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A Hybrid Approach in Contemporary Auditing: A Literature Synthesis on the Integration of Risk-Based Audit and Data Analytics

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ABSTRACT

The advancement of digital technology has fundamentally transformed auditing practice by increasing the volume and complexity of data that auditors must process, necessitating more adaptive and risk-sensitive approaches. Risk-based audit (RBA) and data analytics have emerged as two pivotal responses to this challenge; however, their individual roles and the implications of their integration for audit risk assessment remain insufficiently synthesized in the existing literature. This study aims to analyze the roles of RBA and data analytics, as well as their integration in supporting audit risk assessment. A Systematic Literature Review (SLR) guided by the PRISMA 2020 framework was employed, drawing on 30 peer-reviewed articles published between 2021 and 2026, sourced from Scopus, Web of Science, and Google Scholar, and analyzed using thematic analysis. The findings reveal that RBA improves audit process quality by enabling systematic risk prioritization and strengthening the audit function as a strategic organizational mechanism, while data analytics extends audit coverage through full population testing, enhances fraud and anomaly detection, and facilitates continuous auditing, despite persistent adoption challenges including regulatory barriers, skills gaps, and cognitive risks. The integration of both approaches optimizes risk assessment through five complementary mechanisms: expanding risk identification, improving misstatement risk assessment accuracy, enabling objective high-risk area determination, enhancing audit judgment quality, and optimizing risk-based resource allocation. These findings underscore that the successful integration of RBA and data analytics depends not solely on technological adoption, but equally on governance maturity, human resource capacity, and the development of adaptive audit standards suited to the demands of the digital era.

Keywords: Risk-Based Audit, Data Analytics, Risk Assessment, Audit Quality

INTRODUCTION

The digital transformation has driven significant changes in auditing practice, particularly through the growing complexity of data confronted by auditors. Modern organizations generate data in enormous volumes with highly diverse sources, demanding more sophisticated and comprehensive data integration and analytical capabilities in the audit process (Fitriandini et al., 2025). This transformation has facilitated the emergence of continuous auditing, enabling real-time and ongoing audit processes through integration with organizational information systems (Ningsih et al., 2026). These conditions increasingly require auditors to adapt to a dynamic data environment and to leverage predictive analytics in decision-making.

Risk-based audit (RBA) represents an appropriate response to this data complexity. RBA is an approach centered on the identification, evaluation, and prioritization of risks as the basis for audit planning and execution, enabling auditors to focus audit resources on high-risk areas and thereby improving audit efficiency and effectiveness (Thahirah et al., 2025). Without adequate technological support, however, RBA risks being limited in its capacity to process complex and dynamic data, necessitating integration with more sophisticated data-driven approaches.

The emergence of data analytics has become one of the primary drivers of transformation in data-based decision-making. Big data analytics (BDA) enables the processing of large volumes of high-complexity data more efficiently. In the auditing domain, BDA allows auditors to analyze entire data populations rather than relying solely on samples, thereby improving audit accuracy and reliability. The use of BDA algorithms also contributes to risk identification and fraud detection through more effective anomaly pattern recognition (Hendra et al., 2025). The integration of big data and artificial intelligence further strengthens analytical capabilities in identifying hidden patterns, generating predictions, and automating analytical processes (Hasibuan & Nasution, 2025). Nevertheless, data analytics implementation faces challenges including data quality issues, system interoperability, ethical concerns, and the limited availability of competent human resources (Prabhugouda & Asra, 2024).

Given these developments, the integration of RBA and data analytics has become increasingly critical to improving audit quality in the digital era. Data analytics enables auditors to conduct comprehensive analyses of entire data populations, enhancing the accuracy of risk identification and the ability to detect errors and potential fraud (Ogeh, 2026), consistent with empirical evidence demonstrating that the application of data analytics in audit processes improves the quality of audit reports (Fitria et al., 2025). Furthermore, when integrated with RBA, data analytics enables more automated and comprehensive data analysis, allowing auditors to direct their attention toward high-risk areas in alignment with RBA principles (Dempsey & Van Dyk, 2024). Accordingly, this study aims to analyze the roles of RBA and data analytics and their integration in supporting audit risk assessment, with the expectation of contributing to the development of more adaptive, technology-based, and contextually relevant audit practices in contemporary business environments.

LITERATURE REVIEW

The primary theoretical foundation underpinning this study is agency theory. This theory posits that the divergence of interests between owners (principals) and management (agents) generates information asymmetry and the potential for moral hazard, thereby necessitating an independent oversight mechanism (Jensen & Meckling, 1976). In the audit context, agency theory positions the audit function as a vital instrument for reducing agency costs and enhancing the transparency of financial reporting, which in turn strengthens stakeholder confidence (Almgrashi & Mujalli, 2024). This theoretical perspective becomes particularly relevant when the audit function is viewed not merely as a compliance examination, but as a strategic mechanism within modern organizational governance (Rakipi et al., 2021).

