Artificial Intelligence in Auditing: Transforming Risk Assessment and Fraud Detection

Laura Del Caprio

Haaga-Helia University of Applied Sciences
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Abstract

Author(s)
Laura Del Caprio

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This thesis investigates the transformative impact of Artificial Intelligence (AI) on the auditing profession, with a focus on its applications in risk assessment and fraud detection. Traditional auditing methods, often reliant on manual procedures and sampling techniques, have proven insufficient in today's fast-paced, data-rich financial environment. This study addresses the need for innovation by examining how AI technologies are reshaping audit practices and enhancing the quality and reliability of financial evaluations.

The objective of this thesis was to explore how AI tools, particularly Machine Learning (ML), Natural Language Processing (NLP) and Robotic Process Automation (RPA), are used to identify audit risks and detect fraudulent patterns in structured and unstructured data. The scope of the study was limited to financial statement auditing and the focus was placed on both large audit firms and broader industry practices. The theoretical framework was built on contemporary literature covering AI in auditing, audit risk models, fraud theories and ethical implications. The empirical part employed a qualitative research approach, including expert interviews with audit professionals and AI practitioners. The research was carried out between January and April 2025 and the data were analysed using thematic analysis.

The results indicate that AI significantly improves audit efficiency, enhances anomaly detection accuracy and enables continuous monitoring of financial activities. Auditors reported that AI tools reduced manual workloads and improved decision-making by identifying red flags that might otherwise remain undetected. However, challenges such as algorithmic opacity, data quality issues and ethical risks, such as overreliance on AI and reduced auditor skepticism, were also highlighted. The findings support the need for a balanced integration of AI with human oversight and governance frameworks to ensure accountability and transparency. The study concludes that AI has the potential to foster a more effective, data-driven and sustainable auditing ecosystem but continuous learning, ethical awareness and regulatory updates are critical for its responsible adoption.

Key words
Artificial Intelligence, Auditing, Risk Assessment, Fraud Detection, Machine Learning, Natural Language Processing, ESG

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1 Introduction

This thesis explores the transformative potential of Artificial Intelligence (AI) in auditing, particularly its role in revolutionizing risk assessment and fraud detection. In response to the growing complexity of financial systems, AI is increasingly recognized not just as a tool for automation but as a strategic enabler of more accurate, timely and scalable audit procedures. According to Bose, Dey and Bhattacharjee (2022), big data analytics and AI are reshaping traditional accounting by enabling auditors to analyse large datasets and detect patterns that could indicate potential risks or fraud. This thesis explores AI’s applications in auditing, the challenges and ethical considerations it brings and its potential to influence the profession's future. By analysing both practical implementations and ethical implications, this study provides insights relevant to internal and external auditors, regulators and other financial stakeholders. Through an examination of literature and industry practices, this research aims to provide a comprehensive view of AI’s current and potential impact on auditing. AI-driven auditing has attracted significant interest in recent years, with the Big Four accounting firms (Deloitte, PwC, KPMG and EY) investing heavily in AI technologies to enhance their auditing processes. In this context, this study is particularly relevant as it aims to address both the operational benefits of AI and the associated ethical and regulatory challenges, providing a balanced and thorough exploration of AI in the auditing domain (Deloitte 2024).

1.1 Background

Artificial Intelligence (AI) has fundamentally altered the auditing profession, transitioning from labour-intensive methods to dynamic data-driven approaches. Early auditing relied on manual sampling and expert judgment, which, while effective for smaller datasets, struggled with the complexities of modern financial data (Luthfiani 2024). AI’s evolution, particularly through Machine Learning (ML) and natural language processing (NLP), has revolutionized the field, enabling auditors to manage larger datasets, detect anomalies more accurately and address fraud risks proactively (Bose et al. 2022, 4-6; Sekar 2022). AI’s transformative potential is particularly evident in its ability to identify patterns and provide predictive insights, offering auditors tools to make decisions more strategically.

1.1.1 Historical Context

Traditionally, auditing relied on manual techniques that involved reviewing small samples of financial data to detect irregularities. These methods were sufficient when data volumes were manageable and financial systems less complex. However, the exponential growth in digital transactions exposed the limitations of manual processes particularly in identifying sophisticated fraud schemes

(Omoteso 2017). Early AI systems, while innovative, were primarily rule-based and lacked adaptability to evolving data patterns.

As technology advanced, tools like ML began replacing these rigid systems. Sekar (2022) notes that the shift allowed auditors to handle entire datasets, identifying anomalies with greater accuracy and speed. This evolution was critical in modernizing auditing practices, making them more efficient and aligned with the complexities of global financial markets.

1.1.2 The Rise of AI in Auditing

AI's integration into auditing has been catalysed by advancements in ML and NLP, which enable auditors to process structured and unstructured data seamlessly. Leading firms like EY and PwC have adopted AI technologies to automate tasks such as data reconciliation, risk assessment and fraud detection. For example, EY's Helix GL Anomaly Detector leverages AI to analyse general ledger data, efficiently identifying fraudulent journal entries by processing extensive datasets and uncovering anomalies that may indicate fraud (EY 2023). Similarly, PwC's Halo for Journals employs ML algorithms to scrutinize journal entries, detect unusual patterns and highlight high risk areas, thereby enhancing the precision and efficiency of audits (PwC 2023). These innovations have transformed auditing practices from manual processes to data-driven methods, positioning AI as an essential element of modern financial oversight. While these innovations have undeniably enhanced audit precision, they also raise questions about algorithmic transparency and the auditor's evolving role, issues that this study will explore through both theoretical and practical lenses.

1.1.3 Significance of AI in Modern Auditing

AI-driven auditing practices provide substantial benefits not only in terms of efficiency but also in supporting compliance with evolving regulatory requirements. The increasing focus on Environmental, Social and Governance (ESG) reporting has intensified the demand for accountability, transparency and accuracy in financial disclosures. Regulatory frameworks are expanding globally to ensure companies meet ethical and sustainability standards and AI plays a crucial role in helping firms navigate these complexities. Continuous monitoring and predictive analytics powered by AI allow auditors to proactively identify and address compliance issues, thereby reducing regulatory risks (Luthfiani 2024, 516-530).

One key benefit of AI in this area is its ability to analyse vast amounts of unstructured data related to ESG factors, such as carbon emissions, employee diversity statistics and supply chain practices, to provide an accurate and real-time assessment of compliance with ESG criteria. By automating the extraction and evaluation of this data, AI helps ensure that companies adhere to these standards efficiently. As noted by Brennan & Atkins (2008), regulatory bodies increasingly emphasize transparency and accountability, making AI an essential tool in the auditor's toolkit.

Real-time data processing is another significant advantage. Traditional auditing methods involve periodic assessments, which can delay the identification of compliance issues. In contrast, AI-driven continuous auditing enables real-time tracking of compliance with regulatory changes. This approach allows companies to respond to regulatory shifts more quickly and to maintain adherence to both financial and non-financial reporting standards. For instance, according to Bose et al. (2022), AI can flag irregularities in financial reporting faster than traditional methods, supporting auditors in identifying discrepancies before they escalate into material risks.

On top of that, AI assists in handling complex data privacy and data protection regulations such as the General Data Protection Regulation (GDPR) in Europe. By automating data classification and privacy risk assessment, AI can ensure that companies comply with GDPR and similar regulations globally. KPMG (2024b) highlights the role of AI in navigating ethical data handling practices, emphasizing that responsible AI application aligns well with privacy and compliance expectations.

AI's integration into auditing not only substantially strengthens the ability of auditors to meet compliance demands but also elevates transparency and accountability in financial reporting. The capacity of AI to provide real-time insights and predictive analyses enables companies to align with regulatory standards effectively while maintaining high ethical standards (Omoteso 2012). This background underlines the importance of studying AI's role in auditing as a technology that addresses the limitations of traditional methods and facilitates the profession's evolution to meet the demands of a more complex and regulated financial landscape.

1.2 Significance

This research is relevant for multiple stakeholders in the auditing field, including auditors, regulators, financial professionals and policymakers. The integration of AI in auditing addresses several critical needs in modern financial systems. The use of AI in auditing supports sustainability goals by enabling continuous monitoring of ESG compliance, reducing unnecessary resource use and aligning audit processes with broader corporate responsibility initiatives. By contributing to transparent and data-driven financial oversight, AI tools promote accountability and responsible governance practices.

1.2.1 For Auditors

AI offers auditors a solution to reduce manual workloads and improve the accuracy of risk assessments. By automating repetitive tasks, AI enables auditors to focus on higher-level analysis, enhancing both efficiency and effectiveness. Rozario and Vasarhelyi (2018) report that auditors using AI-based tools can streamline workflows and reduce error rates, ultimately allowing more time for strategic tasks that require human judgment. Furthermore, the real-time capabilities of AI allow auditors to detect anomalies and potential fraud faster, reducing the time needed for traditional sampling methods. This shift not only increases audit quality but also fosters a proactive approach to risk management in complex financial environments.

