



Algorithmic auditors: Ethical considerations in AI-enabled assurance

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Abstract

The auditing profession is changing a lot because of technology and the need for financial reports. The old ways of auditing are not good enough to catch people who are cheating or manipulating money. This study looks at the problems with auditing methods and how Artificial Intelligence can help make audits better. The study uses research and real-life examples like Brightcom Group, Eros International and Knight Capital Group to show that manual checks are not enough and that auditors need to use algorithms to help. It suggests a way of auditing where Artificial Intelligence helps with checking data and finding risks, but human auditors still make the important decisions. Artificial Intelligence should be used to help people make decisions not to replace them. This way AI can make sure that audits are transparent, fair and follow governance. The study looks at how Artificial Intelligence can help with auditing. It suggests that it can make audits more accurate and faster. The auditing profession needs to change. Artificial Intelligence can help with this change. Artificial Intelligence can help with checking all the data, not a sample and can help find unusual activity. This can help catch people who are cheating or manipulating money.

Keywords: Artificial intelligence, algorithmic auditing, full-population testing, audit ethics, human-in-the-loop governance

Introduction

The auditing profession is undergoing a structural transformation driven by rapid digitalization, big data environments, and artificial intelligence (AI). Traditional audit methodologies—primarily based on sampling, manual verification, and retrospective analysis—are increasingly challenged by the scale, velocity, and complexity of modern financial transactions. As enterprises shift toward centralized accounting systems, enterprise resource planning (ERP) platforms, and real-time digital reporting, auditors face significant constraints in detecting anomalies, revenue leakages, window dressing practices, and internal control deficiencies using conventional techniques

Recent academic research demonstrates that AI-enabled auditing systems can evaluate 100% of transaction populations, significantly improving anomaly detection rates compared to traditional sampling methods. (Leocádio, 2024) ^[4] Machine learning-based full-population auditing models have achieved consistency rates exceeding 98%, while effectively flagging bookkeeping inconsistencies and internal control defects for human review (Yasheng Chen, 2022) ^[14]

Similarly, AI-driven audit tools reduce project cycles by 30–50% and increase the number of detected irregularities by 20–30%, thereby enhancing both efficiency and audit quality (SHEHU, 2022) ^[13]

However, the integration of AI into external auditing introduces complex ethical and governance challenges. Algorithmic systems often operate as “black boxes,” limiting transparency and raising concerns regarding explainability, bias, and accountability. Research in accounting ethics emphasizes the risk of a “responsibility gap,” wherein human professionals may over-rely on

algorithmic outputs without adequately exercising professional skepticism

Furthermore, empirical evidence from algorithmic tax administration shows that poorly governed AI systems can produce discriminatory or opaque outcomes, undermining trust in oversight mechanisms

In the context of external auditing, these concerns become particularly critical. External auditors must evaluate financial statements for material misstatements arising from error or fraud while maintaining independence and professional judgment. Yet, access to internal algorithmic monitoring systems—such as anti-money laundering (AML) engines and risk scoring tools—is often restricted. As a result, auditors may rely on management-generated summaries rather than direct algorithmic interrogation, raising questions about transparency, audit evidence reliability, and ethical accountability.

This research therefore examines the emergence of “algorithmic auditors” as augmented assurance mechanisms. It argues that AI should not replace professional judgment but rather function within a human-machine symbiosis model, where algorithms detect patterns and anomalies while auditors retain final evaluative authority.

Review of Literature

Traditional auditing methods rely on sampling and historical data. However, these methods struggle to keep up with today’s volume financial systems. Diogo Leocádio and his team suggest an approach called “Full Population Testing.” (Diogo Leocádio, 2024) ^[4] This involves using Artificial Intelligence and Machine Learning to examine every transaction on a continuous basis. Research by MDPI found that Machine Learning can match records about 98.45

percent of the time in state-owned companies (Yasheng Chen, 2022) ^[14]. It also uncovered errors that were missed in sample-based audits.

SHEHU highlights the use of deep learning models, such as Autoencoder Networks. These models are better than rule-based systems because they learn transaction patterns and can detect unusual activity that may indicate fraud. In 2024 MindBridge used Ensemble Machine Learning to catch a "slicing" fraud scheme that had gone unnoticed for three years. Studies show that using AI tools can cut audit time by 30 to 50 percent. It can also increase the detection of anomalies by up to 30 percent (SHEHU, 2022) ^[13].