Risk-based audit (RBA) is an audit approach that shifts focus from the exhaustive examination of transactions toward the prioritization of areas with the highest risk exposure that could potentially impede the achievement of organizational objectives (Almgrashi & Mujalli, 2024). This approach integrates the risk assessment process into annual audit planning, enabling the optimal direction of auditor resources toward the most material and high-risk areas (Lois et al., 2021). Nevertheless, risk-based planning requires auditors to maintain a current and up-to-date understanding of the organization's risk conditions, an inherent need that drives the integration of analytical technology into the audit process (Álvarez-Foronda et al., 2023).

Audit data analytics (ADA) is defined as the science and art of discovering and analyzing patterns, identifying anomalies, and extracting meaningful information from audit-relevant data through analysis, modeling, and visualization (Rakipi et al., 2021). In the era of big data, characterized by massive volume, velocity, variety, and veracity, traditional sampling-based audit methods have demonstrated their limitations by providing only a partial view of transaction populations (Hezam et al., 2023). ADA enables auditors to examine entire transaction populations through an audit-by-exception approach, whereby attention is redirected from routine transaction inspection toward the investigation of exceptions prioritized by risk level, thereby significantly enhancing the capacity to detect material misstatements and fraudulent activities (Huang et al., 2022).

The deployment of data analytics in auditing practice does not occur in a regulatory vacuum, rather, it operates within a multi-layered normative framework established by international and professional standard-setting bodies. Four principal standard-setting bodies shape the normative framework within which data analytics is deployed in auditing. The International Standards on Auditing (via ISA 315 and ISA 520) encourages the use of analytical procedures in risk identification and assessment, yet provides no specific technical guidance on how ADA tools should be designed, validated, or documented, a regulatory gap consistently identified as the most significant adoption barrier in the literature (Hezam et al., 2023; Ruhnke, 2023). Public Company Accounting Oversight Board (PCAOB AS 2110) similarly contemplates technology-assisted risk assessment without prescribing implementation standards. The American Institute of Certified Public Accountants (AICPA), through its RADAR initiative, has proposed the Multidimensional Audit Data Selection (MADS) framework to guide full-population testing, while acknowledging auditor liability concerns when ML-driven analyses are applied (Huang et al., 2022).

The Institute of Internal Auditors's International Professional Practices Framework (IPPF) (Standard 2010) mandates risk-based audit planning, with the Global Internal Audit Standards (2025) further establishing data-driven planning as a professional expectation. Across all four bodies, a consistent tension emerges, standards neither prohibit nor adequately prescribe analytics use, creating regulatory ambiguity that suppresses adoption. Empirical evidence from 130 Spanish auditors confirms that absence of specific regulation is the single most impactful barrier to DA/AI adoption, exceeding knowledge gaps and trust deficits (Torroba et al., 2025). This underscores the argument of this study that governance maturity, including adaptive standards, is a structural prerequisite for RBA–ADA integration.

METHODOLOGY

This study employs a Systematic Literature Review (SLR) guided by the PRISMA 2020 framework, which enables transparent, reproducible evidence synthesis while minimizing selection bias. The review protocol was established prior to the search process and followed four sequential stages, identification, screening, eligibility, and inclusion. Literature searches were conducted on 5-6 April 2026 across three databases Scopus, Web of Science (WoS), and Google Scholar, covering publications from 2021 to 2026. These databases were selected based on their comprehensive coverage of peer-reviewed accounting and auditing research and access to quality indicators (SJR/JCR).

The following Boolean search string was applied such as *("risk-based audit" OR "risk-based internal audit") AND ("data analytics" OR "audit data analytics" OR "big data analytics" OR "machine learning") AND ("audit quality" OR "risk assessment" OR "audit process")*. Supplementary searches used terms including *"continuous auditing"*, *"fraud detection audit"*, *"full population testing"*, and *"artificial intelligence audit quality"*. Articles were included in the review if they satisfied all of the following criteria (1) substantively address RBA, ADA, or their integration in an audit context; (2) publication year 2021–2026; (3) published in a peer-reviewed journal; (4) written in English or Indonesian; and (5) full text accessible. Conversely, articles were excluded on the basis of the following exclusion criteria (1) outside financial or internal auditing domains; (2) duplicate record across databases; (3) full text unavailable; or (4) grey literature (practitioner reports, non-peer-reviewed working papers).

