The Use of Artificial Intelligence in Accounting Auditing

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Abstract: This article examines the growing role of artificial intelligence (AI) in accounting auditing, the opportunities it presents, methodologies, and challenges encountered from an academic perspective. With the proliferation of Industry 4.0 and big data, sampling-based approaches used in traditional auditing are becoming insufficient, creating a need to analyze the entire data universe. In this context, AI provides auditors with unprecedented capabilities to detect fraud, errors, and irregularities within large data sets, forming the basis of the "Audit 4.0" paradigm. The article addresses the three main areas of AI application in auditing—process automation, risk assessment, and decision support systems—within a theoretical framework. Anomaly detection-focused unsupervised learning methodologies, particularly clustering analysis and deep learning-based autoencoder architectures, are examined at a technical level. However, the practical application of AI also brings significant challenges, such as data imbalance, the interpretability of complex models (the "black box" problem), and potential biases in algorithms. As solutions to these challenges, Explainable Artificial Intelligence (XAI) techniques and the concept of "Trustworthy Artificial Intelligence" are discussed. In conclusion, it is emphasized that AI is not a technology that eliminates the auditor, but rather an "augmented intelligence" tool that enhances their capabilities. It is noted that the auditor's role is transforming from manual data verification to that of an expert who interprets AI models and oversees algorithmic systems. This transformation will shape the future of the auditing profession.

Keywords: artificial intelligence in auditing, AI in accounting, audit 4.0, AI auditing, intelligent auditing systems.
JEL Classification: M40, M42, C55, O33, D83, J24

1 Introduction: Digital Transformation in the Auditing Profession

The digitalization process triggered by Industry 4.0 is fundamentally transforming the accounting and auditing profession (Erdoğan, 2019). The increasing level of digitalization in businesses has led to the production of data at unprecedented volumes, diversity, and speed. This phenomenon, known as "Big Data," has called into question the effectiveness of sampling-based methods, which form the basis of traditional auditing (Warren et al., 2015). Facing data sets consisting of millions or even billions of transactions, drawing a general conclusion based on a small sample increases the risk of overlooking significant errors and fraud. This situation has given rise to the need for a new paradigm that directs auditors to analyze the entire data population (universe). This new approach is expressed by the concept of "Audit 4.0," which integrates Industry 4.0 technologies into audit processes (Erdoğan, 2019).

Artificial intelligence (AI) is at the heart of this new auditing paradigm. AI-based analytical models offer auditors unprecedented capabilities to detect anomalies, fraudulent transactions, and complex patterns of irregularities hidden within large data sets (Serçemeli, 2018). Thanks to these technologies, auditing has the potential to evolve from a reactive, periodic process into a continuous and proactive assurance mechanism (Issa et al., 2016). Auditors can now focus on more complex and judgmental areas by interpreting the findings generated by AI systems, rather than manually verifying the accuracy of data.

The purpose of this article is to outline the theoretical framework for the use of AI in accounting auditing, examine its main areas of application and the methodologies used in these areas. In addition, the technical and ethical challenges encountered during the implementation of AI models will be addressed, and the potential impact of these technologies on the future of the auditing profession will be assessed. The following sections of the article will examine, in turn, the role and application areas of AI in auditing, fundamental technical methodologies, challenges in implementation, and ethical considerations, concluding with a perspective on the future of the profession.

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2 Theoretical Framework: The Role of Artificial Intelligence in Auditing and Its Application Areas

The integration of artificial intelligence into the auditing process is not merely about adopting a set of technological tools; it also provides a conceptual framework that redefines the fundamental logic, scope, and assurance level of auditing. AI enables auditors to analyze large data sets more deeply, revealing risks and anomalies that are difficult to detect using traditional methods. Based on the results of a literature review conducted on the SCOPUS database, the conceptual framework created by Fırat (2025) summarizes AI's role in auditing under three main headings: process automation, risk assessment, and decision-making.