Big firms like Deloitte and PwC are now using systems to automate routine analysis. This lets auditor's focus on tasks that require judgment. According to a study computer-based tools are more effective than methods in detecting money laundering (Mohammed A. Al-Bukhrani, 2025) ^[11]. However, there are concerns about the ethics of using AI. Lehner and Amini point out the "box" problem, where it is hard to understand how AI systems make their decisions. They also note that AI systems lack reasoning. Bhanu Pratap Singh and Sehgal warn that AI can perpetuate biases in the data used to train it leading to proxy discrimination (Bhanu Pratap Singh, 2025) ^[2]. Schweitzer suggests having a "human-in-the-loop" framework to address these issues (Schweitzer, 2024) ^[12].

The risks of not having oversight were clear, in the case of Knight Capital Group, which lost \$440 million in 2012. On the hand the Securities and Exchange Board of India used AI in 2023 to investigate Brightcom and Eros. They were able to uncover window dressing and circular trading showing the power of AI in auditing

Research Methodology

This study adopts a conceptual research design based on secondary data sources. The analysis draws upon peer-reviewed journal articles, industry reports, regulatory case orders, and documented corporate fraud investigations related to Artificial Intelligence in auditing. The study evaluates existing empirical findings concerning machine learning-based anomaly detection, full-population transaction testing, and algorithmic risk scoring systems.

Case study analysis has been used to examine instances where traditional auditing methods failed to detect financial irregularities. Regulatory investigations such as those involving Brightcom Group, Eros International, and Knight Capital Group provide contextual insight into structural assurance gaps. The theoretical foundation of the study is anchored in the Audit Risk Model and Human-in-the-Loop governance principles. Based on this framework, the paper proposes an "Augmented Algorithmic Auditor" model wherein AI systems assist in large-scale data analysis while final audit judgments remain under human authority.

AI-Enabled Assurance and the Emergence of Algorithmic Auditors

The auditing profession has historically relied on sampling-based verification techniques due to time and resource constraints. However, the exponential growth of digital

transactions has rendered traditional sampling increasingly insufficient for detecting complex financial irregularities. Sampling inherently leaves a large proportion of transactional data unexamined, thereby increasing detection risk. Recent machine learning-based full-population auditing models demonstrate that algorithmic systems can reconcile 100% of transactional data with a consistency accuracy of 98.45%, while flagging anomalous entries for human review. (Yasheng Chen, 2022) ^[14]. This marks a significant methodological shift from selective testing to comprehensive digital assurance.

Empirical evidence further supports the effectiveness of AI-enhanced auditing systems. A study published in the Journal of Emerging Technologies in accounting reports that AI-assisted audits achieve a 15–30% improvement in fraud detection accuracy compared to traditional approaches. Similarly, findings presented in SHS Web of Conferences (2025) indicate that AI integration reduces audit cycle time by 30–50% and increases anomaly detection rates by 20–30%. (SHEHU, 2022) ^[13] These findings suggest that AI not only improves efficiency but also strengthens the reliability of audit outcomes.

