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A Comprehensive Review of Predictive Analytics in Audit Risk Assessment for Advancing Data-Driven Decision-Making and Financial Transparency

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ABSTRACT: Audit risk assessment remains a foundational element of the financial statement audit, yet traditional approaches that rely primarily on professional judgment and sampling face growing limitations. Rising volumes of transactional data, increasing complexity in financial reporting, and more sophisticated forms of fraud and misstatement have reduced the effectiveness of conventional risk assessment methods. Although predictive analytics, including machine learning, anomaly detection, deep learning, and generative artificial intelligence, has been proposed as a means of addressing these challenges, existing research remains fragmented across techniques, applications, and institutional contexts. As a result, it is difficult to determine how predictive analytics advances audit risk assessment, under what conditions its benefits are realized, and where important constraints persist. This review addresses the problem by systematically synthesizing the relevant literature. It examines the predictive techniques employed, the audit activities in which they are applied, the conditions that shape their effectiveness, and the barriers that limit implementation. Building on this synthesis, the review develops the Integrated Predictive Analytics–Audit Risk Assessment Framework, which organizes technical capabilities, operating mechanisms, moderating conditions, and outcomes related to audit quality and financial transparency. By clarifying the current state of knowledge and providing an integrative structure, the review offers a foundation for more coherent research and practice in data-driven audit risk assessment.

KEYWORDS: Predictive analytics, Audit risk assessment, Machine learning in auditing, Fraud detection, Financial transparency

1. INTRODUCTION

Audit risk assessment remains a central element of the financial statement audit. Auditors must evaluate the risk of material misstatement and design procedures that reduce detection risk to an acceptably low level. For decades, this process has relied primarily on professional judgment, historical financial analysis, and sampling-based testing. While these methods continue to form the backbone of auditing standards, they face increasing strain. Organizations now generate vast quantities of transactional and non-financial data, financial reporting environments have grown more complex, and schemes involving fraud or earnings management have become more sophisticated (Ogbonna et al., 2025a; Nartey et al., 2026). Traditional approaches that examine only a fraction of available data are limited in their ability to detect subtle or emerging risks on time. In response, researchers and practitioners have turned to predictive analytics. Techniques drawn from statistics, machine learning, deep learning, and, more recently, generative artificial intelligence are being applied to estimate the likelihood of material misstatement, identify anomalous transactions, prioritize high-risk areas, and support continuous monitoring (Zhang et al., 2025; Föhr et al., 2026; Christensen et al., 2025). These methods offer the prospect of moving audit risk assessment from a largely retrospective and periodic activity toward a more proactive and data-driven process. Early evidence suggests that such techniques can improve detection rates and help auditors allocate effort more efficiently, particularly in fraud detection and audit planning (Benyasrisawat & Ounlert, 2026; Ayeomon et al., 2022).

Despite this growing interest, the literature remains fragmented. Studies differ widely in the techniques examined, the audit activities addressed, the quality of empirical validation, and the attention given to organizational and regulatory conditions. Some contributions focus narrowly on algorithmic performance, while others emphasize governance challenges or conceptual frameworks for continuous auditing (Anwar & Akeel, 2026; Zygoulis, 2025; Eulerich et al., 2025). As a result, it is difficult to form a coherent picture of how predictive analytics advances audit risk assessment, under what conditions its benefits are most reliably realized, and where important limitations persist. This review addresses that gap by systematically synthesizing research on the application of predictive analytics to audit risk assessment. It is guided by four research questions: (1) What predictive analytics techniques have been applied in audit risk assessment, and what are their relative strengths and limitations? (2) How has predictive analytics been applied across major audit risk assessment activities, and in which domains is the supporting evidence strongest? (3) What benefits does predictive analytics offer for audit decision-making and financial transparency, and under what conditions are these benefits most reliably realized? (4) What is the current state of the research landscape, and which gaps and emerging directions warrant further investigation? In answering these questions, the review examines the techniques employed, the audit activities in which they are applied, the benefits reported, and the challenges that constrain implementation.

2. REVIEW APPROACH AND LITERATURE SELECTION

The literature was identified through systematic searches of Scopus, Web of Science Core Collection, ScienceDirect, SpringerLink, IEEE Xplore, ACM Digital Library, Emerald Insight, Wiley Online Library, ABI/INFORM, and Business Source Complete. Search queries combined terms including "predictive analytics," "machine learning," "artificial intelligence," "audit risk assessment," "audit risk," "fraud detection," "continuous auditing," and "financial statement fraud." Results were limited to English-language publications from 2020 to 2026. Studies were retained if they examined the application of predictive analytics or machine learning to audit risk assessment, fraud detection, internal control evaluation, or closely related areas and showed relevance to U.S. auditing practice or regulatory settings. Papers that were purely conceptual without analytical substance, fell outside the date range, or lacked a clear connection to audit risk were excluded. After screening titles, abstracts, and full texts, 22 studies met the inclusion criteria and formed the final sample. Relevant data on research design, methods, findings, and limitations were extracted from each study and synthesized thematically to support the analysis presented in this review.