1.2.2 For Regulators

AI supports regulatory goals by enhancing the accuracy and transparency of financial reporting, critical factors as regulatory demands increase, especially in ESG reporting. KPMG (2024a) highlights that as ethical AI implementation grows, it becomes essential for organizations to maintain transparency and ethical accountability, aligning with regulatory expectations for responsible AI use. AI also regulators by providing tools for continuous monitoring, allowing for more frequent assessments of compliance in real-time. This proactive approach helps regulators enforce stricter compliance measures and ensures companies maintain high standards of governance and reporting integrity.

1.2.3 For the Financial Industry

Fraud and risk management are central concerns for the financial industry. AI's predictive capabilities, especially in fraud detection, play a crucial role in maintaining financial stability by identifying and mitigating risks early. Luthfiani (2024) emphasizes the impact of AI in enhancing fraud detection processes, noting that its effectiveness supports both individual companies and the broader stability of financial markets.

This research in sum, provides timely insights for auditors and regulators seeking to navigate the opportunities and challenges posed by AI. It also highlights the broader implications for the financial industry, particularly in terms of sustainability and regulatory compliance.

1.3 Research Questions

This thesis investigates the impact of Artificial Intelligence (AI) on auditing practices, with a specific focus on risk assessment and fraud detection.

RQ: How is AI transforming risk assessment and fraud detection in auditing?
This primary question serves as the foundation for the thesis, aiming to investigate how AI-driven tools are changing the way auditors approach these critical functions. By examining both

theoretical frameworks and practical applications, the study seeks to provide a comprehensive understanding of AI's impact on traditional auditing methodologies.

This main question is supported by the following investigative questions:

1. IQ1: What specific AI tools and techniques are currently used to enhance risk assessment in auditing?

   This question focuses on identifying the technologies that are most employed, such as ML models, NLP tools and anomaly detection systems and understanding how they contribute to improved audit practices.

2. IQ2: How effective is AI in identifying and preventing fraudulent activities compared to traditional methods?

   By comparing AI-driven approaches to traditional fraud detection practices, this question aims to evaluate AI's capabilities, highlighting its strengths while also identifying areas where traditional methods might still hold value.

3. IQ3: What are the primary challenges and limitations of adopting AI in auditing, including ethical concerns?

   This question emphasizes the barriers to AI adoption, such as data privacy issues, algorithmic transparency and the need for human oversight. It also touches on the ethical dilemmas that may arise, which are critical for understanding the broader implications of AI in auditing.

4. IQ4: How does AI contribute to sustainability in auditing, particularly in ESG reporting and sustainable fraud detection?

   This question explores the role of AI in addressing contemporary challenges related to sustainability focusing on its applications in ESG reporting and its ability to support ethical and transparent business practices.

5. IQ5: What are the future trends and long-term implications of AI for the auditing profession?

Concluding the investigation, this question looks at how AI might shape the auditing industry in the years to come, considering advancements in technology, evolving industry standards and emerging challenges.

By addressing these questions this thesis provides a panoramic view of AI's role in modern auditing, covering practical applications, ethical considerations and potential future developments.

1.4 Demarcation

This thesis focuses on the role of AI in transforming risk assessment and fraud detection within auditing. While the study aims to provide a comprehensive understanding of AI's capabilities, it Is necessary to define the boundaries of the research to maintain focus and feasibility. This work includes:

1) Technological Focus: the research examines AI-driven tools such as ML, NLP, RPA and GenAI, as applied in audit processes. Specific emphasis is placed on AI's role in enhancing risk identification, fraud detection and audit efficiency.
2) Target Audience: the thesis is designed for an audience of business professionals, auditors and academics, ensuring technical concepts are accessible to readers without deep AI expertise.
3) Data Sources: the research relies on secondary data from academic journals, industry reports and case studies will form the basis of the analysis.
4) Time Frame: the research primarily focuses on AI advancements in auditing from 2020 onward to ensure the findings are timely and relevant.

This work won't include:

1) Exclusion of Technical AI Development: The study does not delve into the technical development or programming of AI algorithms but focuses on their applications and implications in auditing.
2) Primary Data Collection: Due to time and resource constraints, the research relies on secondary data rather than primary sources, such as interviews with auditors.
3) Geographical Scope: While the research includes global insights, there is a stronger focus on AI adoption within multinational auditing firms and developed markets.
4) Evolving Nature of AI: Given the rapid pace of AI advancements, some findings may have limited applicability over time as new tools and methods emerge.
5) Ethical and Regulatory Aspects: Although ethical and regulatory concerns are discussed, the study does not propose comprehensive solutions but highlights areas for further exploration.

1.5 Use of AI in the Thesis Process

In developing this thesis, AI tools were used in a supportive capacity for example to summarize certain academic chapters and perform language clarity checks. These tools did not generate content or conclusions but were leveraged to ensure precision and readability. The intellectual and analytical work presented remains entirely my own.

1.6 Key Concepts: Audit Risk Assessment and Fraud Detection

In professional auditing, risk assessment is the process through which auditors identify and evaluate the areas where material misstatements are most likely to occur. This includes gaining a deep understanding of the audited entity's environment, internal controls and business operations. The goal is to design audit procedures that are responsive to the nature and level of risk, allowing the auditor to focus efforts where they are most needed (AICPA 2024). Effective risk assessment not only improves audit efficiency but also strengthens the overall quality and credibility of the audit.

Fraud detection, on the other hand, concerns the auditor's responsibility to recognize intentional misstatements arising from deceptive actions. These include acts such as falsifying financial data, misappropriating assets or concealing obligations. According to international standards, auditors must exercise professional skepticism and remain alert to conditions that may indicate the presence of fraud. Although they are not responsible for preventing fraud, auditors are required to evaluate the risk of fraud and respond with appropriate audit procedures (IAASB 2023). Identifying fraud risk factors early supports the integrity of the financial reporting process and the trust placed in audit outcomes.

Table 1 Acronyms Used in the Thesis

Acronym	Full Term
AI	Artificial Intelligence
CSRD	Corporate Sustainability Reporting Directive
ESG	Environmental, Social and Governance
GAN	Generative Adversarial Network
GDPR	General Data Protection Regulation
GenAI	Generative Artificial Intelligence

GLAD	General Ledger Anomaly Detector
ML	Machine Learning
NLP	Natural Language Processing
RPA	Robotic Process Automation
XAI	Explainable Artificial Intelligence

Table 2 Overlay Matrix

RQ: How is AI transforming risk assessment and fraud detection in auditing?			
Investigative Questions (IQs)	**Theoretical Framework**	**Results**	**Interview Questions**
IQ1: What specific AI tools and techniques are currently used to enhance risk assessment in auditing?	2.3	4.1	Q3, Q4; c, d
IQ2: How effective is AI in identifying and preventing fraudulent activities compared to traditional methods?	2.4, 2.5.2	4.2	Q2, Q4; b, d
IQ3: What are the primary challenges and limitations of adopting AI in auditing, including ethical concerns?	2.5.3, 2.5.4, 2.5.5, 2.5.6, 2.5.7	4.4.1	Q6, Q5; f, e
IQ4: How does AI contribute to sustainability in auditing, particularly in ESG reporting and sustainable fraud detection?	2.5.1, 2.5.2, 2.5.4	4.4.2	Q7; g
IQ5: What are the future trends and long-term implications of AI for the auditing profession?	2.5.3, 2.5.7	4.4.2	Q1, Q8, Q10; a, h, j

2 Advances in AI for Auditing

A well-structured theoretical framework is essential in academic research because it defines key concepts, organizes existing knowledge and connects theory to empirical study (Grand & Osanloo 2014). Following this approach, this chapter presents the theoretical framework of the thesis, focusing on how AI is transforming auditing practices. The framework encompasses key themes such as the historical evolution of AI in auditing, current AI technologies and AI's applications in risk assessment and fraud detection. These themes were selected to provide a comprehensive foundation for understanding the role of AI in auditing and to support the empirical study based on expert interviews. The framework is structured to highlight the transition from traditional methods to AI-driven processes offering insights that will be critically examined in the empirical part of the research.

2.1 Historical Evolution of AI in Auditing

AI's introduction to auditing began with basic automation tools designed to handle repetitive tasks. Early AI systems primarily focused on automating repetitive tasks to handle larger datasets, improving efficiency, but struggling to adapt to dynamic environments (Omoteso 2012). This rigidity highlighted the need for more adaptive technologies, leading to the development of ML. As AI technologies evolved, ML emerged as a transformative force, enabling auditors to analyse financial data in real-time. Sekar (2022) emphasizes that ML allowed auditors to move manual sampling by examining entire datasets and identifying anomalies that traditional methods often missed. This evolution has made AI indispensable in auditing, particularly in addressing the challenges of global financial markets.