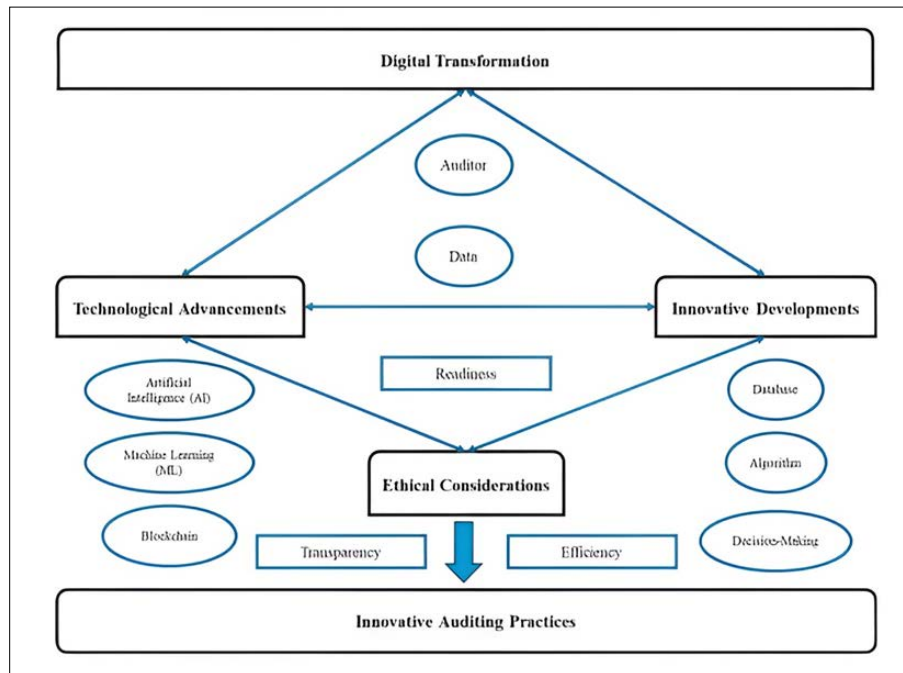
One of the most significant contributions of AI to external auditing is its ability to perform full-population testing in revenue-sensitive areas. In banking environments, revenue leakages such as uncollected locker rent, unauthorized fee waivers, and system-report mismatches often remain undetected due to reliance on periodic sampling and manual reconciliation. An augmented auditing system can reconcile 100% of locker rent records against the Core Banking System (CBS), identify discrepancies between physical registers and system data, and compute the exact leakage amount. This shifts audit practice from reactive error discovery to proactive anomaly identification.

Algorithmic detection techniques such as Benford's Law and clustering algorithms have also demonstrated effectiveness in identifying unnatural financial patterns. High-profile corporate failures such as Wirecard and Luckin Coffee involved fabricated revenues and falsified confirmations that escaped traditional audit scrutiny (Mehta, 2022) ^[10]. Statistical anomaly detection models are capable of identifying irregular digit distributions, revenue spikes inconsistent with historical trends, and unusual journal entry clusters, thereby strengthening early-warning capabilities. (Krahn, 2020) ^[8]

Another critical application of AI in external assurance involves revenue-cash flow correlation analysis. AI-based audit tools such as MindBridge apply machine learning risk scoring to journal entries and examine the relationship between reported revenue and operating cash flow (Analytics, 2025) ^[1].

When revenue growth is not supported by corresponding cash inflows, the system flags a high risk of statement manipulation. Such correlation-based analytics provide auditors with risk intelligence rather than conclusions, preserving the principle that final judgments must remain human.

Despite these advantages, ethical and governance concerns remain central to the discourse on



Source: Artificial Intelligence in Auditing: A Conceptual Framework for Auditing Practices (Leocádio, 2024) [4]

Algorithmic auditing. The “black box” nature of certain machine learning models raises questions about explainability and accountability. (Bhanu Pratap Singh, 2025) [2] If external auditors rely on algorithm-generated outputs without understanding model assumptions or training data, professional skepticism may be weakened. Furthermore, access asymmetry between internal compliance systems and external auditors may create transparency gaps, particularly where management controls the underlying data environment.

Accordingly, this study proposes the concept of the “Augmented Algorithmic Auditor,” wherein AI performs full-population data reconciliation, anomaly detection, and risk scoring, while human auditors retain evaluative authority, contextual interpretation, and materiality assessment. This hybrid model aligns with Human-in-the-Loop governance principles and mitigates the ethical risks associated with autonomous decision-making systems. To substantiate the urgent need for algorithmic intervention, the following section examines four pivotal case studies that expose the structural vulnerabilities of traditional auditing. These real-world scenarios—ranging from the fabrication of assets in Indian markets to high-speed algorithmic failures on Wall Street—demonstrate how manual verification and statistical sampling are increasingly insufficient against sophisticated digital fraud. By juxtaposing these “Audit Failures” with specific “AI-Augmented Pathways,” the analysis maps out how tools like automated API reconciliation, network pattern recognition, and full-population testing serve as proactive shields rather than just retrospective forensic tools.

1. The "Window Dressing" Detective: Finding Fake Assets

One big problem with reports is “window dressing”. This is when companies make their financial situation look better than it is to trick investors and regulators. Let’s look at the Brightcom Group, a company that does digital marketing. They said they were making a lot of money with profits going up by much as 168%. They also said they had a lot of money in the bank, which made them

look stable and attractive to investors. But then the Securities and Exchange Board of India did an investigation and found out the truth: most of the assets they claimed to have were not real. The company said they had a lot of assets and cash in countries but the bank statements they gave to the investigators were fake. This means the profits they reported were numbers on a piece of paper not real money (Brightcom Group Ltd, 2023) [3].