3. FOUNDATIONS OF PREDICTIVE ANALYTICS IN AUDIT RISK ASSESSMENT

Audit risk assessment has long rested on the classical Audit Risk Model, which decomposes audit risk into inherent risk, control risk, and detection risk. Under this model, auditors evaluate the susceptibility of financial statements to material misstatement and design procedures to reduce detection risk to an acceptable level. While the model remains foundational, its traditional operationalization has been constrained by sampling limitations, periodic timing, and heavy reliance on professional judgment applied to relatively small subsets of data (Ampofo et al., 2024; Ogbonna et al., 2025b). Predictive analytics refers to the use of statistical techniques, machine learning algorithms, and related computational methods to identify patterns in historical data and generate forecasts or risk scores concerning future or unobserved outcomes. In the audit context, these techniques are applied to estimate the likelihood of material misstatement, control failure, fraudulent activity, or other risk-relevant events (Yuan et al., 2025; Benyasrisawat & Ounlert, 2026). The shift toward predictive approaches reflects both the growing volume and complexity of organizational data and the limitations of conventional risk assessment methods in detecting subtle or emerging risks.

Several studies describe an evolution from traditional, largely retrospective risk assessment toward more data-driven and forward-looking practices. Traditional approaches typically rely on historical financial ratios, prior-year findings, and auditor experience to form risk assessments at the planning stage. In contrast, predictive models can process large volumes of transactional and non-financial data to generate continuous or frequently updated risk indicators (Duhova et al., 2026; Föhr et al., 2026). This transition aligns with broader developments in risk-based auditing, which emphasize the concentration of audit effort on areas of elevated risk rather than uniform coverage. Theoretical support for the adoption of predictive analytics draws primarily from the Audit Risk Model and the principles of risk-based auditing. By improving the precision with which inherent and control risks are estimated, predictive techniques can enable more efficient allocation of detection effort (Anwar & Akeel, 2026; Zygoulis, 2025). Some researchers further link these developments to continuous auditing concepts, arguing that frequent or real-time data analysis can reduce the lag between the occurrence of a risk event and its identification by the auditor (Föhr et al., 2026; Duhova et al., 2026). The relationship between predictive analytics and audit decision-making is not purely technical. Effective use of model outputs depends on auditors' ability to interpret results, integrate them with other evidence, and exercise professional skepticism. Studies examining machine learning applications consistently note that model transparency and interpretability influence whether auditors trust and act upon algorithmic risk assessments (Benyasrisawat & Ounlert, 2026; Christensen et al., 2025). Without adequate explainability, even accurate predictions may have limited impact on audit planning or substantive testing decisions.

In summary, the foundations of predictive analytics in audit risk assessment rest on the enduring structure of the Audit Risk Model, the practical limitations of traditional methods, and the capacity of data-driven techniques to improve the identification and prioritization of risk. The literature indicates that predictive approaches extend rather than replace established auditing principles, provided that model outputs can be meaningfully incorporated into professional judgment.

4. PREDICTIVE ANALYTICS TECHNIQUES APPLIED IN AUDIT RISK ASSESSMENT

Predictive analytics encompasses a range of statistical and computational techniques used to estimate the likelihood of future or unobserved risk events in the audit process. The literature reveals a progression from relatively simple statistical models toward more complex machine learning, deep learning, and generative approaches. This section synthesizes the principal techniques examined in the validated studies, focusing on their characteristics, typical applications in audit risk assessment, reported strengths, and recognized limitations.

4.1 Statistical Predictive Models

Early and continuing applications of predictive analytics in auditing rely on established statistical methods, particularly logistic regression and related classification techniques. These models are frequently used to estimate the probability of material misstatement, audit modification, or fraudulent reporting on the basis of financial ratios, governance indicators, and other observable firm characteristics. Logistic regression remains attractive because of its interpretability: coefficients can be examined directly, and the contribution of individual predictors is relatively transparent to auditors (Benyasrisawat & Ounlert, 2026; Yuan et al., 2025). Studies applying statistical models report moderate to strong predictive performance when the underlying data are well structured, and the risk event is reasonably frequent (Ogbonna et al., 2025b; Yuan et al., 2025). However, these methods often struggle with highly imbalanced datasets, which are common in fraud detection, and with complex, non-linear relationships among variables. (Esmeralda & Fadhilah, 2026). As a result, purely statistical approaches are increasingly supplemented or replaced by more flexible machine learning methods when large volumes of transactional data are available.

