & Finance*, *n/a*(n/a). https://doi.org/10.1111/acfi.13383
32. Rahul, K., Seth, N., & Dinesh Kumar, U. (2018). Spotting Earnings Manipulation: Using Machine Learning for Financial Fraud Detection. In M. Bramer & M. Petridis (Eds.), *Artificial Intelligence XXXV* (pp. 343–356). Springer International Publishing. https://doi.org/10.1007/978-3-030-04191-5_29
33. Seizov, O., & Wulf, A. J. (2020). Artificial Intelligence and Transparency: A Blueprint for Improving the Regulation of AI Applications in the EU. *European Business Law Review*, *31*(4). https://kluwerlawonline.com/api/Product/CitationPDFURL?file=Journals\EULR\EULR2020024.pdf
34. Sharma, A., Sinhal, A., Tiwari, M., & Patel, M. (2021). Audit Fraud Data Prediction Using Machine Learning Algorithms. In S. D. Purohit, D. Singh Jat, R. C. Poonia, S. Kumar, & S. Hiranwal (Eds.), *Proceedings of International Conference on Communication and Computational Technologies* (pp. 413–419). Springer. https://doi.org/10.1007/978-981-15-5077-5_38
35. Smith, R. J., Maredi, E., & Mthimunye, P. (2025). The Impact of Emerging Technologies on Internal Audit Functions. In T. Moloi (Ed.), *Impacting Society Positively Through Technology in Accounting and Business Processes* (pp. 1115–1137). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-84885-8_60
36. Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039
37. Sun, C., & Zhang, T. (2024). Accounting Fraud Identification Model Based on Random Forest Algorithm and Light GBM Algorithm. *2024 IEEE 2nd International Conference on Electrical, Automation and Computer Engineering (ICEACE)*, 970–974. https://doi.org/10.1109/ICEACE63551.2024.10898611
38. Sunny, F. A., Khan, Md. I., Satu, Md. S., & Abedin, M. Z. (2022). Investigating External Audit Records to Detect Fraudulent Firms Employing Various Machine Learning Methods. In D. Giri, K.-K. Raymond Choo, S. Ponnusamy, W. Meng, S. Akleylek, & S. Prasad Maity (Eds.), *Proceedings of the Seventh International Conference on Mathematics and Computing* (pp. 511–523). Springer. https://doi.org/10.1007/978-981-16-6890-6_38

39. Thomas, D. R. (2006). A General Inductive Approach for Analyzing Qualitative Evaluation Data. *American Journal of Evaluation*, *27*(2), 237–246. https://doi.org/10.1177/1098214005283748

40. Thomas, M. S., & Mathew, J. (2022). Supervised Machine Learning Model for Automating Continuous Internal Audit Workflow. *2022 6th International Conference on Trends in Electronics and Informatics (ICOEI)*, 1200–1206. https://doi.org/10.1109/ICOEI53556.2022.9776888

41. Wang, S., & Meng, Q. (2025). Intelligent Enterprise Financial Anomaly Detection using Association Rule Mining for Enhanced Risk Assessment. *2025 4th International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)*, 1–7. https://doi.org/10.1109/ICDCECE65353.2025.11035797

42. Zhang, C. (Abigail), Cho, S., & Vasarhelyi, M. (2022a). Explainable Artificial Intelligence (XAI) in auditing. *International Journal of Accounting Information Systems*, *46*, 100572. https://doi.org/10.1016/j.accinf.2022.100572

43. Zhang, C. (Abigail), Cho, S., & Vasarhelyi, M. (2022b). Explainable Artificial Intelligence (XAI) in auditing. *International Journal of Accounting Information Systems*, *46*, 100572. https://doi.org/10.1016/j.accinf.2022.100572

44. Zhang, Q. (2025). Current Status and Strategy Research on the Informationization Construction of Audit in Accounting Firms. In M. Virvou, F. Paas, & S. Patnaik (Eds.), *New Paradigm in Digital Classroom and Smart Learning* (pp. 624–634). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-98607-9_58

45. Zhang, Z., Mohi-Ud-Din, G., Xiong, Y., Zhang, X., Lin, X. L., Ai, C., & Min, H. (2024). ML-Driven Audit Risk Assessment with Differential Privacy. *2024 11th International Conference on Soft Computing & Machine Intelligence (ISCMI)*, 257–266. https://doi.org/10.1109/ISCMI63661.2024.10851519

46. Zhang, Z., & Wang, Z. (2021). Design of financial big data audit model based on artificial neural network. *International Journal of System Assurance Engineering and Management*. https://doi.org/10.1007/s13198-021-01258-w

47. Zlobin, M., & Bazylevych, V. (2025). Development of a preprocessing methodology for imbalanced datasets in machine learning training. *Technology Audit and Production Reserves*, *3*(2(83)), Article 2(83). https://doi.org/10.15587/2706-5448.2025.330639