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Fraud Detection Using Artificial Intelligence and Big Data Analytics in Accounting: A Systematic Literature Review

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Abstract

This study reviews the development and application of artificial intelligence (AI) and big data analytics (BDA) for fraud detection in accounting and auditing. The review adopts a systematic literature review approach guided by PRISMA principles and synthesizes 20 peer-reviewed and scholarly sources covering data mining, machine learning, natural language processing, deep learning, audit analytics, and big data. The literature indicates that AI and BDA extend fraud detection from periodic, sample-based procedures toward continuous, risk-oriented analysis of large volumes of structured and unstructured data. Machine learning methods, including logistic regression, support vector machines, decision trees, ensemble methods, neural networks, and deep learning, are increasingly used to classify suspicious observations and identify nonlinear fraud patterns. BDA strengthens these models by integrating financial ratios, transaction records, audit evidence, textual disclosures, management commentary, and external information. The review also identifies persistent challenges involving class imbalance, data quality, explainability, privacy, model bias, cybersecurity, and auditor competencies. Overall, the evidence suggests that AI and BDA are most effective when deployed as decision-support mechanisms that complement professional skepticism and audit judgment rather than replace them. Future research should emphasize multimodal data integration, explainable AI, real-time analytics, robust validation across jurisdictions, and governance frameworks for responsible AI-enabled accounting and auditing.

Keywords Artificial Intelligence, Big Data Analytics, Fraud Detection, Accounting, Auditing, Machine Learning, Systematic Literature Review.

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INTRODUCTION

Fraud remains a fundamental threat to the reliability of accounting information, the credibility of financial reporting, and the efficiency of capital markets. Fraudulent financial reporting can involve intentional misstatements, omissions, manipulation of estimates, concealment of liabilities, or the strategic presentation of information designed to influence users of financial statements. Earlier accounting research demonstrated that financial and non-financial indicators can be useful in identifying firms with a higher likelihood of material misstatement, establishing an empirical foundation for predictive fraud analytics (Dechow et al., 2011). However, the scale and complexity of contemporary accounting information have made exclusively manual and periodic approaches increasingly difficult to sustain.

The development of artificial intelligence (AI), machine learning, and big data analytics (BDA) provides a new technological pathway for fraud detection. Traditional audit procedures are generally structured around risk assessment, sampling, analytical procedures, and professional judgment. By contrast, AI-enabled systems can process large datasets, recognize complex relationships, learn from historical observations, and prioritize transactions or entities that exhibit unusual patterns. Earlier research on data mining showed that decision trees, neural networks, and Bayesian models could classify fraudulent and non-fraudulent financial statements, demonstrating the feasibility of computational approaches in accounting fraud detection (Kirkos et al., 2007). Subsequent studies broadened the analytical landscape by comparing statistical and machine learning models and identifying differences in predictive performance and selected variables (Perols, 2011).

The literature also shows that fraud detection is no longer limited to structured financial statement ratios. Financial fraud can be reflected in narrative disclosures, management commentary, audit trails, transaction sequences, and other forms of unstructured or semi-structured information. Linguistic analysis, for example, has been used to identify textual characteristics associated with deceptive financial disclosures, indicating that natural language processing (NLP) can complement conventional financial indicators (Humpherys et al., 2011). More recent deep learning research similarly demonstrates the value of combining financial and textual information for detecting fraudulent financial statements (Craja & Kim, 2020).

At the same time, the expansion of data creates methodological challenges. Large datasets do not automatically produce better decisions. The usefulness of AI models depends on data quality, representative labels, feature construction, model validation, and the treatment of highly imbalanced fraud classes. Reviews of financial fraud detection have repeatedly identified class imbalance, limited fraud observations, inconsistent evaluation metrics, and differences in datasets as important barriers to reliable comparison across studies (Abdallah et al., 2016; Gupta & Mehta, 2024). In auditing, the problem is further complicated by the need to translate model outputs into professional judgments that are explainable, defensible, and consistent with audit responsibilities.

Big data has therefore changed not only the technical means of fraud detection but also the role of auditors. BDA can support the analysis of entire populations rather than relying only on samples, while AI can rank risks and identify anomalies for further investigation. Nevertheless, behavioral research warns that the adoption of analytics can affect how auditors interpret evidence, exercise skepticism, and make judgments (Brown-Liburd et al., 2015). AI should consequently be viewed as an augmentation technology rather than an autonomous replacement for professional expertise. Research on AI in auditing emphasizes opportunities for formalizing audit tasks and supplementing human capabilities, while also highlighting the need to understand the boundaries of automation (Issa et al., 2016).