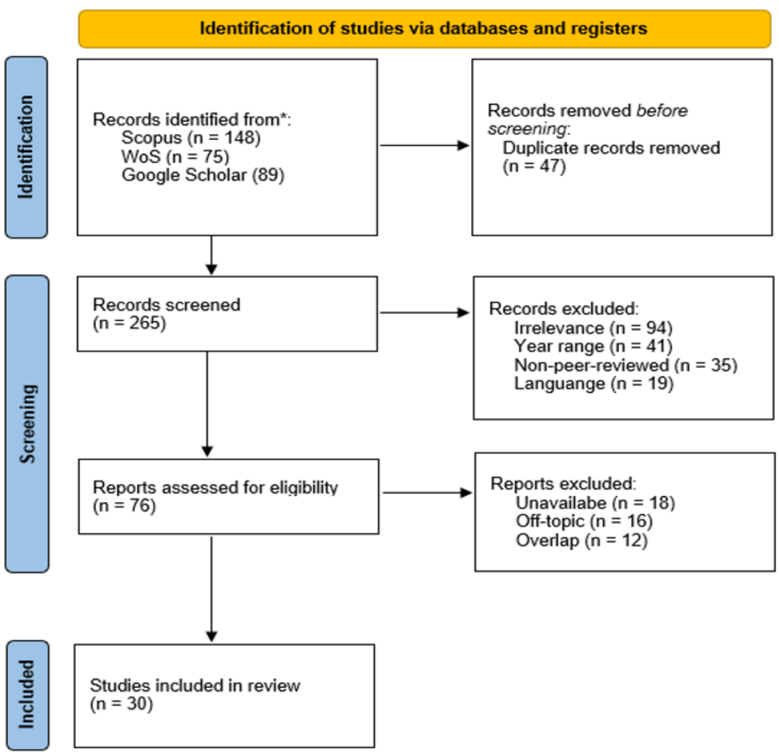

Figure 1. PRISMA Flow Diagram

Beyond the quantitative selection process, a qualitative quality appraisal was applied to the 30 included articles to assess methodological rigor and thematic contribution. Each article was evaluated on the following dimensions, (1) methodological clarity (whether the research design, data collection, and analysis procedures were explicitly documented); (2) theoretical grounding (the presence of a clear theoretical framework underpinning the study); (3) analytical depth (the extent to which findings were analytically derived rather than merely descriptive); and (4) contribution to the RBA–ADA research gap (the degree to which the study adds to the specific integration domain addressed by this review).

To ensure synthesis objectivity, all 30 articles were independently coded by two researchers using a pre-established schema organized around three dimensions such as the role of RBA, data analytics applications, and RBA–ADA integration mechanisms. Coder agreement was assessed using percent agreement, yielding PA = 85%, which reflects an acceptable level of inter-rater consistency for qualitative thematic synthesis. The coding process was conducted at the thematic-unit level, where each article could contribute to multiple analytical categories depending on the focus of findings and conceptual emphasis. The coding schema was pilot-tested on a subset of articles prior to full analysis to improve consistency in thematic interpretation. Disagreements were resolved through discussion and consensus, consistent with best practices for thematic synthesis in qualitative systematic reviews (Nowell et al., 2017; Thomas & Harden, 2008).

FINDINGS

Of the 30 articles analyzed, the publication distribution reveals a trend of growing academic interest in this topic, peaking in 2025 (12 articles, 40%), followed by 2023 (5 articles, 17%), with 2022, 2024, and 2026 each contributing 4 articles (13%), and 2021 accounting for only 1 article (3%). Overall, this trend indicates a significant increase in research on the integration of RBA and data analytics in auditing, particularly in recent years. Table 1 presents the classification by publication year to illustrate this research development trend.

Table 1. Classification by Year of Publication

Year	**Number**	**Percentage**
2026	4	13%
2025	12	40%
2024	4	13%
2023	5	17%
2022	4	13%
2021	1	3%
Total	**30**	**100%**

The subsequent classification by research method identifies the most dominant methodological approach. Qualitative methods predominate with 16 articles (53%), reflecting a tendency toward in-depth exploration. Quantitative methods account for 10 articles (33%), applied research for 2 articles (7%), and mixed-method and conceptual approaches for 1 article each (3%). Overall, this distribution confirms that qualitative methodology is the most prevalent approach, indicating that research in this field tends to prioritize in-depth understanding over quantitative testing or conceptual model development.

The synthesis reveals three dominant patterns across the reviewed studies. First, empirical and quantitative studies consistently report positive associations between ADA implementation and audit quality enhancement, particularly in fraud detection, testing coverage, and risk assessment accuracy. Second, both qualitative and survey-based studies converge in identifying regulatory ambiguity, technological competency gaps, and organizational readiness as the primary barriers to analytics adoption. Third, recent literature increasingly recognizes that although BDA and AI improve analytical capability, they simultaneously introduce cognitive and algorithmic risks including anchoring bias, availability bias, and excessive reliance on automated outputs.

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Table 2. Classification by Research Method

Research Method	Techniques	Number	Percentage
Quantitative	Multiple Linear Regression; PLS-SEM; Experiment; Path Analysis; Machine Learning; Logistic Regression	10	33%
Qualitative	Descriptive; Data Triangulation; Literature Review; SLR-PRISMA; Content Analysis	16	53%
Applied Research	Research and Development; Design Science Research	2	7%
Mixed Method	PLS-SEM & Interview	1	3%
Conceptual	Literature Review	1	3%
Total		**30**	**100%**

The literature was further classified based on thematic synthesis to identify the primary dimensions and focal areas of research. This thematic classification identifies three main dimensions, RBA (focusing on governance and risk management), data analytics (full population testing, fraud detection, and continuous auditing), and their integration (audit resource allocation efficiency, high-risk area identification, and audit judgment enhancement). The results are presented in Table 3.