4.2 Machine Learning-Based Approaches

Machine learning techniques, especially ensemble methods such as random forests and gradient boosting (including XGBoost), appear frequently in the recent literature. These algorithms are applied to tasks such as predicting material misstatements, identifying high-risk transactions for audit planning, and assessing the likelihood of financial reporting irregularities (Zhang et al., 2025; Ayeomon et al., 2022; Benyasrisawat & Ounlert, 2026; Ogbonna et al., 2025b). Ensemble methods generally outperform single classifiers by combining multiple weak learners and by capturing non-linear interactions among predictors. Empirical results indicate that random forests and gradient boosting can achieve high levels of accuracy and area-under-the-curve scores in controlled settings. Feature-importance measures generated by these models also provide a degree of interpretability, allowing auditors to identify which variables most strongly influence risk scores (Benyasrisawat & Ounlert, 2026; Ayeomon et al., 2022). Nevertheless, performance is highly sensitive to data quality and class imbalance. Several studies note that without careful sampling or cost-sensitive learning, models tend to under-predict rare but critical events such as fraud (Esmeralda & Fadhilah, 2026; Gkegkas et al., 2025).

4.3 Anomaly Detection and Pattern Recognition Approaches

Anomaly detection methods occupy a central place in audit applications because many risk events are rare and poorly represented in labeled training data. Unsupervised and semi-supervised techniques are used to flag transactions or patterns that deviate from established norms, thereby directing auditor attention to potentially high-risk areas (Duhova et al., 2026; Nartey et al., 2026). Process mining combined with machine learning has also been employed to detect deviations from expected process flows and to evaluate the effectiveness of internal controls at a transactional level (Duan et al., 2025). These approaches are particularly valuable in continuous auditing and internal audit contexts, where the goal is to monitor large volumes of data for unusual activity rather than to classify known outcomes. Their principal limitation lies in the interpretation of flagged anomalies: not every statistical outlier constitutes an audit risk, and substantial professional judgment is required to distinguish meaningful signals from noise (Duhova et al., 2026; Anwar & Akeel, 2026).

4.4 Advanced Analytics Approaches

More recent research has examined deep learning architectures and generative artificial intelligence. Deep learning models, including convolutional and recurrent networks (such as CNN-LSTM combinations), have been tested for audit risk assessment tasks that involve sequential or high-dimensional data (Föhr et al., 2026; Yan, 2024). These models can capture complex temporal and hierarchical patterns that traditional machine learning methods may miss. However, their limited transparency remains a significant concern for audit applications, where the ability to explain model outputs is often essential for professional skepticism and regulatory acceptance (Föhr et al., 2026; Benyasrisawat & Ounlert, 2026). Generative AI, particularly large language models, represents a further extension of predictive techniques into unstructured textual data. Experimental studies show that large language models can assist auditors in identifying relevant fraud risks and in predicting Critical Audit Matters from management discussion and analysis disclosures (Christensen et al., 2025; Akpan & Ogunade, 2026). Performance gains are especially noticeable for less experienced auditors. At the same time, the same studies indicate that improvements in risk identification do not automatically translate into better audit planning decisions, underscoring the continuing importance of professional judgment (Christensen et al., 2025). Overall, the literature portrays a diverse technical landscape. Statistical and ensemble machine learning methods currently offer the most consistent and interpretable performance for structured risk prediction tasks. Anomaly detection supports broader monitoring applications, while deep learning and generative AI expand the range of data that can be analyzed. Across all categories, the practical value of these techniques depends heavily on data quality, model transparency, and the capacity of auditors to integrate algorithmic outputs into their decision processes.

5. APPLICATIONS OF PREDICTIVE ANALYTICS ACROSS AUDIT RISK ASSESSMENT ACTIVITIES

Predictive analytics has been applied across a range of audit activities, with varying degrees of maturity and empirical support. The literature shows that the most consistent and well-documented applications concern fraud detection and the prioritization of high-risk areas during audit planning. Applications in continuous auditing and financial reporting assurance are also present but remain less extensively validated. This section examines the principal domains of application and evaluates the contribution of predictive techniques to audit effectiveness.

5.1 Audit Planning and Risk Prioritization

A central use of predictive analytics lies in supporting risk-based audit planning. By generating risk scores for accounts, transactions, or business units, predictive models help auditors concentrate substantive testing on areas of elevated risk. Studies employing machine learning techniques on large transaction datasets report that models can identify high-risk items with substantial accuracy, thereby reducing the volume of low-risk testing while increasing the likelihood of detecting material issues (Ayeomon et al., 2022; Ogbonna et al., 2025b). Empirical work on material misstatement prediction further supports this application. Models trained on financial and non-financial indicators have demonstrated the ability to forecast future misstatements more effectively than traditional benchmarks, providing auditors with an additional input for planning decisions (Zhang et al., 2025). The practical value of these approaches depends on the quality of the underlying data and on auditors' willingness to adjust planned procedures in response to model outputs. When these conditions are met, predictive analytics can improve both the efficiency and the focus of the audit.