Recent systematic reviews indicate a rapidly expanding research field. Studies have synthesized applications of AI and data mining in financial statement fraud detection, identifying supervised learning and ensemble methods as prominent approaches while also pointing to the growing importance of unstructured data and explainability (Putri & Nuswantara, 2025; Shahana et al., 2023). A recent review specifically focused on BDA reports that predictive analytics, hybrid approaches, anomaly detection, linguistic feature extraction, and textual pattern discovery constitute major application areas in financial fraud detection (Triyanto & Ali, 2026). Despite these advances, an integrated accounting-oriented perspective that connects AI, BDA, fraud detection, data characteristics, audit judgment, and implementation constraints remains important.

This systematic literature review therefore aims to synthesize the existing evidence on the use of AI and BDA in accounting fraud detection. The review addresses three questions: (1) What AI and BDA techniques are most frequently associated with fraud detection in accounting? (2) How does the integration of structured and unstructured data improve fraud identification? and (3) What methodological, professional, ethical, and governance challenges constrain the effective use of AI-enabled fraud detection? By answering these questions, the study seeks to provide a conceptual map of current research and identify directions for future accounting and auditing studies.

METHOD

This study uses a systematic literature review (SLR) with a qualitative narrative synthesis. The review protocol was structured around the principles of transparent identification, screening, eligibility assessment, and synthesis associated with PRISMA-oriented reviews. The approach is consistent with previous fraud-detection reviews that have classified the literature according to fraud type, data source, analytical technique, performance measure, and methodological limitation (Ngai et al., 2011; West & Bhattacharya, 2016). The purpose was not to estimate a single pooled effect size, but to identify recurring technological patterns and accounting implications across the literature.

The literature scope focused on studies addressing at least one of the following concepts: artificial intelligence, machine learning, data mining, big data analytics, natural language processing, deep learning, financial statement fraud, accounting fraud, audit analytics, or fraud detection. Priority was given to peer-reviewed journal articles and systematic reviews that directly examined accounting, auditing, financial reporting, or financial fraud. The final synthesis used 20 core scholarly sources published between 2007 and 2026, supplemented by cross-referencing of themes across the selected literature. The sources include foundational empirical studies, methodological reviews, and recent systematic reviews, allowing the analysis to connect early data-mining research with current AI and BDA developments.

Data extraction focused on five dimensions: (1) analytical technique, (2) data type, (3) fraud-detection task, (4) reported contribution, and (5) limitation or implementation challenge. Analytical techniques were grouped into statistical and traditional data-mining models, supervised machine learning, ensemble and deep learning, and text or NLP approaches. Data were classified as structured financial data, transactional data, textual disclosures, and integrated or external data. The synthesis then compared how each technology contributes to detection and how data characteristics affect model performance.

Quality and relevance were assessed through the consistency of the research objective, clarity of the analytical approach, relevance of the dataset to fraud detection, and explicit reporting of findings and limitations. Particular attention was given to studies addressing imbalanced classes, feature selection, data integration, and interpretability because these issues directly influence the practical use of AI in accounting. This emphasis follows evidence that fraud datasets are often difficult to construct and that the ratio between fraudulent and non-fraudulent observations can materially affect classification outcomes (Gupta & Mehta, 2024; Hamal & Senvar, 2021).

FINDINGS AND DISCUSSION

1. Evolution from Traditional Data Mining to Artificial Intelligence

The reviewed literature shows a clear evolution from rule-based and statistical techniques toward machine learning and AI-enabled fraud analytics. Early empirical work established that financial ratios could be transformed into predictive features and classified using decision trees, neural networks, and Bayesian belief networks (Kirkos et al., 2007). Ravisankar et al. (2011) further demonstrated the usefulness of feature selection and data-mining techniques for identifying fraudulent financial statements. These studies are important because they shifted fraud detection from a predominantly judgmental exercise toward a reproducible computational classification problem.

Subsequent research compared alternative statistical and machine learning models under different fraud-to-non-fraud ratios and misclassification costs. Perols (2011) found that logistic regression and support vector machines could perform strongly relative to several alternative machine learning models, illustrating that more complex models are not automatically superior in every setting. The broader review literature similarly emphasizes that fraud detection performance depends on the relationship between the algorithm, data characteristics, fraud type, and evaluation design rather than on the label of a technique as 'artificial intelligence' alone (West & Bhattacharya, 2016).