2.1.1 The Shift to Machine Learning and Data Analytics

ML has significantly transformed auditing by enabling AI systems to analyse vast datasets independently. Unlike rule-based systems, ML algorithms learn from data to identify patterns and make predictions. Tools like PwC's Halo exemplify this advancement, detecting anomalies across full datasets and enhancing audit speed and accuracy (PwC 2023). However, despite these improvements, the effectiveness of tools like Halo heavily depends on the quality and representativeness of the training data, which may vary across industries. ML has also empowered predictive analytics, using historical data to forecast future risks. Sekar (2022) explains that predictive models provide auditors with actionable insights, enabling them to prioritize high-risk areas. This shift has enhanced audit quality by reducing reliance on manual processes. Kokina et al. (2017, 15) note that advancements in AI and data analytics have paved the way for real-time decision-making capabilities in complex financial environments. Furthermore, Leocádio et al. (2024, 7) emphasize that combining ML-based tools with big data technologies improves fraud detection across entire datasets. However, data biases and transparency issues remain critical challenges, necessitating continuous oversight during implementation (The CPA Journal 2020).

2.1.2 Key Breakthroughs in Fraud Detection

AI has significantly advanced fraud detection through anomaly detection algorithms and NLP capabilities. Traditional fraud detection methods relied on sampling and manual checks, often limiting scope and accuracy. ML-based anomaly detection now allows continuous monitoring of entire datasets, identifying deviations that could indicate fraudulent behaviour (Luthfiani 2024). NLP has expanded fraud detection by analysing textual data such as contracts and emails. Leocádio et al. (2024, 7) highlights how NLP systems detect suspicious language patterns, offering insights that go beyond numerical data. EY (2023) reports that these technologies have reduced reliance on random sampling, allowing more comprehensive fraud assessments. Nevertheless, the effectiveness of NLP can be hindered by linguistic nuances, cultural differences and evolving fraud tactics, posing a challenge for consistent fraud detection (Business Money 2023).

2.1.3 Integration of Natural Language Processing (NLP)

Natural Language Process (NLP) has emerged as a significant breakthrough in the auditing field, expanding AI's ability to process unstructured textual data. While traditional auditing primarily focuses on numerical data, many fraud cases are hidden in unstructured data such as emails, contracts and communication logs. NLP allows AI systems to analyse this type of data for indicators of potential fraud or compliance risks (The CPA Journal 2020). This capability is particularly useful because much of the information that signals fraud or irregularities is embedded in textual communication that might otherwise go unnoticed in financial reports. NLP algorithms scan financial statements, including the MD&A sections, for unusual language or keywords that may indicate fraud or misrepresentation. They also analyse internal communications to detect discrepancies that might be missed by auditors. Sentiment analysis, now increasingly used in NLP applications, helps identify language shifts that may suggest deceptive behavior, such as overly optimistic tones masking negative realities (Business Money 2023). NLP is also used to flag suspicious activities by analysing transaction data, customer complaints or social media posts for potential fraud patterns. When combined with machine learning, NLP enhances fraud detection by identifying evasive or inconsistent language, helping auditors detect fraud earlier (The CPA Journal 2020).

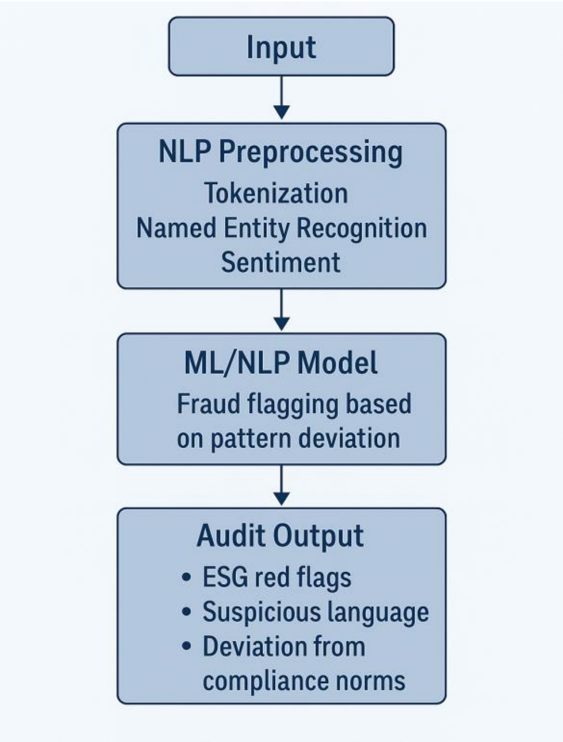

Figure 1 NLP Workflow for Fraud and ESG Detection in Auditing Context

Moreover, NLP's real-time text analysis supports continuous focus on high-risk areas (Leocádio et al. 2024, 4). Although NLP is a valuable fraud detection tool, challenges like language complexity, slang and cultural nuances remain. As the technology advances, NLP's ability to detect fraud and improve audit accuracy is expected to grow making it an essential tool in modern auditing (Business Money 2023; Leocádio et al. 2024, 7). However, challenges remain regarding the complexity of language and cultural variations, which can limit NLP's effectiveness in diverse auditing contexts (Leocádio et al. 2024, 2).

2.1.4 Continuous Auditing and Real-Time Risk Assessment

The adoption of AI enabled the transition from periodic to continuous auditing. AI systems now constantly monitor financial activities allowing auditors to assess risks in real-time, providing more dynamic and proactive risk management. As Leocádio et al. (2024, 4) note, this shift allows audit speed and responsiveness, especially in fast-paced financial environments. The integration of real-time data analytics into auditing processes has become critical for organizations navigating fast-paced financial environments where immediate action is often required (Munoko 2021). Deloitte (2024) notes that continuous auditing ensures more dynamic risk management. However, real-time auditing also raises challenges related to information and the potential for false positives, which may overwhelm audit teams if not carefully managed (Munoko 2021). Sekar (2022) notes that continuous auditing aligns with the "Three Lines of Defense" model, ensuring proactive risk management and improved governance structures. Minkkinen et al. (2022) propose a structured conceptual framework for continuous AI auditing that emphasizes system reliability, transparency and adaptability to different financial contexts.

2.1.5 Role of Big Data in Enhancing AI Capabilities in Auditing

Big data has significantly enhanced AI's effectiveness in auditing by enabling the processing of vast datasets and detecting patterns that would be impossible to identify in smaller data samples. According to Zhang et al. (2020), big data drives predictive analytics, helping auditors assess future risks more accurately. Historical data allows AI can predict potential financial risks, allowing auditors to prioritize high-risk areas before they become significant issues. This capability is vital for improving the strategic decision-making process in auditing (Leocádio et al. 2024, 1). With the increasing volume, variety and velocity of data, big data technologies help auditors gain deeper insights into company operations, providing a broader perspective that improves both risk management and compliance monitoring. Yet, managing big data also introduces significant data governance and privacy concerns, particularly when financial audits involve sensitive client information across multiple jurisdictions. These challenges must be addressed to maintain audit reliability and compliance.

2.1.6 Combining AI Technologies for Comprehensive Auditing Solutions

The evolution of AI in auditing has seen a convergence of ML, NLP and big data analytics. These technologies have collectively enhanced auditors' ability to assess risk, detect fraud and ensure compliance. As Bose et al. (2022, 13) explain that combining structured and unstructured data analysis offers a more holistic audit approach. As AI capabilities continue to advance, auditing is expected to become increasingly proactive, transparent and adaptable (Munoko 2021; KPMG 2024). This holistic approach allows auditors to gain insights into areas that would be difficult or impossible to assess with traditional methods. AI's growing influence in auditing is expected to help address the challenges associated with governance and accountability, particularly in areas like fraud detection and risk assessment. These technologies allow auditors to handle larger and more complex datasets, improving the accuracy and efficiency of audits. As AI continues to evolve, it will undoubtedly introduce further transformative changes to the profession, reinforcing its role as a cornerstone of modern auditing.

2.2 Current AI Technologies in Auditing

AI has shifted from being a peripheral aid to becoming a foundational pillar in the transformation of the auditing profession. Technologies such as ML, NLP, RPA and GenAI now allow auditors to analyse large-scale datasets with unprecedented precision and speed. These tools not only reduce the workload of auditors but also expand the scope and depth of their analysis, particularly in areas like risk identification, anomaly detection and fraud prevention. As Zakaria (2021) shows, AI integration into e-accounting audits enables smaller firms to perform scalable fraud detection tasks that were previously feasible only for larger-scale audits. However, despite their advantages, the successful deployment of these technologies requires addressing issues like data biases, ethical considerations and integration challenges. This section explores the capabilities, real-world applications and quantitative impact of these technologies, drawing on case studies and recent advancements.

2.2.1 Machine Learning: A Game-Changer in Audit Efficiency

ML has fundamentally redefined how auditors approach data analysis. Unlike traditional rule-based systems, ML algorithms learn from data patterns, allowing the detection of trends, anomalies and fraud at an unprecedented scale. Deloitte's Argus tool, for example, uses ML to analyse contracts and identify risk areas that would typically require extensive manual review (Rozario & Vasarhelyi 2018). In financial transaction analysis, Law (2024) highlights that ML systems can process over 1 million transactions in under 30 seconds with an anomaly detection accuracy of 96%. Similarly, PwC Halo employs ML to evaluate journal entries for irregularities, offering a more comprehensive approach to audits by reducing dependence on sampling techniques (Leocádio et al. 2024, 7). In terms of efficiency, KPMG (2024) reports that implementing AI-driven tools, including ML, has reduced total auditing hours by 40% while increasing the identification of risk factors by 25%. Fraud detection has also seen remarkable advancements through ML. These technologies can now process large volumes of transactional data and automatically detect irregularities in real-time, significantly reducing the burden of manual audits. According to Adelakun et al. (2024), ML-based fraud detection tools have improved accuracy and speed, allowing auditors to detect fraudulent transactions with greater consistency while reducing false positives. The authors note that ML enables the assessment of entire data populations instead of small samples, leading to more robust and reliable risk assessment. However, the successful application of ML depends on the continuous calibration of models and the integration of auditor judgment, especially in dynamic or unstructured environments. Beyond operational efficiency, ML fosters continuous auditing by enabling real-time assessments of financial data, a necessity in today's fast-paced regulatory environment. This capability minimizes human error and allows auditors to concentrate on high-value tasks such as strategic planning and ensuring compliance with evolving standards (Zhang et al. 2021).