These three fundamental areas of application can be explained as follows:

- **Process Automation:** AI plays a key role in automating routine and repetitive auditing tasks. Using techniques such as Big Data analysis and Process Mining, tasks such as reviewing millions of journal entries or purchase orders, reconciling accounts, and performing standard controls can be performed at high speed and accuracy without human intervention (Jans et al., 2014). This automation allows auditors to devote their time to more complex, judgmental, and strategically important areas. More importantly, this transformation changes the nature of audit evidence; evidence evolves from manual verification and confirmation to system-level assurance and algorithmic controls. This fundamentally affects the auditor's control risk assessment.

- **Risk Assessment:** While risk assessment in traditional auditing relies heavily on the auditor's experience and sample results, AI makes this process data-driven and proactive. Machine Learning and Data Analysis algorithms scan the entire transaction population to detect transactions that deviate from "normal" behavior patterns (anomalies) (Chandola et al., 2009). The qualitative difference brought by this approach is the potential to reveal "unknown unknowns" that the auditor's experience cannot predict, rather than focusing only on known risk areas. AI enables the identification of high-risk areas with potential for fraud or error before they cause significant damage, even detecting previously unencountered fraud scenarios (Schreyer et al., 2019).

- **Decision Making:** AI is positioned as a tool that supports the auditor's professional judgment rather than replacing it. Technologies such as Fuzzy Neural Networks and Expert Systems assist auditors in decision-making processes by modeling complex scenarios and analyzing possible outcomes (Lin et al., 2003). For example, an expert system can analyze hundreds of different financial and non-financial indicators to provide a fraud risk score. This score serves as a baseline or "second opinion" for the auditor, forcing them to justify deviations from their own judgment. This process enhances the robustness, defensibility, and ultimately the quality of professional judgment.

The integrated use of these application areas has the potential to transform the nature of audit assurance. AI's ability to analyze the entire data universe has the potential to shift the level of assurance provided by the audit from "reasonable assurance" to "full assurance" (Varol, 2023).

3 Artificial Intelligence-Based Audit Methodologies

Understanding "how" artificial intelligence is used in auditing requires examining the technical methodologies that enable the theoretical framework to be translated into practical application. One of the most fundamental challenges in accounting and auditing is the scarcity of labeled and verified data sets related to fraudulent transactions. The vast majority of financial data sets consist of "normal" transactions, while fraudulent transactions constitute a very small portion of this set (Ali et al., 2022). This situation limits the effectiveness of supervised learning algorithms. Therefore, unsupervised learning and anomaly detection approaches, which do not require labeled data, are predominantly used in auditing applications (Chandola et al., 2009). These approaches focus on identifying outliers that do not conform to the general patterns learned from the dataset.

3.1 Clustering-Based Methods

Clustering is one of the most fundamental approaches in unsupervised learning and is widely used for anomaly detection in auditing. The basic logic of this technique is to create natural structures within the data by grouping (clustering) accounting transactions or records with similar characteristics (Thiprungsri & Vasarhelyi, 2011). For example, using algorithms such as K-Means, journal entries can be divided into clusters based on characteristics such as transaction amount, related accounts, and recording time. At the end of this process, clusters containing very few transactions (small populations) or located far from the centers of other clusters are considered suspicious and flagged for the auditor's review (Duan et al., 2009). This method provides an effective starting point for detecting anomalies hidden among similar transactions.

3.2. Deep Learning-Based Methods: Autoencoder Architecture

Deep learning, particularly the Autoencoder neural network architecture, has emerged as a powerful tool for anomaly detection in auditing. An Autoencoder is essentially a neural network that learns to compress data into a representative form (encoding) and then reconstruct the original data from this representation (decoding) (Schreyer et al., 2019). This model is trained solely on accounting records deemed "normal." During the training process, the model learns the underlying patterns and relationships of normal transactions and successfully represents them in a low-dimensional latent space (Hawkins et al., 2002).