Table 3. Classification by Thematic Synthesis

Thematic Category	Number	Key References
Risk-Based Audit (RBA)		
RBA Focus & Audit Result Relevance	2	(Khairunnisa & Wilasittha, 2025); (Ardianingsih & Payamta, 2022);
Audit Resource Efficiency	2	(Thahirah et al., 2025); (Fitriani et al., 2025)
Technology Integration & Other Approaches	5	(Khaerunnisa, 2025); (Zalaan et al., 2024); (Nurhaliza et al., 2026); (Rahayu & Wilasittha, 2023); (Föhr et al., 2026)
Corporate Governance & Risk Management	6	(Almgrashi & Mujalli, 2024); (Astuti & Riyanti, 2025); (Novita & Naswandi, 2022); (Sofa et al., 2025); (Yufantria & Fadhlihi, 2025); (Kirpitsas & Pachidis, 2026)
Data Analytics		
Full Population Testing	4	(Huang et al., 2022); (Álvarez-Foronda et al., 2023); (Hezam et al., 2023); (Rozana et al., 2025)
Fraud Detection & Anomaly	4	(Rakipi et al., 2021); (Putra et al., 2022); (Achmad et al., 2024); (Wijaya et al., 2025)
Continuous Auditing	3	(Álvarez-Foronda et al., 2023); (Ruhnke, 2023); (Ditkaew & Suttipun, 2023)
Analytical Techniques	2	(Ruhnke, 2023); (Álvarez-Foronda et al., 2023)
Adoption Gap	2	(Torroba et al., 2025); (Rakipi et al., 2021); (Ruhnke, 2023)
Integration		

Thematic Category	Number	Key References
Expanded Risk Identification	4	(Ruhnke, 2023); (Álvarez-Foronda et al., 2023); (Rakipi et al., 2021); (Almgrashi & Mujalli, 2024)
Improved Misstatement Risk Assessment Accuracy	3	(Susilawati et al., 2025); (Sofyani et al., 2025); (Ruhnke, 2023)
High-Risk Area Determination	4	(Verna et al., 2026); (Álvarez-Foronda et al., 2023); (Putra et al., 2022); (Hezam et al., 2023)
Audit Judgment Quality & Depth	4	(Sofyani et al., 2025); (Ruhnke, 2023); (Ditkaew & Suttipun, 2023); (Wijaya et al., 2025)
Efficiency & Effectiveness of Audit Resource Allocation	6	(Rozana et al., 2025); (Almgrashi & Mujalli, 2024); (Rakipi et al., 2021); (Hezam et al., 2023); (Torroba et al., 2025); (Susilawati et al., 2025)

Key research gaps include, absence of longitudinal studies tracking the sustained impact of RBA–ADA integration over multiple engagement cycles, limited empirical evidence from developing-country contexts, insufficient attention to AI governance and algorithmic fairness in analytics-driven risk prioritization, and an underdeveloped evidence base for RBA–ADA integration specifically in the external audit context.

DISCUSSION

The Role of Risk-Based Audit in the Audit Process

Risk-based audit (RBA) is a risk-oriented approach that positions the identification and evaluation of risks as the primary foundation of audit planning and execution. By systematically identifying, measuring, and ranking risks, RBA enables auditors to focus their attention on high-risk areas more effectively (Khairunnisa & Wilasittha, 2025). This approach directs the audit process toward alignment with the organization's strategic objectives, making audit activities more targeted rather than general, and ultimately enhancing the relevance of audit outcomes for decision-making (Ardianingsih & Payamta, 2022). RBA directly contributes to improving audit efficiency and effectiveness by enabling the optimal allocation of audit resources to the most significant risk areas, so that auditors need not examine all areas uniformly but instead focus on the most critical ones (Thahirah et al., 2025). This concentration on critical areas generates tangible added value from audit activities and enhances the organizational impact of audit engagements (Fitriani et al., 2025).

Technological support and artificial intelligence further strengthen RBA effectiveness across various audit phases. The utilization of regional computing, parallel computing, and mobile edge computing (MEC) technologies, alongside the application of machine learning and AI algorithms, facilitates simultaneous, rapid, and accurate risk assessment, thereby enhancing the capacity for anomaly detection, fraud prediction, and comprehensive risk exposure evaluation (Khaerunnisa et al., 2025; Nurhaliza et al., 2026). Additionally, the use of ATLAS software in RBA has been shown to assist auditors in conducting more focused audit processes and improving overall audit quality (Rahayu & Wilasittha, 2023). Furthermore, deep learning frameworks integrated with RBA enable auditors to analyze complex data and detect patterns or anomalies that are difficult to identify manually, thereby supporting the effectiveness and efficiency of the audit process (Föhr et al., 2026).