2.2.2 Natural Language Processing: Bridging the Gap in Data Analysis

NLP has emerged as a critical tool for auditors, by enabling the analysis of unstructured textual data such as contracts, emails and financial reports. Traditionally, auditors focused on structured numerical data, often overlooking valuable information hidden within texts. NLP bridges this gap by extracting meaningful insights from large volumes of textual information, supporting a more comprehensive audit. One of the most impactful applications of NLP is sentiment analysis, where algorithms assess the tone and language of financial disclosures to flag potential risks. For example, KPMG’s Clara leverages NLP to highlight risky contract clauses, expediting compliance checks and reducing manual workloads significantly (Fedyk et al. 2022). The same study reports that NLP-driven tools can process unstructured datasets previously requiring extensive manual review, saving auditors thousands of hours annually. Wolters Kluwer (2023) further highlights the efficiency of these tools citing a case where NLP applications reduced the review time for 50000 contracts from two weeks to just two days, with an 89% accuracy rate in identifying irregularities. In the realm of fraud detection, NLP tools analyse communication logs and textual datasets to identify linguistic patterns indicative of deceptive behavior. By examining tone and sentiment, these systems can pinpoint overly optimistic or ambiguous language, often associated with financial misrepresentation. Leocádio et al. (2024) observed that sentiment analysis tools achieve a 91% success rate in detecting deceptive language, providing auditors with actionable insights to assess financial risks more effectively. Beyond these applications, NLP technologies also enhance collaboration between human auditors and AI systems. By generating summaries of complex documents, NLP not only accelerates workflows but also ensures that auditors focus on high-value tasks like strategic decision-making and stakeholder communication. Additionally, the integration of NLP with other AI-driven tools, such as ML, creates a more comprehensive framework for risk identification and compliance monitoring.

2.2.3 Robotic Process Automation: Simplifying Repetitive Tasks

RPA automates repetitive, high-volume tasks such as data entry, reconciliation and report generation. By automating these time-intensive processes, RPA reduces the risk of human error and frees auditors to focus on high-value activities like strategic decision-making and risk analysis. This shift not only improves audit efficiency but also enhances the overall accuracy of financial oversight. A prime example of RPA’s impact is EY’s deployment of automated ledger reconciliation tools, which have significantly shortened processing times while ensuring greater precision (Munoko 2021). Similarly, KPMG integrated RPA into invoice reconciliation and journal entry reviews, achieving a 65% reduction in workload and freeing audit teams to concentrate on analysing discrepancies flagged by the system (KPMG 2024). The same technology has transformed how auditors’ approach large-scale projects, enabling faster identification of anomalies across complex datasets. Deloitte’s AI-integrated RPA tools have also enabled real-time monitoring of audit processes, improving transparency and adherence to regulatory standards (Deloitte 2024). This capability is particularly beneficial for large-scale audits, where real-time updates improve team coordination and decision-making across teams. Reports show that organizations implementing RPA experience a 50% reduction in audit preparation times and accuracy improvements of up to 85% in data reconciliation tasks, underscoring the transformative potential of automation in auditing. Despite its benefits, RPA is not without limitations. Its effectiveness is generally confined to structured data environments; when encountering less organized datasets, RPA solutions require complementary AI technologies such as ML for unstructured data analysis. Additionally, the upfront costs and training investments needed for RPA implementation may pose barriers for smaller firms, despite long-term efficiency gains.

2.2.4 Generative AI: Improving Audit Depth and Analysis

GenAI is reshaping the auditing landscape by improving efficiency, accuracy and decision-making capabilities. Unlike traditional AI tools that focused on analysis alone, GenAI excels at creating narratives, summarizing data and synthesizing insights from complex datasets, making it an invaluable addition to modern auditing practices. For example, Synergy Labs (2024) highlights how generative models have enhanced fraud detection systems by reducing false positives by up to 30% while maintaining high accuracy in identifying suspicious transactions. Similarly, Leeway Hertz (2024) reports that firms implementing GenAI in audit processes have observed a 40% reduction in time spent on data analysis and reporting, significantly boosting overall productivity. In fraud detection, GenAI complements ML models by identifying complex fraud patterns hidden in unstructured data, such as emails and contracts. The integration of Generative Adversarial Networks (GANs) has enabled organizations to simulate diverse fraud scenarios, improving detection capabilities. Despite its benefits, GenAI also presents challenges, particularly around ethical concerns and transparency. For instance, biases in training data can lead to inaccuracies and auditors must validate AI-generated outputs to ensure reliability. Challenges such as biases in training data and the “black-box” nature of GenAI outputs require auditors to validate AI-generated results carefully to ensure reliability and maintain ethical standards. GenAI represents a transformative shift in auditing, allowing auditors to manage complex datasets, enhance fraud detection and streamline reporting processes. However, addressing its challenges is essential to fully realizing its potential and ensuring ethical implementation in the field.

2.3 AI in Risk Assessment

AI has revolutionized risk assessment in auditing by overcoming the limitations of traditional methods, which often relied on manual sampling and subjective judgment. Through advanced algorithms and predictive analytics, AI enables auditors to analyse vast datasets in real time, uncovering risks with unprecedented efficiency and precision.

2.3.1 The Role of Predictive Analytics in Risk Assessment

Predictive analytics has emerged as a cornerstone of AI-driven risk assessment. By examining historical financial data, AI models can identify trends and anomalies that signal potential risks before they materialize. For instance, firms utilizing predictive analytics tools have reported a 30% increase in the accuracy of risk identification compared to traditional sampling methods. According to KPMG (2024) firms using predictive analytics have seen a 30% increase in the accuracy of risk assessment, demonstrating how these tools surpass the capabilities of traditional sampling techniques. A study by ISACA (2024) further highlights the power of predictive analytics into enterprise risk management systems allows auditors to address vulnerabilities proactively rather than reactively. By integrating AI into enterprise risk management systems, auditors can proactively address vulnerabilities rather than reacting to them after they escalate. Even so, predictive models depend heavily on the quality of historical data. If the data is biased or incomplete, risk forecasts may be misleading, emphasizing the need for rigorous data validation.

2.3.2 Machine Learning Models for Risk Identification

ML is integral to AI’s role in risk identification processes. Unlike rule-based systems, ML algorithms adapt to evolving data patterns, enhancing their ability to detect irregularities. For example, AI-powered audit tools can analyse millions of transactions in seconds, identifying anomalies that may indicate fraud or compliance risks (ISACA 2024). Similarly, research from Leeway Herts (2024) highlights how ML has enabled a 40% reduction in the time spent on manual transaction reviews, underscoring the efficiency of AI-driven risk assessments. Another key advantage of ML is its ability to process unstructured data, such as emails and contracts, alongside structured datasets. This capability provides auditors with a comprehensive understanding of risk across various data types, making it a crucial component of modern risk assessment frameworks. But challenges such as model drift, where predictive accuracy declines over time due to changes in data patterns, require auditors to continuously recalibrate their models.

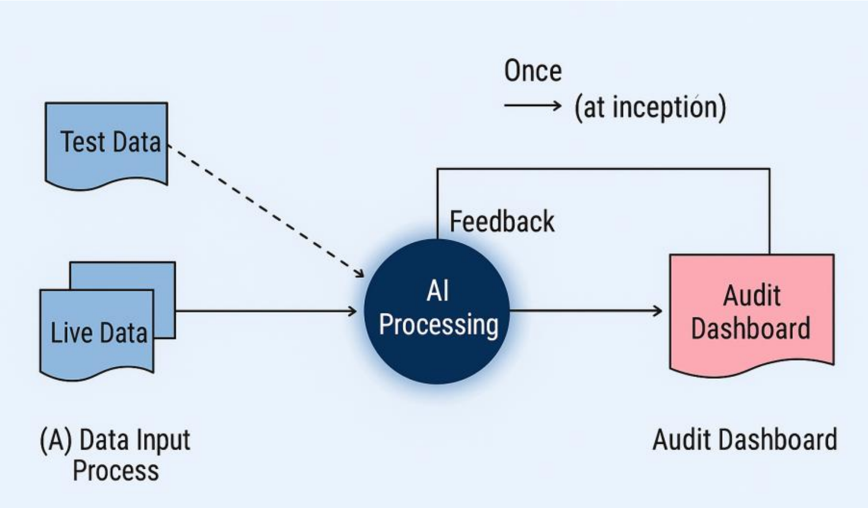

Figure 2 Simplified ML Workflow in AI-based Risk Assessment

2.3.3 Advantages of AI in Risk Assessment

One of the primary benefits of AI in risk assessment is its capacity for real-time monitoring. Traditional audits often rely on periodic reviews, leaving gaps in risk identification. In contrast, AI tools enable continuous auditing, flagging risk as they arise. ISACA (2024) reports that firms implementing AI-driven continuous auditing have achieved a 25% reduction in missed risk factors, highlighting the reliability of AI in dynamic financial environments. AI also enhances the scalability of risk assessments. Tools discussed in AI in the report “AI in Financial Reporting and Audit: Navigating the New Era” (KPMG 2024) can evaluate entire datasets instead of small samples, improving the comprehensiveness of audits. This ensures that even complex financial systems are thoroughly analysed, reducing the probability of undetected risks. Despite these benefits, over-reliance on automated systems without adequate human oversight could result in overlooked contextual factors critical for accurate risk assessment.