The problem here is with the way of checking financial reports. This method often uses bank statements that’re easy to fake or letters that can be manipulated. A better way to do this is to use Automated Cash Reconciliation Bots, which are helped by Artificial Intelligence. These bots do not just look at a document like a human would. Instead, they use a connection, to the banks computer system to check the cash balance in real-time. This means they can immediately see if there is a problem like if the money the company says they have is not really there. If the Brightcom Group had used this system the fake assets would have been found away and the fraud would not have been able to trick the market. The Window Dressing Detective, which is the Automated Cash Reconciliation Bots would have caught the Window Dressing problem and stopped the fraud.

2. The "Circular Trading" Buster: Uncovering Revenue Manipulation

Revenue manipulation can be really tricky to find because it usually involves plans.

Case Study of Eros International, a media company. They wanted to make their financial books look good so they said they made a lot of money from “content advances” and film rights. When people looked into it, they found out that Eros International was using a sneaky trick called “round-tripping”. They were taking money out of the company. Giving it to fake companies saying it was for making movies. Then these fake companies would send the money back to Eros International. They would say it was new money coming in. If a person was looking at these deals one by one, they would look real because the money going out and coming in seemed like business deals (Interim Ex-parte Order in Matter of Eros International Media Ltd., 2023) [6].

The solution to this problem is using computers to look at all the money movements. While people usually just check each deal computers can look at all the money going between companies at the time. By looking at how all these companies are connected the computer can find the money going around in circles. It can see that money leaving one company goes to another and then comes back. This helps people find the picture and see that the money is not real. It flags the deals as fake. The money as made up. The Circular Trading Pattern Recognition is, like a tool that helps people see what is really going on with the money.

3. The "Salami Slicing" Stopper: Stopping Revenue Loss

Old ways of auditing rely on checking transactions, usually 5-10%. This means most of the data is not checked. People who commit fraud take advantage of this by doing small transactions that are not big enough to be noticed by humans. These small transactions are like slices of salami.

A mid-sized accounting firm found a way to stop this type of fraud by using MindBridge AI (Analytics, 2025) ^[1]. Of just checking a few transactions the firm used the AI to look at every single transaction in a client's general ledger. There were millions of transactions.

The AI used a combination of rules and statistics to give a risk score to each transaction. This helped find some expense reimbursements that human auditors had missed because they were too small. These transactions showed that someone was cheating the company and this had been going on for three years.

This case shows that using AI is a way to find fraud than just checking a small part of transactions. With AI every transaction is checked. No fraud is too small to be found. This helps stop companies from losing money due to fraud that old auditing methods might miss. The Salami Slicing Stopper is important, for stopping revenue loss.

4. The "Velocity Risk" Mitigator: Preventing Operational Collapse

In contemporary high-frequency trading environments, financial disruptions can materialize within seconds, limiting the capacity for human intervention. The collapse of Knight Capital Group in 2012 illustrates the phenomenon commonly described as "velocity risk." During a system deployment, an outdated trading algorithm known as "Power Peg" was inadvertently activated. Due to the absence of effective real-time monitoring controls, the malfunctioning algorithm executed more than four million unintended trades within approximately 45 minutes. By the time the anomaly was detected and halted, the firm had incurred losses of approximately \$440 million, ultimately exhausting its capital base and forcing an expedited sale of the company (Knight Capital Group, 2013) ^[7].

This incident demonstrates the structural inadequacy of retrospective oversight mechanisms in automated financial environments. Traditional monitoring approaches that rely on post-event review are insufficient in contexts where algorithmic systems operate at extreme speed. Continuous AI-driven surveillance frameworks, incorporating anomaly detection thresholds and automated circuit breakers, provide a more effective control architecture. Such systems are capable of identifying abnormal transaction velocity, pattern deviations, and execution irregularities in real time.

The concept of a "Velocity Risk Mitigator" therefore emphasizes proactive algorithmic supervision rather than

reactive documentation. Real-time continuous monitoring enhances operational resilience by enabling early intervention before irregularities escalate into systemic failure. This shift redefines oversight from post-incident reporting toward preventive control, thereby strengthening institutional stability in digitally accelerated markets.