RBA also plays a strategic role in supporting good corporate governance and risk management. In this capacity, RBA functions as an assurance mechanism that provides management and the board of directors with reasonable confidence that risks have been managed in accordance with established policies, thereby contributing to improved organizational performance (Novita & Naswandi, 2022). Empirical evidence demonstrates significant relationships between the role of internal auditors, risk management training, and management support in relation to the effective implementation of risk-based internal auditing (Almgrashi & Mujalli, 2024). The synergy between internal audit and RBA has further been shown to strengthen organizational accountability through the reinforcement of internal control systems and the enhancement of oversight quality (Sofa et al., 2025).

RBA also serves as an effective instrument for maintaining organizational integrity by proactively enhancing auditors' capacity to detect and prevent fraud. A systematic risk analysis allows auditors to identify potential irregularities at an early stage before they escalate into more significant fraudulent activities (Astuti & Riyanti, 2025). The implementation of continuous auditing, supported by a range of audit tools and external collaboration, further reinforces this ongoing monitoring function (Zalaan et al., 2024).

From the perspective of the business environment, RBA provides auditors with the flexibility to adapt to constantly evolving organizational dynamics. RBA has evolved into a more responsive approach that adjusts to shifting organizational risk profiles, ensuring the audit process remains relevant in the face of dynamic external challenges (Yufantria & Fadhlihi, 2025). Empirical evidence further confirms that approaches integrating governance, risk management, and continuous auditing within dynamic environments are capable of improving process quality, efficiency, and system reliability, as evidenced by accelerated task completion, reduced problem incidence, and improved stakeholder satisfaction (Kirpitsas & Pachidis, 2026). Taken together, RBA not only improves the quality of the audit process but also reinforces the role of auditing as a strategic organizational function.

The Use of Data Analytics in the Audit Process

Conceptually, data analytics in the audit context may be understood as the science and art of discovering and analyzing patterns, deviations, and inconsistencies embedded in data underlying or related to the audit subject, through analysis, modeling, and visualization. This definition reflects the broad spectrum of data analytics applications in modern auditing practice, extending beyond transactional data processing toward in-depth analysis that supports substantive decision-making (Rakipi et al., 2021). Based on the reviewed literature, the application of data analytics in auditing can be grouped into five principal themes.

The first theme concerns the use of data analytics for full population testing. In the era of big data, traditional audit sampling has lost its relevance because it provides only a partial view of very large populations (Huang et al., 2022). Through the concepts of *audit-by-exception* and *exceptional exceptions*, data analytics and machine learning enable auditors to analyze entire transaction populations and prioritize exceptions based on suspicion scores and materiality impacts. Empirical evidence from one study recorded a 44% reduction in audit execution time and an 80% increase in the number of tests performed following data analytics implementation, providing tangible evidence of the resulting efficiency gains (Álvarez-Foronda et al., 2023). This evolution from a sample-based approach toward full population analysis has been confirmed as one of the primary opportunities offered by big data analytics for improving audit efficiency and quality (Hezam et al., 2023; Rozana et al., 2025).

The second theme encompasses the use of data analytics for fraud and anomaly detection. Data analytics' capacity to process entire data populations consistently enhances auditors' ability to detect anomaly patterns associated with fraud. The involvement of the Internal Audit Function (IAF) in fraud detection activities correlates positively and significantly with the level of data analytics adoption, confirming that fraud detection is one of the primary drivers of this technology's utilization (Rakipi et al., 2021). Big data analytics facilitates the automated scanning of transactions to trace potential fraud in Indonesian local governments (Putra et al., 2022), while Generalized Audit Software (GAS) has been demonstrated to enhance the effectiveness of forensic auditors in identifying fraud as a positive moderating factor (Achmad et al., 2024). Fraud detection has even been identified as the dominant research theme in the AI and audit quality literature for the period 2010–2025, underscoring its centrality in the field's development(Wijaya et al., 2025).

The third theme reflects a paradigm shift toward continuous auditing, audit processes that operate continuously and in real time rather than periodically. Data analytics drives a fundamental change from static, periodic audit models toward continuous audit models in which tests can be scheduled automatically and monitoring results reported in near-real time (Álvarez-Foronda et al., 2023). Within a multidimensional framework grounded in socio-technical theory, continuous auditing is identified as a key concept in the data analytics diffusion process, as continuously available data demands processes that are equally continuous (Ruhnke, 2023). Empirical findings from a survey of 452 CPAs in Thailand confirm the significant positive effect of Audit Data Analytics (ADA) on Audit Review Continuity (ARC), supported by resource advantage theory (Ditkaew & Suttipun, 2023).