2.3.4 Challenges, Limitations and Opportunities of AI in Risk Assessment

Despite its transformative potential, AI in risk assessment is subject to challenges. One major concern is represented from the quality of data used to train AI models because biases or inaccuracies in training data can compromise the reliability of risk assessments. Leeway Hertz (2024) emphasizes the importance of rigorous data validation and cleansing to mitigate this risk. Another challenge is the “black box” nature of many deep learning models, where the decision-making process is not transparent. This lack of explainability raises concerns for auditors who must justify their findings to stakeholders and regulators (CPAB 2024). To address this, advancements in Explainable AI aim to make Ai decision-making processes more interpretable. As Hennick et al. (2023) argue, anticipatory audits, which involve pre-emptive identification of AI model vulnerabilities, are essential to mitigating risks before they escalate, thus enhancing trust in AI-driven risk assessment systems. The future of AI in risk assessment is promising, particularly with advancements in Explainable AI (XAI), which address critical transparency issues in AI-driven auditing. XAI techniques improve the interpretability of AI models, allowing auditors to understand and trust the decision-making processes behind AI-generated risk assessments. By providing clear explanations of how results are derived, XAI enhances accountability and aligns with auditing standards, ensuring that AI outputs are both auditable and actionable (Waterloo Centre for Information System Assurance 2024; ISACA 2022).

2.4 AI in Fraud Detection

Fraud detection has traditionally relied on manual reviews and rule-based systems, both of which are limited in their ability to adapt to the growing complexity and volume of financial data. Manual methods while effective for small datasets, often fail to detect subtle patterns associated with sophisticated fraud schemes. Rule-based systems, on the other hand, are rigid and struggle to adapt to evolving fraud tactics. The integration of AI technologies, such as ML models, anomaly detection systems and NLP tools, has fundamentally reshaped fraud detection process by enhancing accuracy, efficiency and scalability (Bello & Olufemi 2024). Fraud remains a pervasive issue across industries with significant financial consequences. According to the Federal Trade Commission (2024), consumers in the United States lost over $10 billion to fraud in 2023, representing a 14% increase from the previous year. On global scale, Nasdaq (2024) estimates annual fraud losses exceeded $485 billion, illustrating the urgent need for more effective detection and prevention systems. These staggering figures highlight the limitations of traditional methods and underscore the necessity of adopting AI-driven solutions. AI technologies offer unprecedented levels of precision and scalability in fraud detection, enabling more proactive and data-driven audit strategies. ML models, anomaly detection systems and NLP tools are key innovations reshaping how fraud is identified and managed. Unlike traditional method, which often rely on sampling or predefined rules, AI systems analyse entire datasets in real time, uncovering anomalies and fraudulent patterns that would otherwise go undetected.

2.4.1 GANs: Enhancing Data Robustness

Fraud detection often struggles with imbalanced datasets, where legitimate transactions vastly outnumber fraudulent ones. This imbalance poses challenges for traditional models, which struggle to identify rare fraud events. GANs address this issue by creating synthetic fraud scenarios, enriching datasets and enabling models to learn from diverse patterns of fraudulent behavior. For instance, a study in Engineering, Technology & Applied Science Research (2023) demonstrates the effectiveness of GAN-augmented models, reporting an accuracy over 85%, precision over 95% and recall above 90% in detecting fraudulent activities. Precision refers to the proportion of correctly identified fraud among all transactions flagged as fraudulent, while recall measures the model's ability to detect actual frauds among all fraudulent transactions. High values in both metrics indicate the model is highly reliable in minimizing false positives and false negatives. Despite their promise, GAN-generated datasets may not fully capture the complexity and unpredictability of real-world fraud, potentially limiting the generalizability of the models trained on them. Continuous refinement and integration with real-world case studies are necessary to maintain model effectiveness.

2.4.2 NLP: Detecting Deception in Text

Fraud often leaves linguistic traces in emails, contracts and financial disclosure. NLP tools are instrumental in analysing unstructured text to detect deceptive patterns and risky clauses. For example, NLP-driven systems have been used to analyse financial contracts and emails for language suggestive of misrepresentation or collusion. According to Shehnepoor et al. (2021), NLP tools combined with GANs achieved higher than average precision in identifying fraudulent communications. Additionally, Wolters Kluwer (2023) reported that NLP tools reduced the time required to review 50000 documents from two weeks to two days, achieving an accuracy rate of 89% in flagging risky clauses. Yet, the effectiveness of NLP in fraud detection depends on the system's ability to handle context, ambiguity and linguistic diversity, requiring ongoing model training and refinement.

2.4.3 Real-World Impact of AI-Driven Fraud Detection and Its Challenge

AI's adoption in fraud detection is not theoretical; its real-world applications are already yielding significant results. Visa, for instance, reported preventing over $40 billion in fraudulent transactions in 2023 using AI technologies (Reuters 2024). A case study by A&I Financials (2024) highlights that AI reduced anomaly detection time in financial institutions by 40%, enabling real time responses to suspicious activities. AI also offers operational efficiency. Organizations using AI tools report substantial cost savings by reducing manual reviews and focusing resources on higher-risk areas. A study on AI in Financial Fraud Detection (Ahsun et al. 2025) highlights that AI-driven solutions reduced operational costs by 35% while improving fraud detection accuracy by 50%. These results illustrate the scalability and adaptability of AI systems in high-risk environments. Despite its advantages, AI-driven fraud detection is not without challenges. One significant issue is data bias, which can twist model predictions if training datasets are not representative. According to Chen et al. (2023), fairness in AI requires not only unbiased training data but also mechanisms to continually evaluate model outputs for systemic discrimination particularly in high-stakes domains such as auditing. To address these issues, Explainable Artificial Intelligence (XAI) frameworks, AI system designed to make decision-making processes transparent and understandable to humans, are becoming increasingly important. Nasdaq (2024) emphasizes that XAI enhances the interpretability of

AI models, ensuring that auditors and regulators can trust the decisions generated by these systems. Ethical considerations also play an essential role; AI tools must handle sensitive financial data securely and comply with privacy regulations. Organizations need robust governance frameworks to ensure AI systems are implemented responsibly and transparently.

The reviewed literature reveals both the transformative potential and the current limitations of AI tools in auditing. While many sources highlight increased accuracy, speed and cost-efficiency in risk assessment and fraud detection, other studies stress concerns such as data bias, transparency and the evolving role of the auditor. Yet, there remains a noticeable gap between what the literature reports and how these tools are experienced in real-world auditing contexts, particularly in practical implementation, decision making and the differences between internal and external audit functions. To address this gap, the next chapter presents the research methodology used in this thesis based on interviews with auditing professionals. Their insights provide a grounded, practice-based understanding of how AI tools are currently applied in auditing, where challenges remain ad how their role may evolve in the future.

2.5 AI Auditing Sustainability

A sustainability becomes central to corporate accountability, auditors are increasingly expected to assess ESG (Environmental, Social and Governance) practices. AI supports this shift by enabling real-time analysis, detecting greenwashing and enhancing ESG reporting. Yet, it also raises new challenges, including algorithmic bias and the environmental impact of large AI models. This section explores how AI contributes to sustainable auditing while critically examining the ethical and environmental trade-offs it introduces.

2.5.1 AI in ESG Reporting

AI is transforming ESG (Environmental, Social and Governance) reporting by enabling faster, more accurate and scalable analysis of sustainability data. Traditional tools often fall short when faced with unstructured or fragmented ESG data. AI technologies, especially NLP and ML, address this challenge by extracting insights from diverse sources such as sustainability reports, media and supply chain data (Key ESG 2024; Litvinets & Pijselman 2024). For example, NLP can assess qualitative ESG disclosures for tone, clarity and risk indicators while ML models identify anomalies in quantitative metrics like carbon emissions or diversity ratios (Martin 2025). These tools are already deployed by firms like PwC and Key ESG to streamline reporting and support compliance with global frameworks (Lakshmanan 2025; Key ESG 2024). A significant advantage of AI is its ability to monitor ESG data in real time. This allows auditors to flag inconsistencies proactively rather than waiting for year-end reports. It also supports dynamic assurance, especially useful for sustainability-linked disclosures such as ethical sourcing or environmental impact metrics (Litvinets & Pijselman 2024). However, AI adoption in ESG reporting is not without concerns. The lack of global ESG standards poses risk to the accuracy of AI outputs. Biases in training data or opaque model logic can lead to flawed results, which may compromise audit credibility. This raises the need for explainable AI and robust governance frameworks to ensure ethical use (CFA Institute 2024; Zewe 2025). Despite these challenges, AI significantly strengthens ESG reporting by enhancing transparency, timeliness and auditability. When responsibly implemented, it enables auditors to assess both financial and non-financial risks with greater confidence and depth.