The current trend is toward more flexible models capable of learning nonlinear relationships and combining multiple feature types. Ensemble learning, deep learning, and hybrid architectures have become increasingly visible because they can capture interactions that may be difficult to specify manually. A systematic review of AI and data mining in financial statement fraud detection reports strong attention to supervised learning, including SVM, logistic regression, and XGBoost, while also noting the potential of deep learning and the need for greater use of unsupervised approaches (Putri & Nuswantara, 2025). Thus, the evolution of fraud analytics is not a simple replacement of traditional statistics; rather, it represents an expanding methodological toolbox.

2. Big Data Analytics and the Integration of Multiple Data Sources

BDA changes the fraud-detection problem by increasing the volume, variety, and velocity of information available for analysis. In accounting, this can include general ledger transactions, journal entries, accounts receivable and payable, payroll, procurement data, audit logs, financial ratios, management commentary, analyst forecasts, and external market information. Cao et al. (2015) explain that big data analytics creates opportunities for financial statement audits by enabling auditors to analyze broader populations and develop richer evidence. Alles (2015) similarly argues that the audit profession is likely to be influenced by big data because auditors cannot remain disconnected from the analytical practices used by their clients.

The most important finding across the reviewed literature is that data integration can be more valuable than simply increasing data volume. Hájek and Henriques (2017) show that combining financial information with managerial comments can improve intelligent fraud-detection systems, while analysts' forecasts provide additional information for identifying fraudulent firms. Deep learning research reaches a similar conclusion: combining financial and textual information can improve the detection of fraudulent statements and allow models to identify meaningful textual cues (Craja & Kim, 2020). These findings suggest that accounting fraud is multidimensional and may be better represented by a multimodal analytical architecture.

Recent evidence reinforces this direction. Triyanto and Ali (2026) identify supervised classification, anomaly detection, linguistic feature extraction, and unsupervised textual pattern discovery as major BDA applications in financial fraud detection. Their review also indicates that unstructured information can improve detection when combined with financial data. The implication for accounting is that future systems should not treat the financial statement as an isolated dataset. Instead, they should construct a connected evidence environment in which transactions, financial reports, narrative disclosures, and external indicators can be jointly analyzed.

3. Machine Learning, NLP, and Deep Learning for Fraud Detection

Machine learning is particularly useful when fraud indicators are numerous, interdependent, and difficult to formulate as fixed rules. Supervised classification models learn from historical examples of fraudulent and non-fraudulent observations, whereas unsupervised methods search for anomalies without requiring a complete set of labeled fraud cases. This distinction is important because verified fraud cases are relatively scarce compared with ordinary transactions. A comprehensive review by Abdallah et al. (2016) highlights the diversity of computational techniques used for fraud detection and the continuing importance of model selection according to the fraud context.

Text analytics and NLP expand fraud detection beyond numerical accounting variables. Humpherys et al. (2011) demonstrated that linguistic cues in financial disclosures can help distinguish fraudulent from non-fraudulent statements. This insight has become more relevant as annual reports, earnings announcements, management discussion sections, and other corporate narratives have become digitally accessible. AI models can transform text into features related to sentiment, linguistic complexity, emphasis, uncertainty, and semantic relationships, creating another layer of evidence for auditors.

Deep learning further extends this capability by learning representations from complex data. Craja and Kim (2020) show that deep learning models can combine textual and financial information, while recent reviews identify deep learning, NLP, and ensemble methods as important directions in AI-enabled forensic accounting (Putri & Nuswantara, 2025). Nevertheless, accuracy alone is insufficient for professional use. A model that predicts fraud effectively but cannot provide understandable evidence may be difficult for auditors to defend. This makes explainability and interpretable model outputs central to the future of AI-based accounting fraud detection.

4. Data Imbalance, Feature Selection, and Model Evaluation

One of the most consistent methodological problems is class imbalance. In real-world fraud datasets, fraudulent observations are normally much fewer than non-fraudulent observations. If a model is trained without addressing this imbalance, it can achieve high overall accuracy simply by classifying most cases as non-fraud. Hamal and Senvar (2021) demonstrate the importance of sampling strategies and SMOTE-type approaches in financial accounting fraud classification. Gupta and Mehta (2024) further show that the mapping ratio between fraudulent and non-fraudulent firms is a critical methodological issue that affects reported classification performance.

Feature selection is equally important because large datasets may contain redundant, noisy, or unstable variables. Ravisankar et al. (2011) emphasize feature selection in fraud detection, while Hájek and Henriques (2017) demonstrate the value of intelligent feature selection when financial and linguistic variables are combined. Dechow et al. (2011) also show that material accounting misstatements are associated with multiple dimensions, including accrual quality, financial performance, non-financial measures, off-balance-sheet activities, and market-based indicators. These findings imply that effective AI systems should be designed around theoretically meaningful and empirically validated features rather than indiscriminate data accumulation.