The fourth theme pertains to the diversity of analytical techniques employed across audit phases. The analytical techniques used in auditing span a wide spectrum, encompassing data visualization, process mining, text mining, clustering, regression, simulation, machine learning, causal and predictive analytics, and social network analysis (Ruhnke, 2023). Each technique is associated with a specific audit phase, exploratory techniques such as cluster analysis and data mining are applied during risk identification and assessment, while substantive analytics and full population testing are deployed during procedure design and execution. Mapping the benefits of data analytics by audit phase reveals that in the planning phase, the primary benefit lies in trend and population analysis. In the execution phase, the greatest value derives from test automation and fraud detection. In the reporting phase, data analytics enhances the visibility and communicative impact of audit findings (Álvarez-Foronda et al., 2023). Process mining is specifically noted as an effective tool for analyzing business processes and identifying control risks in event logs.

Although the theoretical benefits of data analytics are well established, its actual implementation in practice remains limited. The most significant barrier is regulatory constraints, followed by knowledge gaps and trust deficits (Torroba et al., 2025). Global data from 1,681 Chief Audit Executives across 82 countries reveals that 54.5% of IAFs do not use or use data analytics only minimally, while 45.5% employ it moderately to extensively (Rakipi et al., 2021). This adoption gap is influenced by reporting relationships to the audit committee, CAE competencies, and involvement in high-value activities such as fraud detection and IT risk auditing. Ruhnke (2023) further identifies that barriers to ADA diffusion are rooted in uncertainty regarding audit standards, auditors' cognitive burden, and the risk of expectation gaps, a significant contrast between the theoretical potential of data analytics and its adoption realities.

The Role of Data Analytics in Supporting Risk Assessment in Risk-Based Audit

RBA allocates audit resources proportionally to identified risk levels, with the objective of ensuring that the most intensive audit procedures are directed toward the highest-risk areas. The effectiveness of RBA depends not solely on technology but on a broader risk governance ecosystem, encompassing the roles of internal auditors, risk management training, and management support as key mediating factors in its implementation (Almgrashi & Mujalli, 2024). Within this ecosystem, data analytics plays a critical role as a mechanism that systematically strengthens the capacity for risk identification and assessment. Five principal roles illustrate this contribution.

The first role is the expansion of risk identification. Exploratory techniques such as data visualization, cluster analysis, data mining, text mining, process mining, and social network analysis enable auditors to uncover patterns, trends, and anomalies that remain undetected by traditional procedures, thereby producing a more comprehensive understanding of the entity and its internal controls (Ruhnke, 2023). Data analytics also enables real-time risk monitoring, freeing auditors from sole reliance on static historical data (Álvarez-Foronda et al., 2023). From an institutional perspective, data analytics adoption is driven by the functional needs of the IAF, while the maturity of the risk management system constitutes an important prerequisite for effective RBA implementation (Almgrashi & Mujalli, 2024; Rakipi et al., 2021). A synthesis of these perspectives confirms that the integration of data analytics with RBA is inherently reciprocal, data analytics strengthens risk identification, while risk management maturity provides the necessary foundation for its optimal utilization.

The second role concerns the improvement of misstatement risk assessment accuracy. Knowledge of BDA has been demonstrated to improve risk assessment accuracy and to help auditors reduce common cognitive biases, including anchoring, recency bias, and confirmation bias (Susilawati et al., 2025). Consistently, BDA-based audit system quality has been shown to influence public sector audit performance through audit judgment as a mediator, indicating that data analytics not only improves technical efficiency but also enhances the quality of auditors' professional judgment (Sofyani et al., 2025) On the other hand, the literature also identifies a counter-intuitive dimension, if big data is not adequately synthesized, BDA involvement in risk assessment may introduce new biases such as availability bias, dilution effect, and inattentional blindness (Ruhnke, 2023). These findings underscore that data analytics is not a constraint-free solution; rather, its effectiveness is substantially determined by auditor competence and contextually appropriate application.

The third role is data analytics' capacity to support the accurate and objective identification of high-risk areas. The application of CatBoost machine learning enables audit authorities to prioritize manual verification of high-

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risk documents while automating the validation of low-risk ones, with financial variables and beneficiary characteristics serving as the primary predictive features, consistent with auditor intuition (Verna et al., 2026). Risk-based audit planning supported by data analytics allows for the dynamic, data-driven prioritization of high-risk areas rather than reliance on historical experience alone (Álvarez-Foronda et al., 2023). BDA also functions as a proactive instrument for detecting fraud-prone areas in Indonesian regional government settings prior to audit execution (Putra et al., 2022), while predictive techniques in the global literature enable auditors to anticipate potential risks from historical data patterns (Hezam et al., 2023).

The fourth role pertains to the impact of data analytics on audit judgment quality. Audit judgment has been conceptualized as a mediator between BDA-based audit system quality and public sector performance, with the finding that the effect of BDA operates through the enhancement of auditors' professional judgment quality (Sofyani et al., 2025). The use of ADA restructures the processes of problem representation, hypothesis formation, information search, and conclusion-drawing, rendering the audit process more iterative and exploratory (Ruhnke, 2023). ADA has been confirmed to enhance auditors' capacity to identify significant risks, fulfill audit objectives, and mitigate potential risks (Ditkaew & Suttipun, 2023). However, the extension toward AI raises ethical concerns regarding the accountability of algorithmic decision-making, necessitating a clear governance framework to prevent excessive reliance on algorithmic outputs in the absence of critical human evaluation (Wijaya et al., 2025).