2.5.2 AI for Greenwashing and Sustainable Fraud Detection

As sustainability gains strategic importance, the risk of misleading ESG claims, commonly known as greenwashing, has increased. Traditional audit methods often struggle to detect these practices due to the unstructured nature of sustainability data and the lack of standardized metrics. AI helps close this gap by identifying inconsistencies and verifying ESG disclosures across multiple data sources (CFA Institute 2024; Key ESG 2024). ML algorithms can spot suspicious trends in sustainability reports, such as unrealistic emission reductions or unverified diversity claims. NLP tools enhance this by analysing the language used in ESG narratives. Vague or overly optimistic phrases without measurable targets are flagged as potential red flags (Key ESG 2024; Litvinets & Pikselman 2024). AI also enables triangulation of ESG data through external sources like satellite imagery, news feeds or environmental databases. This allows auditors to cross-check reported information against observable evidence, making it harder for companies to hide harmful practices behind polished narratives (Martin 2025). Despite its strengths, AI in sustainable fraud detection is not immune to challenges. Biased training data and model opacity can lead to misinterpretation and firms may try to game the system by tailoring disclosure to appear credible to AI tools. Therefore, transparency and explainability must be embedded into these systems to ensure reliability and accountability (CFA Institute 2024). Overall, AI strengthens the detection of greenwashing and enhances the reliability of ESG audits. Its capacity to automate cross-checking, highlight inconsistencies and monitor sustainability performance in real time makes it an essential tool in ethical and transparent auditing.

2.5.3 Challenges and Solutions in Sustainable Auditing

While AI presents remarkable opportunities for advancing sustainability in auditing, it also introduces complex challenges that must be addressed to ensure ethical and effective implementation. These challenges span environmental, technical and ethical domains, calling for strategic solutions that integrate sustainability into the AI lifecycle itself.

2.5.4 Environmental costs of AI

One of the most pressing concerns is the environmental footprint of AI technologies themselves. The development and deployment of AI systems, especially large-scale models used for NLP or image recognition, require substantial computing power and data centre infrastructure. Studies show that training a single large model can emit as much carbon dioxide as five cars over their entire lifetimes (Zewe 2025). A study published by Xiao & Xiao (2025) found that training state-of-the-art AI models can produce emissions comparable to those generated by multiple vehicles over several years, depending on the hardware and energy source used. Continuous auditing, which relies on real-time monitoring and frequent model updates, may further amplify these environmental impacts. This creates a paradox where tools meant to support sustainability contribute to resource depletion and greenhouse gas emissions (Ren & Wierman 2024). To address this issue, organizations are increasingly adopting green computing practices. These include the use of energy-efficient algorithms, carbon-aware computing schedules and partnerships with cloud providers committed to renewable energy. Intel (2024) emphasizes the importance of AI optimization techniques such as model pruning and edge computing, which reduce energy consumption without compromising performance. Furthermore, companies are encouraged to calculate and disclose the environmental impact of their AI systems as part of their broader ESG transparency commitments.

2.5.5 Algorithmic Bias and Transparency

Another major challenge lies in the potential for algorithmic bias and the lack of transparency in AI decision-making. AI systems used in ESG evaluations may unintentionally perpetuate discrimination or ignore relevant sustainability dimensions if trained on biased or incomplete data. For instance, models that rely heavily on Western-centric ESG standards may undervalue the environmental performance of firms operating in developing economies or misinterpret region-specific social initiatives. To mitigate these risks, developers and auditors must ensure diverse, representative training datasets and apply fairness-aware ML techniques. Transparency is equally vital. AI systems used in auditing should offer explainability features that allow users to understand how conclusions were reached, particularly when these insights inform investment or compliance decisions. As noted by Litvinets (2024), audit firms are starting to adopt “responsible AI” frameworks that emphasize fairness, transparency, accountability and ethical alignment across all stages of model development and deployment. Pratt (2024) highlights the increasing responsibility of CIOs in balancing ESG compliance with technological transparency and performance, urging organizations to embed sustainability goals into AI lifecycle management.

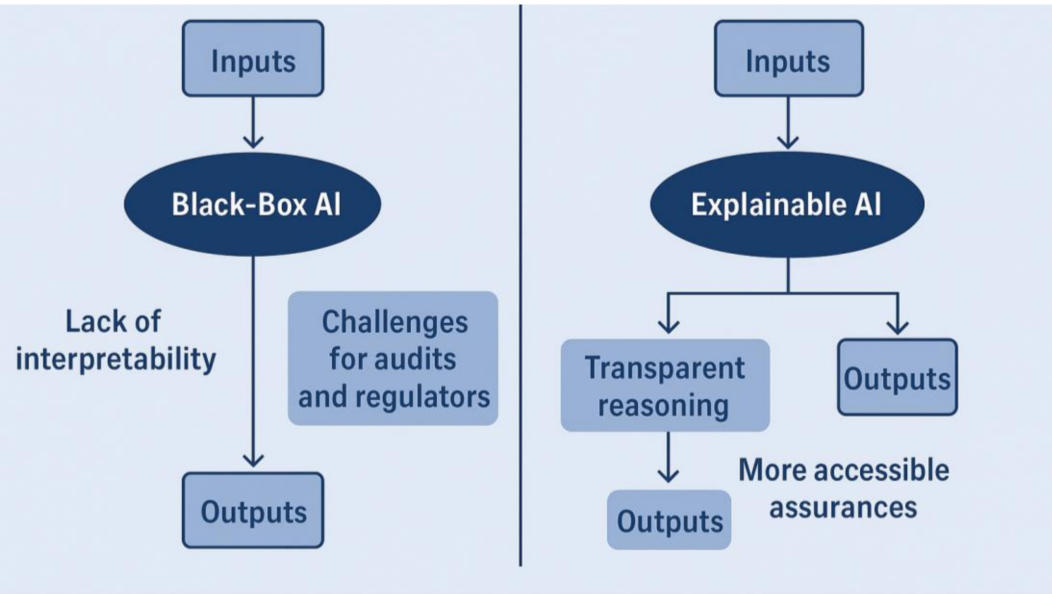

Figure 3 Differences Between Black-Box and Explainable AI Models in the Auditing Context

2.5.6 Ethical Risk of Overreliance on AI

While the technical and operational role of human oversight in AI auditing has been discussed in Section 4.4, an additional sustainability concern lies in the ethical implications of overreliance on algorithmic outputs. As AI becomes more embedded in audit processes, there is a growing risk that auditors may treat their assessments as definitive, inadvertently eroding critical thinking and professional accountability. This trend, often described as “automation bias”, can lead to complacency, where flawed AI outputs go unchallenged. In sustainability audits, where disclosure affects investor decisions and corporate reputation, such errors can have far-reaching consequences. If AI is used to verify ESG claims or detect greenwashing without robust human validation, firms may avoid responsibility by blaming technological flaws rather than addressing systemic issues. Also, excessive dependence on AI can gradually deskill audit teams, weakening their ability to detect fraud or misreporting in contexts where AI is less effective. Ethical audit practice requires maintaining a balance: using AI to enhance decision-making while ensuring human auditors retain full accountability for the outcomes. This hybrid approach not only reinforces ethical standards but also supports long-term professional resilience in an AI-driven audit environment.

2.5.7 Regulatory and Ethical Obstacles

The evolving nature of AI poses a regulatory challenge. ESG reporting standards are still under development globally and the integration of AI into this domain often outpaces legal frameworks. Without clear regulations, the use of AI in sustainability auditing may lack accountability, opening the door to inconsistencies, malpractice or even “ESG washing” through AI. To overcome this, both companies and regulators must collaborate to set ethical standards and compliance requirements for AI in auditing. Initiatives such as the EU’s Artificial Intelligence Act and the CSRD signal progress in establishing legal safeguards. Additionally, industry-led guidelines, such as those promoted by KPMG (2024) and Key ESG, advocate for AI governance frameworks that align with environmental and social responsibility goals.

2.6 From Theory to Practice: Setting the Stage for Empirical Research

This chapter has explained the key advancements in AI that are transforming auditing practices. It traced the historical evolution from basic automation to sophisticated AI technologies, examined current tools such as ML, NLP, RPA and GenAI and explored their applications in risk assessment and fraud detection. While the potential of AI to enhance audit quality, efficiency and fraud prevention is substantial, critical challenges such as data bias, model transparency and ethical considerations remain. The literature reveals that despite significant technological progress, practical implementation challenges persist, highlighting the importance of empirical investigation. To bridge this gap, the next chapter presents the research methodology, detailing how interviews with auditing professionals will provide grounded insights into the real-world application, limitations and future potential of AI-driven auditing.