5.2 Fraud Detection and Irregularity Identification

Fraud detection represents the most extensively researched application domain. Multiple studies document the use of machine learning and related techniques to identify fraudulent transactions, financial reporting irregularities, and money-laundering patterns (Nartey et al., 2026; Benyasrisawat & Ounlert, 2026; Esmeralda & Fadhilah, 2026). Ensemble methods such as random forests and gradient boosting frequently appear as high-performing approaches, particularly when combined with careful handling of class imbalance. Research focused on the U.S. financial and banking sectors reports that machine learning and deep learning models can improve detection rates relative to traditional rule-based systems (Amoako et al., 2025). Experimental studies of generative AI further indicate that large language models can assist auditors in identifying relevant fraud risks from textual sources, with particularly noticeable benefits for less experienced practitioners (Christensen et al., 2025; Akpan & Ogunade, 2026). At the same time, these studies caution that improved risk identification does not automatically lead to changes in audit strategy, highlighting the continuing role of professional judgment. Overall, the evidence suggests that predictive analytics can meaningfully enhance the detection of fraud and irregularities, provided that models are appropriately validated and that their outputs are integrated into the broader audit process.

5.3 Continuous Auditing and Monitoring

A smaller but growing body of work examines the use of predictive analytics for continuous or near-real-time monitoring. Machine learning models applied to enterprise resource planning data have been shown to support ongoing risk assessment and the timely identification of anomalous transactions (Duhova et al., 2026). Framework-oriented studies argue that deep learning and related techniques can be embedded within continuous auditing architectures to move assurance from a periodic to a more proactive orientation (Föhr et al., 2026; Zygoulis, 2025). Process mining combined with machine learning offers an additional avenue for continuous control monitoring by detecting deviations from expected process flows (Duan et al., 2025). Despite these developments, empirical evaluations of full continuous auditing implementations remain limited. Many contributions are conceptual or based on pilot applications, and questions persist regarding scalability, data integration, and the organizational changes required to sustain continuous monitoring.

5.4 Financial Reporting Assurance

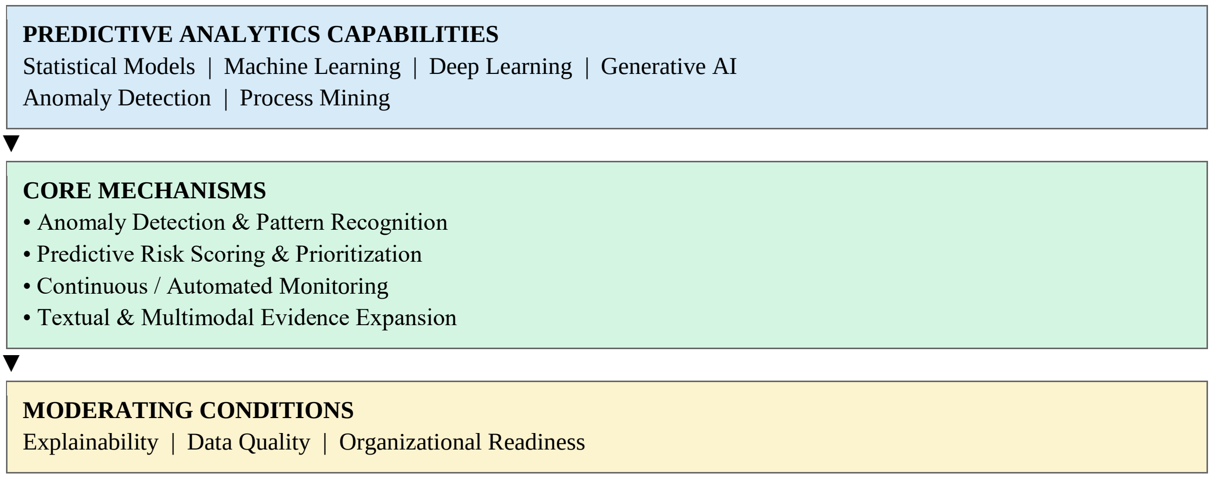
Predictive analytics also contributes to broader financial reporting assurance by improving the reliability of risk assessments that underpin audit opinions. Studies examining artificial intelligence in audit workflows suggest that predictive tools can enhance coverage of the financial statement population and support more robust evaluations of management assertions (Anwar & Akeel, 2026; Yeboah et al., 2026). Generative AI applications that assist in the identification of Critical Audit Matters further illustrate the potential for these techniques to inform key assurance judgments (Akpan & Ogunade, 2026). In addition, emerging work on cybersecurity risk assessment within capital market contexts indicates that predictive and data-driven approaches are beginning to extend into non-traditional areas of audit risk (Onyekwuluje et al., 2025). While the evidence base in this domain is still developing, it points to a gradual broadening of the scope of predictive analytics beyond conventional financial statement risks.