The fifth role involves data analytics' contribution to improving the efficiency and effectiveness of risk-based audit resource allocation. BDA enables more in-depth risk analysis by simultaneously accounting for multiple variables, allowing resources to be allocated more efficiently to high-risk areas while reducing unnecessary audit procedures (Almgrashi & Mujalli, 2024; Rozana et al., 2025). Data analytics also supports continuous monitoring across the entire risk management cycle, not only the initial assessment phase, fundamentally transforming the way auditors proactively manage risk (Rakipi et al., 2021). Nevertheless, implementation challenges remain significant such as skills gaps, data quality issues, technological infrastructure limitations, and regulatory constraints constitute barriers that differ between developed and developing countries (Hezam et al., 2023; Torroba et al., 2025), findings that are equally relevant to the Indonesian context, as reflected in the limited adoption of BDA by junior auditors in misstatement risk assessment (Susilawati et al., 2025).

Table 5. Conceptual Framework: Integration of RBA and Data Analytics Across Audit Stages

RBA Stage	Data Analytics Techniques	Data Requirements	Key Controls	Expected Audit Evidence
Risk Identification	Data visualization, cluster analysis, process mining, text mining, social network analysis	Transaction data, ERP logs, unstructured narrative data, external risk indicators	Data completeness checks, source validation, access controls	Risk universe map, preliminary risk register, anomaly indicators
Risk Assessment	Regression, machine learning (Random Forest, CatBoost), predictive analytics, Benford's Law	Full transaction population, historical audit data, entity-level variables	Model validation, bias diagnostics, cross-validation	Risk heat map, materiality-weighted risk scores, misstatement probability estimates
Risk Response (Procedure Design)	Full-population testing, audit-by-exception, exceptional exceptions, substantive analytics	Stratified transaction populations, journal entries, A/R & A/P data	Threshold calibration, exception review, professional judgment checkpoints	Prioritized exception list, suspicion score rankings, coverage documentation

RBA Stage	Data Analytics Techniques	Data Requirements	Key Controls	Expected Audit Evidence
Execution & Testing	Automated test scripts, fraud detection algorithms, process mining, clustering	Full population or stratified samples, IT control logs	IT access controls, data integrity validation, human oversight	Substantive evidence, anomaly investigation outcomes, control deficiency reports
Reporting	Data visualization, dashboards, natural language generation	Aggregated findings, comparative period data	Output review, materiality thresholds, professional review	Audit findings report, management letter, exception summary, opinion support

A critical distinction insufficiently addressed in the existing synthesis literature concerns the fundamentally different mandates, governance structures, and operational constraints of internal audit and external audit when implementing RBA and data analytics. Understanding this distinction is essential because the nature and scope of analytics deployment including data access, accountability relationships, and applicable standards differs substantially between the two functions, and conflating them produces an inaccurate picture of adoption realities.

Internal audit, as defined by the IIA, is an independent assurance and consulting activity designed to improve organizational operations through systematic evaluation of risk management, control, and governance (Álvarez-Foronda et al., 2023). Operating within the organization's governance ecosystem, internal auditors enjoy continuous access to enterprise-wide data, which makes full-population testing, real-time anomaly monitoring, and process mining operationally feasible (Álvarez-Foronda et al., 2023; Rakipi et al., 2021). In the RBA context, the IAF leverages data analytics not merely for evidence gathering but for strategic assurance, directing resources toward fraud detection, IT risk, and governance monitoring aligned with organizational objectives (Almgrashi & Mujalli, 2024; Sofa et al., 2025). The IIA's Standard 2010 mandates risk-based audit planning, and empirical evidence confirms that IAF adoption of analytics is driven by CAE competencies, reporting relationships to the audit committee, and involvement in high-value activities such as fraud detection. Despite this favorable structural positioning, 54.5% of IAFs globally remain minimal or non-users of data analytics, reflecting persistent governance maturity and skills gaps (Rakipi et al., 2021).

External audit, by contrast, is a time-bound, third-party assurance engagement whose primary objective is expressing an opinion on the fair presentation of financial statements (Dempsey & Van Dyk, 2024). External auditors operate under the ISA framework, are accountable to shareholders and regulators, and have limited, engagement-specific data access. Within this context, data analytics is applied primarily in the risk assessment phase (ISA 315), as substantive analytical procedures (ISA 520), and for full-population journal entry testing (Dempsey & Van Dyk, 2024; Huang et al., 2022). Evidence from Big Four firms in South Africa demonstrates that analytics enhances external audit quality through improved fraud risk identification, expanded transaction coverage, and stronger audit evidence (Dempsey & Van Dyk, 2024). However, external auditors face constraints absent in internal audit such as data privacy obligations, documentation requirements under ISA evidentiary standards, and professional liability for analytics-generated outputs (Huang et al., 2022).