3 Methodology

3.1 Research Design

This thesis adopts a qualitative research approach to investigate how AI is transforming risk assessment and fraud detection in the auditing profession. The goal of the study is to gain an in-depth understanding of how audit professionals perceive and experience the integration of AI tools in their day-to-day work. Given the complex, evolving and context-dependent nature of AI implementation, qualitative research allows for flexibility and nuance in capturing lived experiences and professional interpretations that quantitative data alone may not fully reflect (Saunders, Lewis, Thornhill 2019). A qualitative method was chosen over a quantitative one because the nature of the research questions required open discussion and contextual detail which cannot be effectively captured through surveys or numerical analysis (Creswell & Poth 2018). Semi-structured interviews were selected as the primary data collection method, enabling guided yet open conversations as reported from Gill et al. (2018) to balance structure and flexibility, making them ideal for professional interviews. This format allows for comparison across key themes while offering participants the freedom to elaborate based on their unique professional roles and experiences. The research questions guiding this thesis focused on effectiveness, accuracy, risks, opportunities and the evolving role of the auditor are best answered through such in-depth, reflective dialogue.

3.2 Data Collection and Participants

The data for this thesis was gathered through three semi-structured interviews conducted between February and March 2025. The interviews lasted approximately 30 to 45 minutes each and were held either remotely or in person, depending on the participant's availability. All interviews were recorded with the participants' consent and subsequently transcribed for analysis. Each participant was selected to represent a different area of auditing to provide a more holistic view of AI's impact on the profession. Naoto Ichihara, Assurance partner at EY Japan and developer of the company AI, EY Helix GLAD (GL Anomaly Detector), provided insights rooted in the traditional financial audit process, reflecting on how AI tools are increasingly embedded in external assurance engagements. Lídia Fonseca, Manager in IT Compliance and Assurance in UPM Kymmene, brought more systems focused perspective, particularly regarding the implementation and capabilities of AI in fraud detection and risk modelling. The third interviewee is Arla Ketolainen Internal Audit Manager for Kesko Group and offered detailed input on how AI tools are influencing internal risk assessment, control testing and compliance related audit tasks, including those tied to ESG reporting. Although the core interview questions were consistent across participants, they were subtly adapted in language and emphasis to reflect the specific context of each interviewee's professional role. This ensured relevance while maintaining thematic consistency. The complete interview questions guide is available in Appendix 1. All participants were informed about the purpose of the study and how the data would be used. Participation was entirely voluntary.

3.3 Analytical Approach

After transcription, the interviews were analysed using a thematic analysis method. According to Braun and Clarke (2006), the key source about thematic analysis methodology explaining that it is an accessible yet theoretically flexible method for identifying, analysing and reporting patterns within data. This involved a close reading of the data to identify recurring patterns, keywords and ideas that aligned with the research questions and theoretical framework established in Chapter 2. The themes that emerged include the perceived accuracy of AI tools in risk identification, their role in automating fraud detection, the extent to which AI is seen as replacing or complementing human judgment and the practical constraints that limit AI adoption, such as data availability, ethical concerns and regulatory uncertainty. The small number of interviews was not a limitation in this context but rather a deliberate choice to allow for in depth discussion and rich qualitative dataset. The variety in professional backgrounds helped ensure tat the findings are grounded in real-world practice and reflective of multiple facets of the auditing profession today.

3.4 Ethical Considerations

Ethical integrity was maintained throughout the research process in accordance with Haaga-Helia guidelines for research-based theses. Prior to each interview, participants were informed about the nature and objectives of the research, the voluntary nature of participation and the measures taken to protect their privacy. Where anonymity was requested, names and identifying details were withheld or pseudonymized. The recorded audio files and transcripts have been securely stored and they are accessible only by the researcher. These materials will be deleted after the thesis has been submitted and graded, in accordance with data protection regulations. The interview content has been used solely for academic purposes and no confidential information about companies or clients was requested or recorded. By adhering to these ethical standards, the research maintains both academic credibility and respect for the professional confidentiality of all contributors.

4 Results

This chapter presents the key findings that emerged from the thematic analysis of three semi-structured interviews with professionals working in external, internal and IT audit roles, offering a distinct perspective. The results are structured around the main research questions: how AI is influencing risk assessment and fraud detection in auditing, what limitations and opportunities are observed in practice and how human oversight continues to shape AI-supported audit work. The responses from each participant were compared and analysed to identify shared themes and divergent viewpoints. The interview guide used to explore these themes is provided in Appendix 1. While the full methodology is detailed in Chapter 3, this section focuses solely on presenting the results of the research, without interpretation, which will be addressed in the Discussion chapter.

4.1 AI's Impact on Risk Assessment in Auditing

One of the most prominent themes emerging from the interviews was the evolving role of AI in audit risk assessment. All three participants acknowledged that AI has significantly influenced how auditors identify, evaluate and respond to risk, particularly by enabling deeper and faster analysis of transactional and operational data. While adoption levels and sophistication varied across organizations, common benefits included improved efficiency, broader coverage and enhanced ability to detect anomalies and patterns that might otherwise be overlooked using traditional sampling methods. Lídia Fonseca, Manager of IT Compliance & Assurance at UPM Kymmene, described how AI tools, specifically Microsoft Copilot embedded within Excel, are being used internally to streamline the identification of high-risk transactions. Rather than manually combing through large datasets, auditors now rely on AI to filter out standard entries and surface exceptions that warrant further investigation. Fonseca emphasized that this shift allows auditors to allocate more time to professional judgement and deeper analysis, rather than data cleansing or preparation:

> "Before, we needed to sort the data and look for patterns ourselves; now it's automatically done. We can focus on what's most important instead of spending time preparing the data for analysis."

Naoto Ichihara, Assurance Partner at EY Japan and developer of EY Helix GLAD (General Ledger Anomaly Detector), provided a more technical view of how AI enables full-scope transactional analysis. Unlike traditional audit sampling, which relies on pre-set thresholds or judgmental selection, EY's AI tools allow auditors to model expected values for each account based on daily activity patterns and detect outliers through statistical and machine learning techniques. This enables risk identification across 100% of the dataset, fundamentally shifting the approach from reactive to predictive:

> “We can build the expectation for receivables based on cash, sales and inventory movement and compare that with actual entries to detect deviations. It’s no longer about just selecting a sample based on size.”

In contrast, Arla Ketolainen, Internal Audit Manager at Kesko Group, described the organization’s AI usage as being in early-stage exploration, particularly in relation to risk assessment. Although AI is not yet integrated into core risk scoring models or control testing, it’s being used experimentally to support planning processes and generate ideas during audit scoping. For example, internal auditors may prompt AI systems with questions about pricing risks or ESG-related exposures to inform which risk should be prioritized in upcoming audits. Ketolainen noted that while this use of AI is still limited in analytical depth, it supports auditors in staying current with evolving risk areas:

> “We are not yet doing any formalized risk assessment with AI, but we do use it for planning and brainstorming. It helps identify things we might not have considered otherwise.”

Despite differences in technological maturity, all interviewees recognized that AI has expanded the auditor’s field of vision when it comes to risk identification. Where traditional approaches often relied on static models or subjective thresholds, AI enables the continuous scanning of large datasets and real-time identification of irregularities, particularly those that do not fit known risk profiles. This capability is especially relevant in complex or decentralized organizations where risk exposure may vary across entities, geographies or functions. However, participants also acknowledged certain limitations. Ketolainen emphasized that inconsistent data formats across subsidiaries make it difficult to apply a standardized AI model across the entire organization, limiting scalability. Fonseca and Ichihara both noted that while AI tools are powerful, they still require well-prepared input data, raising challenges related to data integration and quality. Moreover, the human auditor remains responsible for validating AI-flagged risk before they can influence audit procedures which places boundaries on the extent to which AI can independently determine audit direction. Overall, the results indicate that AI is not replacing the auditor’s judgment in risk assessment but rather augmenting it by providing a broader, faster and more data-driven foundation for decision-making. The transition from manual sampling toward full-scope, AI-assisted risk analysis reflects a major procedural shift in the audit profession and highlights the growing importance of data governance and auditor-AI interaction in future assurance work.

4.2 AI’s Impact on Fraud Detection in Auditing

The application of AI in fraud detection was another key area where all interviewees observed meaningful transformation within their audit practices. While the scope and maturity of these tools varied between internal and external auditing environments, all participants agreed that AI has introduced a more dynamic and data-centric approach to identifying fraudulent activity. ML models, anomaly detection systems and pattern recognition algorithms have enabled auditors to detect outliers or irregularities in large volumes of data that would likely go unnoticed using traditional audit procedures. At EY Japan, Naoto Ichihara emphasized the role of AI-powered tools in improving both the breadth and depth of fraud detection efforts. He described the use of the GLAD, an in-house ML model developed to flag suspicious journal entries by building expected daily behavior for key accounts and highlighting transactions that deviate from these expectations. This tool integrates statistical and ML techniques to examine the co-movement of accounts and provides auditors with risk scores and visualizations for targeted investigation.