In summary, predictive analytics has demonstrated clear value in fraud detection and audit planning, where both technical performance and practical relevance are relatively well established. Applications in continuous auditing and financial reporting assurance show promise but currently rest on a thinner empirical foundation. Across all domains, the contribution of these techniques depends not only on algorithmic performance but also on the capacity of auditors and organizations to incorporate model outputs into professional decision-making and quality control processes.

6. INTEGRATED FRAMEWORK OF PREDICTIVE ANALYTICS-ENABLED AUDIT RISK ASSESSMENT

The preceding synthesis of techniques and applications reveals that predictive analytics can improve audit risk assessment, yet the conditions under which these improvements materialize remain unevenly understood. Technical performance alone does not guarantee better audit outcomes. Model outputs must be interpretable, data must be of sufficient quality, organizational capabilities must support adoption, and regulatory expectations must provide adequate clarity. To organize these interrelated elements, this review proposes the Integrated Predictive Analytics–Audit Risk Assessment (IPARA) Framework. The IPARA Framework conceptualizes the contribution of predictive analytics as a multi-layered process. At the foundation are predictive analytics capabilities, encompassing statistical models, machine learning algorithms, deep learning architectures, anomaly detection methods, process mining, and generative artificial intelligence. These capabilities enable a set of core mechanisms: the detection of anomalous patterns, the generation of risk scores for prioritization, the support of continuous or frequent monitoring, and the analysis of unstructured textual evidence. The effectiveness of these mechanisms is shaped by several moderating conditions identified across the literature. Explainability of model outputs influences whether auditors trust and incorporate algorithmic insights into their judgments (Benyasrisawat & Ounlert, 2026; Christensen et al., 2025). Data quality and governance affect the reliability of predictions. Organizational readiness, including skills and process adaptation, determines the extent of actual use. Regulatory clarity, particularly regarding expectations from bodies such as the PCAOB, further conditions both investment decisions and the manner in which tools are deployed (Eulerich et al., 2025; Yeboah et al., 2026). When these conditions are favorable, the mechanisms support concrete audit processes, most notably risk-based planning, fraud detection, internal control evaluation, and, to a lesser extent, continuous auditing. Improved risk identification and more focused auditor attention constitute intermediate outcomes. These, in turn, contribute to the ultimate objectives of higher audit quality and greater financial transparency.

The framework also recognizes important boundary conditions. Empirical support is currently strongest for applications in fraud detection, anti-money laundering, and audit planning. Evidence for continuous auditing and cybersecurity risk assessment remains more limited and variable. Consequently, the IPARA Framework does not assume uniform transformation across all audit domains.



Regulatory Clarity (e.g., PCAOB) | Accountability & Governance

▼

AUDIT RISK ASSESSMENT PROCESSES
Audit Planning & Risk Prioritization
Fraud Detection & Irregularity Identification
Internal Control Evaluation
Continuous Auditing & Monitoring
Financial Reporting Assurance

▼

INTERMEDIATE OUTCOMES
Improved Risk Identification | Enhanced Auditor Judgment
More Efficient Resource Allocation

▼

ULTIMATE OUTCOMES
Higher Audit Quality → Greater Financial Transparency

Figure 1. Integrated Predictive Analytics Framework for Audit Risk Assessment

Boundary Condition: Strongest evidence in Fraud Detection / AML and Audit Planning; more limited and variable evidence in Continuous Auditing and Cybersecurity Risk Assessment.

Figure 1 presents a schematic representation of the IPARA Framework, illustrating the relationships among capabilities, mechanisms, moderating conditions, audit processes, and outcomes. By integrating technical, professional, and contextual dimensions, the framework offers a structured basis for understanding how predictive analytics advances audit risk assessment and where its benefits are most reliably realized.

7. BENEFITS AND CONTRIBUTIONS OF PREDICTIVE ANALYTICS TO AUDIT DECISION-MAKING AND FINANCIAL TRANSPARENCY

The literature indicates that predictive analytics can generate meaningful improvements in audit risk assessment and related decision processes, although these benefits are neither automatic nor uniform across contexts. When technical capabilities are effectively combined with favorable moderating conditions, predictive techniques contribute to more accurate risk identification, more efficient allocation of audit effort, and ultimately to higher-quality assurance and greater financial transparency.