When presented with a new accounting transaction, the trained model attempts to compress and reconstruct it. If the transaction fits a "normal" pattern, the model can reconstruct it with a low error rate. However, if the transaction has an "abnormal" feature that deviates significantly from previously learned patterns (e.g., an unseen account combination or an unusual amount), the model struggles to reconstruct it and produces a high "reconstruction error" (Sweers, 2019). This high error is considered a strong signal that the transaction is anomalous. The greatest advantage of autoencoders is their potential to detect even previously unencountered and undefined fraud scenarios.

3.3. Other Statistical and Machine Learning Methods

AI methodologies used in auditing are not limited to clustering and autoencoders. In rare cases where labeled data is available, supervised classification algorithms such as Decision Trees, Support Vector Machines (SVM), and Random Forest can also be used to distinguish between fraudulent and normal transactions (Ali et al., 2022; Biau & Scornet, 2016).

A more innovative approach is the application of Social Network Analysis (SNA) metrics to audit data. In this method, the relationships between transactions are modeled as a network graph. For example, the parties involved in a transaction (customer, seller, employee) can be represented as nodes, and the money transfer between them as edges. Metrics calculated on this network, such as PageRank or degree centrality, can be used as features to identify actors that are unusually connected or centrally located within the network (Ball et al., 2023). These metrics are particularly effective in revealing hidden relationships and key players in organized fraudulent activities involving multiple actors.

While these methodologies, particularly deep learning models such as Autoencoders, offer unprecedented power in anomaly detection, the complexity of these models poses significant challenges in terms of interpretability and reliability. The "black box" problem, which must be addressed before they can be fully trusted in a high-stakes field such as auditing, is at the forefront of these challenges

4 Challenges in Implementation and Ethical Considerations

The integration of artificial intelligence (AI) technologies into audit processes offers revolutionary opportunities for detecting errors and fraud by increasing data processing capacity. However, a review of the existing literature and application examples reveals that the focus has been on the technical success of the technology, while the impact of AI on the structural, ethical, and legal foundations of the audit profession has not yet been sufficiently researched. This study examines critical areas that still require in-depth research in auditing literature and practice, such as the interpretability of algorithms, legal liability, professional independence, and ethical biases.

Successfully integrating artificial intelligence models into audit processes is not merely a technical achievement. This process also brings with it serious challenges related to data, models, and ethics that must be overcome. Properly managing these challenges is critical to the reliability and acceptability of AI-based auditing.

4.1. Imbalanced and Quality of Data

One of the most prominent characteristics of financial datasets is the extreme imbalance between classes (highly imbalanced dataset). The number of normal (non-fraudulent) transactions can be millions of times greater than fraudulent transactions (Ali et al., 2022). This poses a serious problem for training machine learning models. Since the model constantly sees normal transactions during training, it becomes overly focused on learning this class and tends to disregard the rare fraudulent transactions as "noise" or "outliers." As a result, the risk of the model failing to detect fraudulent transactions, i.e., producing "false negatives," increases significantly (Khoshgoftaar et al., 2010). From an auditing perspective, missing or failing to detect fraud can lead to unacceptable consequences, making data imbalance a fundamental challenge that must be addressed with specialized techniques (e.g., resampling or cost-sensitive learning) during model development.

4.2. Algorithmic Bias, and Data Privacy

AI models can learn biases from the data they are trained on, which can lead to unfair or incorrect outputs in audit results. Algorithmic bias can undermine trust in audit processes (Ağdeniz, 2024). In particular, whether data collected during an audit can be used for model training (purpose change) creates an ethical dilemma (ICAEW, 2024).

The confidentiality of customer data and the protection of trade secrets are at risk during the training of AI models. The lack of regulatory frameworks to ensure a balance between data privacy and algorithmic transparency necessitates increased academic and practical work in this area (ISACA, 2018; cited in Ağdeniz, 2024).