The cases of Brightcom Group, Eros International, and Knight Capital collectively highlight the widening "assurance gap" within traditional audit frameworks. These incidents reveal structural limitations in manual verification, sampling-based review, and delayed oversight mechanisms. In response to such vulnerabilities, leading global accounting firms have progressively integrated advanced data analytics and artificial intelligence into their audit methodologies.

Major firms, including Deloitte and KPMG, have transitioned from experimental adoption of AI tools to structured implementation within core audit processes. Their initiatives demonstrate that algorithmic systems not only enhance fraud detection and anomaly identification but also improve efficiency, data coverage, and analytical depth. The following case studies examine how these firms operationalized full-population testing and predictive risk assessment within professional audit environment.

The following industry illustrations function as applied case-based examples demonstrating how leading audit firms have operationalized AI-enabled methodologies within real-world assurance engagements.

1. Deloitte: Revolutionizing Document Review with "Argus" and "Omnia"

Deloitte changed the way they do audits by fixing a problem. They used to have to look at thousands of documents by hand. This took a lot of time. Was easy to get wrong. The people doing the audits would have to go through leases and contracts and other documents line by line. This was work and people would make mistakes.

Deloitte found a solution with a tool called "Argus". This tool can. Understand complicated documents. It gets better at this job the more it is used. Deloitte also used another tool called "Omnia". This tool helps with all parts of the audit process. (Heye, 2021) ^[5]

By using "Argus" and "Omnia" Deloitte was able to review all of the documents they needed to. This used to take a time but now it happens quickly. The company was also able to keep their employees because they did not have to do boring work anymore. The employees could focus on important tasks and the company was able to give better advice to their clients.

Deloitte was able to do audits faster with "Argus" and "Omnia". The company was more accurate. Was able to keep their employees from getting too tired. This was a change for Deloitte and it helped them to be more successful. They were able to use "Argus" and "Omnia" to review documents and do audits in a way. This new way was better, for the company and their clients. Deloitte used "Argus" and "Omnia" to make their audits better. (Heye, 2021) ^[5]

2. KPMG: From Hindsight to Foresight with "Clara"

KPMG did something to stand out in the market. They went beyond just looking at the past with their audits. They used a platform called KPMG Clara to predict and focus on risk. KPMG Clara is a change from the traditional way of doing audits. (Leocádio, 2024) ^[4]

KPMG knew that clients needed more than someone to verify what happened in the past. So they added some capabilities to KPMG Clara. They worked with IBM Watson and MindBridge to make it smart. KPMG Clara can look at all the data and find problems that might not be seen otherwise.

The platform can look at a lot of data and give each transaction a risk score. This means KPMG can find transactions that're high risk and might have been missed. The good thing, about KPMG Clara is that it helps KPMG tell clients about problems that might happen in the future. KPMG is not just reporting on what went wrong in the past. They are using KPMG Clara to give clients an understanding of their data. This helps KPMG stay ahead of the competition. KPMG is moving from doing audits to helping clients manage risk. This is a change and it is working well for KPMG. (Leocádio, 2024) [4].

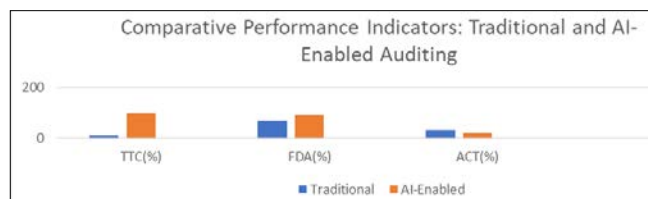
Comparative Performance Indicators: Traditional and AI-Enabled Auditing

Metric	Traditional	AI-Enabled
Transaction Testing Coverage (%)	10	100
Fraud Detection Accuracy (%)	70	90
Audit Cycle Time (Days)	30	20

Source: Author's Compilation based on report (SHEHU, 2022) [13]

Findings of the Study

1. Operational Efficacy and the Shift to Full-Population Testing



The primary finding of this study is that AI-enabled auditing overcomes the inherent limitations of traditional sampling by enabling the examination of 100% transaction populations. Research indicates that machine learning-based full-population models can reconcile transactional data with a consistency accuracy of 98.45%, effectively identifying errors that selective testing misses. Furthermore, the integration of these tools has been found to reduce audit cycle times by 30–50% while simultaneously increasing anomaly detection rates by 20–30%. This confirms that the transition to "Algorithmic Auditors" yields measurable improvements in both efficiency and the reliability of audit outcomes.