One of the most consistently reported benefits is enhanced risk identification. Machine learning models trained on financial and transactional data have demonstrated the ability to predict material misstatements and high-risk transactions more effectively than traditional benchmarks or purely judgmental approaches (Zhang et al., 2025; Ayeomon et al., 2022). By analyzing larger portions of the data population, these models surface patterns and anomalies that sampling-based methods are likely to miss. Similar advantages appear in fraud detection, where ensemble methods and related techniques improve the identification of irregular transactions and reporting anomalies (Benyasrisawat & Ounlert, 2026; Esmeralda & Fadhilah, 2026). Improved risk identification supports more efficient resource allocation. When auditors receive reliable risk scores, they can concentrate substantive testing on higher-risk areas and reduce effort on low-risk populations (Ogbonna et al., 2025a). Studies examining transaction-level prediction report that prioritization of high-risk items can reduce the volume of low-risk testing while maintaining or improving detection performance; however, most studies do not quantify the magnitude of these efficiency gains in terms of testing hours or sample size reductions (Robertson & Smith, 2025; Ogbonna et al., 2025). In this respect, predictive analytics reinforces the core logic of risk-based auditing by making risk assessments more data-informed and granular. Predictive techniques also contribute to auditor decision-making, particularly through decision-support rather than full automation. Experimental research on generative artificial intelligence shows that large language models can help auditors, especially those with less experience, identify a greater number of relevant fraud risks from textual information (Christensen et al., 2025; Akpan & Ogunade, 2026). These tools expand the evidence base available to the auditor and can improve the comprehensiveness of risk assessments. At the same time, the same studies indicate that gains in risk identification do not always translate directly into changes in planned audit procedures, underscoring that professional judgment remains central. At a broader level, these improvements in risk assessment and decision support have implications for financial transparency. More effective detection of material misstatements and irregularities increases the credibility of audited financial statements. Framework-oriented and review studies argue that the integration of predictive analytics into audit workflows can enhance coverage, reduce detection lag, and support more robust evaluations of management assertions (Anwar & Akeel, 2026; Zygoulis, 2025; Yeboah et al., 2026). In principle, such gains strengthen the informational value of financial reports for external users. Nevertheless, the literature also makes clear that realized benefits depend heavily on contextual conditions. Models that lack interpretability are less likely to influence auditor judgments (Benyasrisawat & Ounlert, 2026; Christensen et al., 2025). Poor data quality or severe class imbalance can degrade predictive performance. Organizational factors, including skills, process design, and change readiness, further shape the extent to which technical capabilities are translated into practice. Regulatory uncertainty regarding the appropriate use of artificial intelligence in auditing can similarly constrain adoption and impact (Eulerich et al., 2025). In sum, predictive analytics offers well-documented contributions to risk identification, audit efficiency, and decision support. These contributions are most evident in fraud detection and planning applications and are strongest when model outputs are interpretable and organizational and regulatory conditions are supportive. Under less favorable conditions, the same techniques may deliver only limited improvements in audit outcomes and financial transparency.

8. CHALLENGES AND IMPLEMENTATION BARRIERS

Despite the documented potential of predictive analytics, the literature consistently identifies substantial barriers that limit successful implementation and constrain realized benefits. These challenges span data infrastructure, model characteristics, professional and organizational factors, and the broader governance and regulatory environment. Understanding these obstacles is essential for realistic assessment of the technology's contribution to audit risk assessment.

8.1 Data-Related Challenges

Data quality and availability constitute foundational constraints. Predictive models depend on large volumes of reliable, well-structured data, yet audit-relevant datasets frequently suffer from incompleteness, inconsistency across systems, and limited historical coverage (Duhova et al., 2026; Anwar & Akeel, 2026). Class imbalance presents a further difficulty, particularly in fraud detection: fraudulent or high-risk events are rare relative to normal transactions, causing many algorithms to under-predict the events of greatest audit interest (Esmeralda & Fadhilah, 2026; Gkegkas et al., 2025; Amoako et al., 2025). Integration of data from disparate financial, operational, and external sources remains technically and organizationally demanding. Without adequate investment in data governance and infrastructure, even sophisticated algorithms produce unreliable or non-generalizable results.

8.2 Model-Related Challenges

A second cluster of difficulties concerns the models themselves. Many high-performing machine learning and deep learning techniques operate as relative "black boxes," offering limited insight into why a particular risk score was generated (Benyasrisawat & Ounlert, 2026; Föhr et al., 2026). Limited explainability reduces auditor trust and complicates the exercise of professional skepticism. Validation poses additional problems: models that perform well on training data may degrade when applied to new periods, entities, or economic conditions, yet rigorous out-of-sample and temporal validation is not uniformly reported (Yuan et al., 2025; Yan, 2024, 2025). Generative AI introduces further concerns regarding hallucination, consistency, and the stability of outputs across slight variations in prompts (Christensen et al., 2025; Akpan & Ogunade, 2026). These model-related limitations mean that technical accuracy alone is insufficient for audit use.