The synthesis of reviewed literature suggests that internal audit, by virtue of its organizational embeddedness, benefits from broader operational latitude to institutionalize advanced analytics. External audit, however, faces more pronounced regulatory and liability constraints that moderate the pace of adoption (Ruhnke, 2023; Torroba et al., 2025). In both contexts, effective RBA–ADA integration is ultimately mediated by the same foundational prerequisites like governance maturity, auditor competency, and adaptive professional standards (Almgrashi & Mujalli, 2024; Dempsey & Van Dyk, 2024).

As the integration of RBA and data analytics evolves beyond descriptive and predictive analytics toward AI-assisted audit decision systems, governance and auditability concerns become increasingly central to the credibility of audit outcomes. The growing reliance on machine learning and automated risk prioritization introduces new questions regarding transparency, accountability, explainability, and ethical oversight within audit processes. Consequently, discussions surrounding AI governance are no longer peripheral to audit analytics adoption, but constitute an essential component of sustainable and professionally defensible RBA–ADA integration.

The progressive adoption of AI and machine learning within risk-based audit frameworks introduces governance and ethical dimensions that are structural, not peripheral, without adequate governance mechanisms, the credibility and professional defensibility of AI-assisted audit evidence cannot be assured (Föhr et al., 2026; Wijaya et al., 2025). The central governance challenge is the "black box" nature of many ML models, which prevents auditors and regulators from scrutinizing model-derived conclusions (Wijaya et al., 2025). Explainable AI (XAI) tools such as SHAP and LIME address this by providing instance-level explanations that can be documented in audit working papers (Torroba et al., 2025). Complementing this, audit cards (structured artifacts documenting a model's purpose, training data, performance metrics, and ethical risk profile) provide an accountability mechanism for both internal oversight and regulatory inspection. AI assurance levels, calibrated through validation rigor and temporal robustness testing, further formalize confidence thresholds for analytics-generated outputs (Verna et al., 2026). Blockchain audit trails offer an additional layer of auditability by creating immutable records of data provenance and analytical transformations, directly addressing ISA documentation requirements as full-population analytics become more prevalent (Hezam et al., 2023).

A distinct but related concern is algorithmic bias in risk prioritization. When ML models direct auditor resources toward high-risk areas, outputs reflect the representativeness of training data. Historical biases in audit data such as disproportionate scrutiny of certain entity types may be amplified in model predictions, producing systematic misallocation of audit effort. Ruhnke (2023) identifies this as availability bias leading to inattentional blindness, while Susilawati et al. (2025) confirm that over-reliance on algorithmic outputs introduces anchoring and confirmation bias in auditor judgment. Effective mitigation requires human-in-the-loop oversight, which preserves professional skepticism by positioning AI scores as decision support rather than deterministic outputs (Wijaya et al., 2025), fairness diagnostics, involving periodic evaluation of model outputs for systematic disparities across entity subgroups (Verna et al., 2026), and documented governance protocols, including audit cards and model performance reports that create the accountability infrastructure required for regulatory inspection (Föhr et al., 2026). The absence of such frameworks represents the most consequential gap between the theoretical potential of RBA–ADA integration and its responsible operationalization in professional practice.

CONCLUSION

Risk-based audit (RBA) positions the identification and evaluation of risks as the primary foundation of auditing, and has been demonstrated to improve audit process quality while reinforcing the audit function as a strategic organizational mechanism. Data analytics reflects a shift from descriptive techniques toward predictive approaches, characterized by full population testing, fraud and anomaly detection, and continuous auditing. The integration of both approaches supports risk assessment through five mechanisms, the expansion of risk identification, improved assessment accuracy, the objective determination of high-risk areas, the strengthening of audit judgment, and the optimization of audit resource allocation. Nonetheless, the implementation of this integration continues to face challenges including competency gaps, regulatory constraints, and the risk of excessive dependence on algorithmic outputs, which may undermine auditors' professional skepticism.

This review further contributes to the literature by articulating distinctions between internal and external audit contexts in the application of RBA–ADA integration, establishing their differential governance structures, data access conditions, and regulatory constraints as critical moderating variables. The analysis of AI governance dimensions (including auditability frameworks, fairness audits, and bias risks in algorithmic risk prioritization) highlights a frontier of emerging concern that existing audit standards have yet to adequately address. The regulatory ambiguity surrounding the use of advanced analytics in auditing, consistently identified as the most significant adoption barrier across empirical studies, underscores the urgent need for adaptive, technology-responsive standards from the ISA, PCAOB, AICPA, and IIA.

From a broader theoretical perspective, this study demonstrates that the integration of RBA and data analytics should be understood not merely as a technological enhancement of audit procedures, but as a transformation of the audit function itself toward a more adaptive, continuous, and governance-oriented assurance model. Future research should therefore move beyond exploratory adoption studies toward longitudinal and empirical investigations examining how governance structures, AI explainability mechanisms, and professional standards shape the sustainability of analytics-driven auditing practices across different institutional contexts.

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