2. Detection of Sophisticated Fraud Schemes

The analysis of high-profile audit failures reveals that AI tools are uniquely capable of detecting complex financial irregularities that manual oversight often overlooks:

Revenue Manipulation (Circular Trading): The study finds that traditional transaction-level verification fails to detect "round-tripping," as seen in the Eros International case. However, AI-driven network pattern recognition successfully identifies these circular flows by mapping the interconnectivity between entities, flagging money that leaves and returns to the same source.

Asset Fabrication (Window Dressing): In cases like Brightcom Group, where manual verification of bank

statements proved susceptible to forgery, the findings suggest that Automated Cash Reconciliation Bots offer a robust solution. By utilizing API connections to verify balances in real-time, these tools eliminate the risk of relying on manipulated static documents.

Granular Fraud (Salami Slicing): The research highlights that fraud often occurs below the "materiality threshold" used in human sampling. The MindBridge case study demonstrated that AI algorithms, by scoring every single transaction, could detect a "salami slicing" scheme involving small, irregular expense reimbursements that had persisted unnoticed for three years.

3. Drivers of Audit Efficiency

Contrary to traditional assumptions, empirical evidence from the Sudanese financial sector indicates that technology adoption is the primary driver of audit effectiveness. The study found that the use of advanced analytics tools had the strongest positive impact on money laundering detection, whereas years of practical experience showed no significant relationship with AML performance. This suggests that a "seasoned" auditor without digital tools is less effective than a digitally augmented auditor, highlighting a critical need for technological upskilling over traditional tenure.

4. Mitigation of Velocity Risk

The study identifies "velocity risk" as a critical vulnerability in modern finance, exemplified by the Knight Capital collapse where a manual monitoring lag led to a \$440 million loss in 45 minutes. The findings indicate that retrospective auditing is insufficient for such environments; instead, Real-Time Continuous Monitoring acts as a necessary "safety switch," capable of identifying and halting algorithmic errors instantaneously before they result in operational collapse.

5. Institutional Adoption and Role Transformation

Evidence from the "Big 4" firms confirms that AI implementation shifts the auditor's role from data aggregation to strategic risk assessment.

Deloitte's Implementation: The deployment of tools like "Argus" and "Omnia" was found to automate the labor-intensive review of leases and contracts, significantly reducing human error and allowing auditors to focus on high-value advisory tasks.

KPMG's Predictive Approach: The use of KPMG "Clara" demonstrates a shift from hindsight to foresight. By integrating predictive risk scoring, the platform allows auditors to provide clients with forward-looking insights into potential future risks rather than merely verifying past events.

6. Ethical and Structural Challenges

Despite these operational successes, the study finds that the "black box" nature of machine learning models introduces significant governance challenges regarding transparency and explainability. The research concludes that a "Human-in-the-Loop" model—the "Augmented Algorithmic Auditor"—is essential to mitigate these risks, ensuring that while AI handles data reconciliation, human professionals retain final evaluative authority and moral responsibility.

Recommendations & Suggestions

▪ **Adoption of "Augmented Intelligence" Models**

The industry must transition from a fear of replacement to a strategy of "Human-Machine Symbiosis." Research emphasizes a "Human-in-the-Loop" governance framework where AI performs high-volume data reconciliation and anomaly detection, but human auditors retain final evaluative authority for high-stakes decisions. This ensures that "substantive rationality" (human values and ethics) is not lost to "formal rationality" (strict algorithmic efficiency).

▪ **Bridging the "Data Access Gap" via Standardized APIs**

To resolve the asymmetry where external auditors rely on static files while auditees use advanced internal monitoring, regulators should mandate "Audit APIs". This would allow external auditors to connect directly to a client's banking or ERP system in a read-only capacity, enabling continuous "Health Checks" on the full data population rather than relying on potentially manipulated manual reports.

▪ **Establishing AI Governance Committees**

Firms should establish internal governance bodies to audit the algorithms themselves before deployment. These committees must test for "proxy discrimination" in training data and ensure model explainability, preventing the "black box" phenomenon from undermining professional skepticism.