4.3. The "Black Box" Problem and Explainability (XAI)

Complex AI models such as deep learning, despite offering high accuracy rates, are often characterized as "black boxes." This means that the model cannot provide a clear explanation of which factors it relied on and what logical sequence it followed to arrive at a particular decision or prediction. This situation is unacceptable for the auditing profession, as auditors must defend and justify their findings and conclusions to clients, regulatory bodies, and even courts (Fırat, 2025). An AI model flagging a transaction as "suspicious" is insufficient as audit evidence unless the underlying "reason" can be explained.

The field of Explainable Artificial Intelligence (XAI) has developed as a solution to this problem. XAI techniques such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) aim to make the decisions of black box models interpretable (Ribeiro et al., 2016; Lundberg & Lee, 2017). These techniques analyze why the model flagged a particular transaction as suspicious and present the auditor with how each feature of the transaction (e.g., transaction amount, time, related account) contributed to this decision and to what extent (Ball et al., 2023). This allows the auditor to translate the AI's "intuition" into a concrete and defensible rationale.

While research has demonstrated the technical success of methods such as unsupervised anomaly detection, there is a lack of guidance on how these results should be presented to auditors and how they should be integrated into the audit process (Nonnenmacher & Marx Gómez, 2021). The limited interpretability of the results undermines transparency and has the potential to create problems in regulatory reviews (Sattarov, Herurkar, & Hees, 2022). Therefore, how explainable artificial intelligence (XAI) techniques can be applied in the context of financial auditing is an area requiring urgent research (Manoharan et al., n.d.).

4.4. Trustworthy Artificial Intelligence and Algorithm Auditing

AI models carry the risk of learning and reproducing existing biases and prejudices in the data they are trained on. For example, if transactions belonging to a certain demographic group have been scrutinized more closely in past data, the AI model may learn this bias and disproportionately focus on transactions belonging to that group in the future. This situation may violate fundamental ethical principles such as fairness, transparency, and accountability (Munoko et al., 2020). These risks necessitate the adoption of "Trustworthy AI" principles in auditing. Trustworthy AI is a framework that aims to ensure that systems operate in a manner that is compliant with laws and ethical norms, robust, and reliable (Ağdeniz, 2023).

This new paradigm also expands the role of the auditor. Auditors are now responsible not only for auditing financial data and processes but also for auditing the AI algorithms that analyze this data. This new field, called "algorithm auditing," aims to ensure that algorithms are fair, do not increase biases in data, and function as expected (Ağdeniz, 2023; Bandy, 2021).

4.5. Responsibility and Accountability in Automated Results

The question of who bears legal and professional responsibility when AI systems produce erroneous results remains a gray area in the literature. A recent incident at Deloitte, which resulted in AI producing erroneous references ("hallucinations"), has highlighted the risks of this technology. Discussions following this incident emphasized that AI cannot be held responsible for its work and that ultimate responsibility lies with humans (Vietnam.vn, 2025).

However, the risk that auditors may reach erroneous judgments if they place excessive trust in evidence produced by AI, and consequently be held liable in court, is an important legal dimension that needs to be explored (Özçetin, 2022). The issues of whether robots or autonomous software should be given a legal status such as "electronic person" and how the hierarchy of responsibility (software developer, user, auditor) should be established in the event of damage represent a major legal and ethical gap (Erdoğan, 2019).

4.6. Impact on Auditor Professional Independence and Competence

The inclusion of AI in audit processes may pose threats to auditor independence and professional skepticism. The extent to which external auditors can rely on businesses' own continuous monitoring systems or AI algorithms is debatable in terms of the independence principle (Fırat, 2025). If the auditor becomes overly dependent on the client's system or shows a tendency to accept the results provided by AI without questioning them, this may lead to an erosion of professional skepticism (Özçetin, 2022).

Furthermore, although the International Ethics Standards Board for Accountants (IESBA) is working to develop ethical rules for the use of technology by professionals, whether auditors have the technological competence to evaluate AI outputs and how this competence gap affects audit quality requires further research (ICAEW, 2024).