8.3 Professional and Organizational Challenges

Even when data and models are adequate, human and organizational factors can impede effective adoption. Auditors require new skills to interpret algorithmic outputs, assess model limitations, and integrate quantitative risk scores with other forms of evidence. Several studies note persistent skill gaps and uneven readiness across audit teams (Anwar & Akeel, 2026; Christensen et al., 2025). Resistance or skepticism toward algorithmic recommendations is also documented, particularly when model logic is opaque. Experimental evidence suggests that less experienced auditors may benefit more visibly from generative AI support, while experienced auditors may be more cautious in adjusting their judgments or planned procedures (Christensen et al., 2025). At the organizational level, successful implementation often requires changes in workflow design, quality control processes, and performance metrics that many firms have only begun to address (Zygoulis, 2025; Anwar & Akeel, 2026).

8.4 Governance and Regulatory Challenges

Governance and regulatory issues form a final, and particularly consequential, set of barriers. Questions of accountability remain unresolved: when an auditor relies on or overrides a model-generated risk assessment, the allocation of responsibility is not always clear. Ethical concerns regarding bias, fairness, and the potential for models to embed historical discrimination have received limited attention in the audit literature to date. Most significantly, regulatory uncertainty, especially regarding the expectations of the PCAOB and other oversight bodies, affects both the willingness of firms to invest in advanced analytics and the manner in which such tools are deployed (Eulerich et al., 2025; Yeboah et al., 2026; Nartey et al., 2026). Analytical work suggests that unclear or evolving regulatory guidance can distort incentives, leading to either under-investment or overly cautious use of predictive technologies. Until clearer standards emerge concerning documentation, validation, and the appropriate role of artificial intelligence in the audit, many firms are likely to proceed incrementally rather than transformatively. In combination, these challenges help explain why the benefits of predictive analytics, although real, remain unevenly distributed. Technical capability is a necessary but insufficient condition for improved audit outcomes. Sustainable gains depend on concurrent progress in data quality, model transparency, professional capabilities, organizational adaptation, and regulatory clarity.

9. RESEARCH LANDSCAPE AND EMERGING DIRECTIONS

The body of research on predictive analytics in audit risk assessment has expanded considerably since 2020, yet it remains uneven in both topical coverage and methodological maturity. The majority of empirical and review studies concentrate on fraud detection, anti-money laundering, and the prediction of material misstatements or high-risk transactions (Benyasrisawat & Ounlert, 2026; Esmeralda & Fadhilah, 2026; Gkegkas et al., 2025; Amoako et al., 2025; Zhang et al., 2025). Machine learning techniques, particularly ensemble methods such as random forests and gradient boosting, dominate the technical literature, while a smaller set of studies examines deep learning architectures and, more recently, generative artificial intelligence (Föhr et al., 2026; Christensen et al., 2025; Akpan & Ogunade, 2026). Applications in audit planning and risk prioritization are reasonably well represented and generally report positive results (Ogbonna et al., 2025a; Ayeomon et al., 2022). In contrast, continuous auditing and real-time monitoring, although frequently discussed in conceptual and framework-oriented papers, rest on a thinner base of rigorous empirical evaluation (Duhova et al., 2026; Zygoulis, 2025). Cybersecurity risk assessment within the audit context appears in only a limited number of studies and has yet to be systematically integrated with predictive modeling approaches (Onyekwuluje et al., 2025). Longitudinal research examining the sustained performance of predictive systems, organizational adaptation over time, or changes in audit quality outcomes is largely absent. Several emerging directions are visible. Generative AI is beginning to extend predictive analytics into unstructured textual data, offering new possibilities for risk identification and Critical Audit Matter assessment (Christensen et al., 2025; Akpan & Ogunade, 2026). Work on explainable models and the combination of process mining with machine learning reflects growing attention to interpretability and process-level insight (Benyasrisawat & Ounlert, 2026; Duan et al., 2025). Regulatory and governance questions, particularly those surrounding PCAOB expectations and accountability for algorithmic judgments, are receiving increased attention, although empirical investigation of these issues remains limited (Eulerich et al., 2025; Anwar & Akeel, 2026; Yeboah et al., 2026).