▪ **Curriculum Reform and Upskilling**

There is a critical "skill gap" where the current workforce lacks the "compound talents" of auditing standards and data science. Academic institutions and professional bodies must revamp training programs to prioritize digital literacy and forensic analytics over rote memorization, as empirical evidence suggests that technology adoption is now a stronger predictor of audit success than traditional tenure.

Future Prospects

The future of auditing lies in the deep integration of distinct AI technologies to create a seamless, proactive assurance ecosystem:

▪ **Natural Language Processing (NLP) for Unstructured Data**

Future audit cycles will increasingly utilize NLP to "read" and interpret unstructured data such as contracts, board minutes, and emails. Tools like Deloitte's Argus are already demonstrating how NLP can extract key revenue recognition terms (e.g., right-of-return clauses) from thousands of PDF documents in minutes, a task that is currently labor-intensive and error-prone.

▪ **Machine Learning (ML) and Deep Learning for Anomaly Detection**

The use of Deep Autoencoder Networks will become standard for journal entry testing. Unlike static rule-based tests, these unsupervised deep learning models learn the "normal" behavior of a transaction environment and flag

non-linear anomalies—such as complex fraud schemes—that do not fit the learned pattern.

▪ **From Hindsight to Foresight (Predictive Auditing)**

The audit function will evolve from merely verifying past financial statements to providing forward-looking risk intelligence. Platforms like KPMG Clara are paving the way for predictive auditing, where systems analyze historical trends to forecast future risks, such as "going concern" issues, with greater accuracy than traditional financial ratios.

▪ **Blockchain and Immutable Ledgers**

Future research and development will likely focus on combining Blockchain's immutable record-keeping with AI's pattern recognition. This convergence could create "tamper-resistant" continuous auditing systems where transaction data is verified cryptographically at the source and monitored instantly by algorithmic auditors.

Conclusion

The auditing profession is changing a lot because of technology and complicated financial systems that use a lot of data. The old way of checking a sample of things is not good enough anymore when there are so many transactions and everything is digital. This study found that using intelligence to check everything at once is better at finding unusual things makes audits more efficient and helps identify risks. When we use computer systems that make decisions, we have to make sure we can understand how they work and who is responsible. The Augmented Algorithmic Auditor framework is a way of working that combines humans and machines where artificial intelligence helps with analysis. People are still, in charge of making decisions. To use intelligence in auditing in a good way we need to make sure that new technology, following rules and doing the right thing all work together. The auditing profession needs intelligence to make audits better and artificial intelligence needs the auditing profession to make sure it is used correctly. Auditing is changing and artificial intelligence is a part of that change so we need to get it right.

References

1. Analytics M. AI-Powered Financial Risk Intelligence: A Case Study in Full Population Testing, 2025.
2. Singh BP, GS. From Audit to Algorithm: Ethical Challenges of AI Inclusion in Public Tax Administration. International Journal of Computer Applications, 2025.
3. Brightcom Group Ltd (SEBI 2023).
4. Leocádio D, LM. Artificial Intelligence in Auditing: A Conceptual Framework for Auditing Practices. Administrative Sciences, 2024.
5. Heye AM. The Future of Auditing: An Analysis of AI Implementation in the Big Four Accounting Firms, 2021.
6. Interim Ex-parte Order in Matter of Eros International Media Ltd. (SEBI 2023).
7. Knight Capital Group, File No. 3-15570. (U.S. Securities and Exchange Commission (SEC) 2013).

8. Krahen JP. The Wirecard lessons: A reform proposal for the supervision of securities markets in Europe. Goethe University Frankfurt - Center for Financial Studies, 2020.
9. Leocádio DM. Artificial Intelligence in Auditing: A Conceptual Framework for Auditing Practices. Administrative Sciences (MDPI), 2024.
10. Mehta A. Luckin Coffee Inc.: brewing fraud. Journal of Financial Crime, 2022.
11. Al-Bukhrani MA, N HM. Assessing the Efficiency of the External Auditor in Combating Money Laundering. Journal of Governance and Regulation, 2025, 14(1).
12. Schweitzer B. Artificial Intelligence (AI) Ethics in Accounting. Journal of Accounting, Ethics & Public Policy, 2024.
13. Shehu TS. Integrating Artificial Intelligence in Financial Auditing: Enhancing Accuracy and Efficiency. IRE Journal, 2022, 5.
14. Chen Y, WZ. A Full Population Auditing Method Based on Machine Learning. Sustainability, 2022.