A review of the literature reveals a broad consensus that AI increases efficiency in auditing; however, beyond the "how" of implementing the technology, there are significant gaps in the "how to manage it" and "how to oversee it." In particular, explainability, legal liability sharing, safeguarding auditor independence, and data ethics are key areas that future research should focus on for the reliable adoption of the technology.

Overcoming these challenges is critical for AI to evolve beyond being merely a technological innovation in the auditing profession and become a reliable and valuable tool. These efforts will also shape the future role and competencies of the auditing profession.

5 Artificial Intelligence in Audit and Financial Analysis: Current Applications and Research Findings

Digitalization and Industry 4.0 processes have led to fundamental changes in the audit and finance sectors. Particularly in the post-2020 literature, studies focusing on the integration of artificial intelligence (AI) algorithms into error detection, customer loss prediction, and continuous auditing processes are noteworthy. In this section of the study, several recent applications and research studies added to the literature are analyzed in the context of the work, findings, and results.

A report prepared for the Australian government examined the outputs of the Generative AI model used by Deloitte. Following this incident, the AI usage policies of major audit firms such as EY, KPMG, PwC, and BCG were reviewed. The report prepared by Deloitte found that the AI generated three references that did not actually exist and a fabricated Federal Court citation ("hallucination"). It was emphasized that artificial intelligence cannot be held solely responsible, and that the ultimate responsibility lies with humans; the audit giants have adopted strict rules requiring AI outputs to undergo human review (Vietnam.vn, 2025).

Fırat (2025) examined the transformative role of artificial intelligence in the auditing profession through a qualitative study based on secondary sources. The study focused on the impact of machine learning technologies on risk assessment, anomaly detection, and continuous auditing. It was found that AI technologies can identify patterns that may be overlooked in manual audits by processing large data sets, but they also carry risks such as data privacy, the "black box" problem (lack of explainability), and ethical biases. It was concluded that AI provides speed and accuracy in auditing, but regulatory frameworks and auditor competencies (skill sets) need to be developed for the effective use of these technologies (Fırat, 2025).

Ball, Krüger, and Drevin (2023) proposed a "unified approach" to detect anomalies in financial transactions. In the study, a model was trained by combining autoencoder neural networks with Social Network Analysis (SNA) metrics. SHAP (Shapley Additive Explanations) analysis revealed that network metrics such as "PageRank" and "degree centrality" were the features that contributed most strongly to anomaly detection. Enriching transactional data with network metrics reduced the model's false positive rates and yielded successful results that reduced operational costs in fraud detection (Ball, Krüger, & Drevin, 2023).

Özcan, Kayapınar, and Adem (2023) predicted customer churn using Random Forest, Decision Tree, Logistic Regression, Gaussian, and K-Nearest Neighbor (KNN) algorithms on a 10,000-record bank customer dataset. The models were tested with hyperparameter optimization. Among the compared algorithms, the Random Forest algorithm showed the highest success with an accuracy rate of 84%. Logistic Regression, on the other hand, showed the lowest performance with 71%. It was concluded that tree-based algorithms (especially Random Forest) are more successful than other methods in analyzing banking data and can be used as an effective tool in preventing customer churn (Özcan, Kayapınar, & Adem, 2023).

Gür (2023) designed a Python-based application system for detecting fraudulent disbursements in businesses and used the Decision Tree algorithm. The study was conducted on an artificial dataset consisting of normal and fraudulent transactions belonging to a bank. The decision tree model demonstrated high success, achieving 97.1% accuracy, 98.4%

F1-score, and 98% sensitivity. It was determined that the designed system allows auditors to make meaningful selections based on machine learning outputs instead of random document selection and speeds up the fraud detection process (Gür, 2023).

Sattarov, Herurkar, and Hees (2022) proposed a framework using a "Denoising Autoencoder" to detect errors in complex financial data (e.g., Investment Funds Statistics). The model aims not only to find anomalies but also to explain which cell (column) the error originated from. The developed DAE (Denoising Autoencoder) model showed 5% to 30% higher performance in cell-based error detection compared to traditional autoencoders and principal component analysis (PCA). It was concluded that the model can answer the questions "why is it an anomaly?" and "what should be in its place?", thus providing an explainable tool that overcomes the "black box" problem for auditors and domain experts (Sattarov, Herurkar, & Hees, 2022).