Table 1. Taxonomy of Predictive Analytics Applications in Audit Risk Assessment

Predictive Analytics Category	Representative Techniques	Primary Audit Applications	Primary Contributions	Reported Benefits	Common Challenges	Representative Literature
Statistical Models	Logistic regression, classification models	Material misstatement prediction, risk scoring	Interpretable baseline risk estimates	Transparency of coefficients; moderate predictive power	Limited handling of non-linearity and class imbalance	Benyasrisawat & Ounlert, (2026); Yuan et al. (2025)
Machine Learning (Ensemble)	Random Forest, XGBoost, gradient boosting	Fraud detection, high-risk transaction prioritization, audit planning	High predictive accuracy on structured data	Improved detection rates; feature importance measures	Data imbalance; variable generalizability	Zhang et al. (2025); Ayeomon et al. (2022); Ogbonna et al. (2025a)
Anomaly Detection & Process Mining	Unsupervised anomaly detection, process mining + ML	Continuous monitoring, internal control evaluation	Identification of deviations from expected patterns	Early warning capability; process-level insight	High false-positive rates; interpretation burden	Duhova et al. (2026); Duan et al. (2025); Nartey et al. (2026)
Deep Learning	CNN-LSTM, neural network architectures	Complex sequential risk assessment	Capture of hierarchical and temporal patterns	Potential performance gains on high-dimensional data	Limited explainability; data and computational demands	Föhr et al. (2026); Yan, (2024)
Generative AI / LLMs	Large language models	Fraud risk identification, Critical Audit Matter prediction	Analysis of unstructured textual evidence	Support for less experienced auditors; expanded evidence base	Hallucination risk; limited effect on planning decisions	Christensen et al. (2025); Akpan & Ogunade (2026)
Integrated / Framework Approaches	Hybrid ML + process mining; AI workflow architectures	Full audit workflow, risk-based internal auditing	Structured guidance for implementation	Conceptual roadmap for transformation	Implementation and governance barriers	Anwar & Akeel (2026); Zygoulis (2025); Föhr et al. (2026)

Table 1 provides a taxonomy of predictive analytics applications in audit risk assessment, organizing the validated literature by technique category, primary audit application, and principal contribution. The taxonomy underscores both the concentration of research in fraud detection and planning and the relative underdevelopment of continuous auditing, cybersecurity, and long-term implementation studies. Overall, the current landscape is characterized by strong technical progress in selected domains, accompanied by persistent gaps in theory development, longitudinal evidence, fairness considerations, and the organizational and regulatory conditions required for reliable large-scale adoption.

10. FUTURE RESEARCH DIRECTIONS

Several priorities for future research emerge directly from the gaps and tensions identified in the current literature. First, there is a clear need for longitudinal and multi-firm studies that examine how predictive analytics systems perform over time, how organizations adapt their processes and controls, and whether initial gains in risk detection are sustained. Most existing empirical work remains cross-sectional or limited to single settings, leaving questions of durability and generalizability unanswered. Second, research should more rigorously evaluate continuous auditing implementations. While conceptual frameworks are relatively well developed, evidence on operational performance, cost-effectiveness, and integration with existing audit methodologies remains sparse. Third, greater attention is required to the human–AI interface. Experimental work has begun to explore how auditors use generative AI for risk identification, yet little is known about how model outputs influence final judgments, documentation practices, or skepticism when predictions conflict with other evidence. Fourth, studies addressing explainability, bias, and fairness in audit risk models are needed. The literature repeatedly notes interpretability concerns but offers limited tested solutions or examinations of differential impacts across entities. Finally, research on regulatory and governance mechanisms, particularly the effects of clearer PCAOB or equivalent guidance, would help clarify the institutional conditions under which predictive analytics can be adopted responsibly and effectively. Addressing these priorities would strengthen both the theoretical and practical foundations of the field.

11. LIMITATIONS

This review has several limitations that should be considered when interpreting its findings. First, the literature search was restricted to English-language publications from 2020 to 2026 and to selected academic databases. As a result, relevant studies published in other languages, outside the chosen time window, or in sources not covered by the search may have been omitted. Second, the review employed a thematic synthesis approach rather than a formal systematic review protocol with quantitative quality scoring or meta-analysis. While this approach is suitable for organizing a diverse and still-emerging body of work, it does not support statistical aggregation of effect sizes or formal risk-of-bias assessment across studies. Finally, the emphasis on literature with relevance to U.S. auditing practice and regulatory contexts means that the findings may not fully generalize to jurisdictions with different institutional arrangements. These constraints bound the scope and methodological reach of the review and should be kept in mind when applying its conclusions.

12. CONCLUSION

Traditional audit risk assessment, built on sampling and professional judgment, faces increasing difficulty in environments characterized by large data volumes and complex financial reporting. This review set out to clarify how predictive analytics addresses that difficulty and under what conditions it does so effectively. The synthesis shows that the primary contribution of predictive techniques lies in expanding the scope and timing of risk identification, most reliably in fraud detection and audit planning. These gains, however, depend on model interpretability, data quality, organizational readiness, and regulatory clarity. The Integrated Predictive Analytics–Audit Risk Assessment Framework developed here brings these elements together, making visible the mechanisms through which technical capabilities translate into audit outcomes and the boundary conditions that limit uniform claims of transformation. Readers of this review now have a structured account of where predictive analytics currently adds the most value, why benefits remain uneven across application domains, and which conditions must be managed for those benefits to be realized in practice.

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