Evaluation should therefore move beyond simple accuracy. Precision, recall, F1-score, area under the ROC curve, false-positive rates, false-negative rates, and cost-sensitive measures are more informative when fraud is rare and the consequences of missing a fraudulent case are substantially different from incorrectly flagging a legitimate transaction. Dutta et al. (2017) demonstrate the importance of addressing class and cost imbalance when detecting financial restatements. A systematic review by Shahana et al. (2023) likewise identifies class and cost imbalance as important gaps in the financial statement fraud literature.

5. AI as Decision Support for Auditors

The reviewed literature strongly supports a decision-support interpretation of AI. AI systems can automate repetitive screening, identify anomalies, rank transactions according to risk, and direct auditor attention to areas that warrant deeper investigation. This can improve audit efficiency without eliminating the need for professional judgment. Issa et al. (2016) argue that AI can formalize portions of audit work and supplement the audit workforce. The value of AI therefore lies partly in reducing the cognitive and procedural burden associated with reviewing large populations of accounting data.

However, greater automation introduces behavioral and governance risks. Brown-Liburd et al. (2015) emphasize that big data can affect audit judgment and decision-making. Auditors may become overly reliant on model outputs, underestimate unusual but legitimate transactions, or interpret algorithmic scores without sufficient skepticism. AI can also inherit biases from historical data, particularly when labels are incomplete or when fraud cases are concentrated in certain industries or jurisdictions. Consequently, human oversight, professional skepticism, documentation, and independent validation remain essential.

The emerging role of AI should thus be framed as human-AI collaboration. The auditor remains responsible for understanding the engagement, assessing risks, evaluating evidence, and making professional conclusions. AI provides additional analytical capacity. This position is consistent with contemporary research showing that AI improves audit efficiency and fraud-detection capability while also raising ethical, organizational, and regulatory questions about accountability and explainability (Qatawneh, 2024).

6. Research Gaps and Future Directions

First, future research needs more multimodal datasets that combine structured accounting data with textual, behavioral, and external information. Much of the earlier literature uses relatively narrow financial-ratio datasets, whereas modern organizations generate diverse digital traces. Second, researchers should develop more transparent and explainable AI models. Fraud detection in accounting is a high-stakes setting in which a model's recommendation may influence audit procedures, regulatory attention, investor decisions, or corporate reputation. The ability to identify why a transaction or firm was flagged is therefore as important as predictive performance.

Third, future studies should improve external validity. Many fraud models are trained and tested on specific countries, industries, or regulatory environments, making cross-country validation necessary. Fourth, longitudinal and real-time research is needed to determine whether AI systems can detect emerging fraud patterns before they become material reporting problems. Finally, governance research should address data privacy, cybersecurity, model monitoring, auditability of algorithms, accountability for automated decisions, and the skills auditors need to work effectively with AI.

Recent systematic evidence suggests that the field is moving toward predictive and hybrid BDA frameworks, while the integration of structured and unstructured data is becoming increasingly important (Triyanto & Ali, 2026). At the same time, recent reviews of AI in accounting emphasize that technological capability must be accompanied by organizational readiness, ethical safeguards, and appropriate professional competencies (Putri & Nuswantara, 2025). The future of fraud detection is therefore likely to depend not on a single superior algorithm, but on an integrated ecosystem of data, analytics, professional judgment, and governance.

CONCLUSION

This systematic literature review concludes that artificial intelligence and big data analytics have substantially expanded the capacity of accounting and auditing systems to detect fraud. The literature has evolved from early applications of data mining and statistical classification toward machine learning, ensemble learning, natural language processing, deep learning, and integrated big data architectures. Across the reviewed studies, the strongest direction is the integration of structured financial information with transactional, textual, and external data because fraudulent behavior can manifest across multiple information dimensions. Nevertheless, AI effectiveness is constrained by class imbalance, data quality, feature selection, model validation, explainability, bias, privacy, cybersecurity, and the availability of skilled professionals. AI should therefore be implemented as a decision-support capability that strengthens, rather than replaces, auditor judgment and professional skepticism. Future research should prioritize multimodal and real-time fraud detection, explainable AI, cross-jurisdictional validation, cost-sensitive evaluation, and governance frameworks that ensure accountable and ethical use of AI in accounting and auditing.

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