Hemati, Schreyer, and Borth (2022) proposed a "Continual Learning" framework to solve the problem of catastrophic forgetting, where AI forgets old information while being trained on new data in continuous auditing scenarios. The study was tested on Philadelphia and Chicago city payment datasets. The Experience Replay (ER) method outperformed the sequential fine-tuning method and reduced false positive alarms. The proposed framework has been proven to be more sustainable and transferable than existing methods for anomaly detection in non-stationary (time-varying) financial data (Hemati, Schreyer, & Borth, 2022).

Gür and Tarhan Mengi (2022) comparatively analyzed Decision Tree, Support Vector Machine (SVM), Logistic Regression (LR), and Artificial Neural Networks (ANN) methods on a 594,643-row bank dataset. The Decision Tree algorithm was the fastest and most successful model, with an accuracy rate of 99.42% and a processing time of 1.32 seconds. In contrast, the recall rates of the SVM and LR models remained low at 24% and 43%, respectively. It was found that time is critical in fraud detection and that the Decision Tree algorithm outperforms other methods in detecting fraudulent transactions in terms of both speed and accuracy (Gür & Tarhan Mengi, 2022).

Ali et al. (2022) analyzed machine learning techniques used in financial fraud detection by reviewing 93 articles published between 2010 and 2021. They determined that the most frequently used methods were Support Vector Machines (SVM) and Artificial Neural Networks (ANN), and that the most studied type of fraud was credit card fraud. However, it was found that unsupervised learning methods such as clustering were not sufficiently used in the literature. It was suggested that future studies should focus on text mining (Word2Vec, BERT, etc.) and unsupervised learning techniques (Ali et al., 2022).

Aksoy (2021) used data from 88 companies listed on the Istanbul Stock Exchange to predict financial statement fraud a year in advance using ANN, Decision Trees (CART), SVM, and Logistic Regression models. Artificial Neural Networks (ANN) and Decision Trees (CART) achieved a 96.15% overall accuracy rate by correctly classifying 100% of the fraudulent companies in the test set. The success rate of SVM and Logistic Regression remained at 80.77%. It was concluded that ANN and CART methods are highly effective in predicting fraudulent financial reporting and can be used by auditors as an early warning system (Aksoy, 2021).

6 Conclusion and Future Perspective

The findings examined in this article reveal that artificial intelligence is a force fundamentally transforming accounting auditing. AI is shifting auditing from a sampling-based approach relying on a limited data set to a technology-supported, risk-focused, and proactive paradigm that analyzes the entire data population. Through process automation, advanced risk assessment, and decision support systems, AI significantly increases the efficiency, accuracy, and scope of auditing.

One of the most important outcomes of this transformation is the redefinition of the auditor's role. The auditor of the future will no longer be someone who spends most of their time performing manual data checks and routine tests. Instead, they will become an expert who interprets the complex analysis results produced by AI models, thoroughly investigates the exceptional cases flagged by algorithms, and, most importantly, audits the fairness, transparency, and reliability of these algorithmic systems. This new role will require advanced competencies such as data science, statistical analysis, critical thinking, and ethical judgment, and will increase the auditor's professional value (Erdoğan, 2019).

Looking ahead, the impact of AI on auditing will deepen. With the proliferation of concepts such as continuous auditing and continual learning, auditing will evolve from a periodic activity into a real-time assurance mechanism integrated into the enterprise's systems (Hemati et al., 2022). AI models will be able to instantly adapt to changing business processes and emerging risks by continuously updating themselves with new data. Ultimately, artificial intelligence is not a technology that eliminates the auditor, but rather an "augmented intelligence" tool that enhances their perception, analytical ability, and judgment. This collaboration will solidify the future of the auditing profession by providing stakeholders with deeper and more timely assurance than ever before.

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