> "We show the entries with the highest risk scores, so auditors can select which ones to look at. We also provide flag indicators to identify different types of risk, it's much more precise than random sampling."

Ichihara acknowledged, however, that these systems are not flawless. He noted that false positives remain common, but audit teams prefer this trade-off rather than risk missing significant red flags. He further explained that retrospective testing using historical fraud cases confirmed the system's ability to detect fraudulent behavior that would have otherwise remained hidden, which supports the decision to prioritize *sensitivity* over *specificity* in risk scoring. At UPM Kymmene, Lídia Fonseca described a more practical day-to-day use of AI in fraud detection. Her team primarily relies on Microsoft Excel Copilot to filter and analyse transactional data, isolating abnormal cases for review. While not as technically advanced as GLAD, the approach supports auditors by narrowing the scope of manual review and enabling more targeted audits.

> "It helps us identify those transactions that don't fit the expected filters. AI tells us what is abnormal, we don't have to look at every line ourselves anymore."

Fonseca emphasized that this automation has significantly reduced the time required to detect potential fraud and has increased audit coverage. Moreover, the increased speed and consistency of detection were seen as key factors in moving from a reactive model of fraud investigation toward a more preventive approach, especially in large organizations with high transaction volumes. In contrast, Arla Ketolainen from Kesko Group reported that AI is not yet actively deployed in fraud detection within internal audit, though exploratory steps are underway. Current efforts include the use of process mining tools that help map transaction flows and detect deviations from standard operating procedures, an approach that has potential fraud-related applications even if not explicitly labelled as such.

> "We've used process mining to spot exceptions in how transactions move through systems. For example, why some transactions follow route B instead of route A. that gives us a starting point."

Ketolainen explained that data inconsistency across different systems and entities present a substantial barrier to applying standardized fraud detection algorithms. In addition, the internal audit team is currently focused on ensuring data security and privacy, especially when considering the integration of third-party AI tools that might not meet the company's internal governance standards. Across all three interviews, a consistent message emerged: AI has enhanced the auditor's ability to detect anomalies quickly, but it's not yet a substitute for professional judgment. Both Fonseca and Ichihara noted that human oversight is essential in verifying whether anomalies flagged by AI truly represent fraudulent activity. Initial skepticism and "double-checking" were common when these tools were first introduced, but confidence has grown over time as the results proved reliable. Another point raised by participants is that AI is particularly useful in highlighting non-obvious patterns, such as subtle shifts in transactional behavior, unusual journal entry pairings, or inconsistencies across different datasets. These capabilities not only support fraud detection but also contribute to a more comprehensive understanding of organizational risk exposures. While the interviewees revealed clear advantages, limitations were also acknowledged. Challenges included the interpretability of AI results, especially in models that function as "black boxes" without transparent logic and the regulatory uncertainty surrounding the use of AI-driven evidence in audit conclusions. Ichihara noted that audit standards have yet to fully incorporate the role of AI, which sometimes creates tension between what Ai tools can do and what is formally allowed or required in audit documentation. In summary, AI is making fraud detection more efficient, data-driven and proactive, particularly in environments where transaction volumes are high, and traditional sampling would be insufficient. However, the adoption of AI in this context still depends heavily on data infrastructure, organizational maturity and a willingness to integrate AI tools into established audit processes, always under the guidance of human judgment.

4.3 Role of Human Oversight in AI Auditing

While AI has enhanced various auditing processes, all interviewees emphasized that human oversight remains not only relevant but essential in ensuring the quality, accuracy and ethical soundness of audit work. The extent to which auditors rely on AI varies across organizations and audit types, yet none of the participants viewed AI as a fully autonomous tool. Instead, they described it as an assistant, valuable in processing information and identifying anomalies, but ultimately dependent on professional judgment for interpretation and final decision-making. At EY Japan, Naoto Ichihara articulated a clear boundary between AI-generated insights and human conclusions. Although the firm's AI tools, such as the GLAD, can highlight irregular transactions with precision, Ichihara underscored that auditors must still evaluate flagged entries within context, using their expertise to decide whether further investigation is warranted:

> "At this moment, decision-making remains on the human side. AI provides information but it's the auditor's responsibility to judge whether that output is accurate and meaningful."

Moreover, he raised concerns about a potential overreliance on AI in the future particularly if audit teams begin to treat AI outputs as definitive rather than suggestive. He emphasized that audit standards currently position AI as a supporting mechanism rather than a replacement for core audit judgment, a distinction that protects the integrity of audit conclusion. Similarly, Lídia Fonseca described how, during initial adoption of Excel Copilot and other AI tools at UPM Kymmene, her team actively validated AI results by running manual checks in parallel. This approach built internal confidence in the tool's reliability while preserving accountability. Over time, as the AI consistently produced accurate outputs the need for double-checking diminished, yet human oversight remained embedded in the process:

> "At first, we compared AI's sampling with our own manually selected transactions and found that AI was often more accurate. That's when we started trusting it. But still, we're responsible for reviewing and explaining the final choices."

This evolution, from skepticism to partial reliance, highlights a natural learning curve in AI adoption, where auditors must gradually build trust without abdicating responsibility. Fonseca also noted that internal guidelines dictate how AI can be used, ensuring that critical decision remain auditable and accountable. Arla Ketolainen from Kesko Group echoed these sentiments, describing AI as a helpful assistant, especially in supporting audit planning and documentation. However, she warned against assuming AI can replace contextual understanding, particularly in internal audits where organizational nuances, informal practices and cross-functional dynamics play a central role:

> AI doesn't understand our full organizational context. It can't know all the factors behind why something looks the way it does. That's why human review is always essential."

She also stressed that internal audit teams must stay vigilant about the accuracy of AI-generated summaries and outputs, especially in environments with low AI maturity or inconsistent data quality. In her experience, AI is most valuable when it accelerates low-risk tasks, such as drafting parts of audit reports or extracting themes from interview transcripts, but it should never be used to draw conclusions without human validation. Across all three interviews a clear consensus emerged: AI may support the auditor, but it cannot replace the auditor. Whether analysing patterns, detecting fraud, or assessing risk, the need for ethical reasoning, contextual knowledge and professional skepticism persists. This view aligns with the broader audit principle of professional judgment, a concept that cannot be outsourced to algorithms, regardless of their technical sophistication. In summary, AI's current role in auditing is that of an intelligent tool, not a decision maker. While it improves efficiency and consistency, it must be used responsibly under the supervision of qualified professionals. Human oversight ensures that AI-generated outputs are interpreted accurately and ethically, minimizing the risks of blind reliance and reinforcing the integrity of the audit process.

4.4 Challenges and Opportunities Identified

The integration of AI into auditing processes has brought both significant benefits and notable obstacles, as reflected in the perspectives shared by the interviewees. While each participant represented a different audit function, external, internal and IT audit, several cross-cutting themes emerged regarding what enables or hinders effective AI implementation.

4.4.1 Challenges

A commonly cited challenge was the maturity of data systems and infrastructure. Both Ketolainen and Fonseca emphasized that AI tools rely heavily on clean, structured and consistent datasets. In internal audit where different subsidiaries may use different systems or formats, applying AI uniformly becomes complex and sometimes unfeasible. Ketolainen noted:

> “Inconsistent documentation across companies means we can’t just plug AI in and expect it to work everywhere. You need to train it differently depending on the material.”

This limitation also affects fraud detection and control testing, where automation depends on stable input sources. Another significant issue raised by Ichihara was auditor skepticism and resistance to technological change. Despite the advantages of tools like GLAD, auditors were initially reluctant to adopt them due to uncertainty about their reliability and a lack of explicit guidance in audit standards. He explained that while automation is generally accepted, AI-based analytics remain poorly integrated into formal audit procedures:

> “There is no clear guidance on how AI changes traditional audit work. Right now, AI is an add-on, not yet embedded in the core methodology.”

This regulatory ambiguity creates hesitation in adoption, especially in highly regulated environments where documentation and justification of audit procedures must align with national and internal standards. Data privacy and ethical governance were also flagged, particularly by Fonseca and Ketolainen. Both noted that they are not permitted to feed sensitive company data into public AI tools and must rely on in-house or private solutions. Ensuring compliance with data protection laws and internal policies is a prerequisite to using AI, especially in ESG-related or sensitive audit contexts. Ketolainen added that even where tools are technically available, their use may be limited by policy restrictions or unresolved legal risks. Finally, all participants expressed concern over over-reliance on AI, particularly if audit teams begin to view AI recommendations as unquestionable. This was closely tied to issues of interpretability and explainability, especially when working with advanced ML models that behave like “black boxes”. Without transparency, auditors may find it difficult to justify their conclusions based on AI results, posing risks both to audit quality and to compliance with standards of professional skepticism.

4.4.2 Opportunities

Despite the challenges, interviewees highlighted several powerful opportunities offered by AI, both in improving audit quality and in expanding the scope of audit activity. A key opportunity identified by Fonseca and Ichihara was the ability to analyse 100% of transactions, shifting from sample-based audit models to full-population testing. This not only increases accuracy but also allows auditors to detect subtle or rare anomalies that traditional methods may overlook. Fonseca described AI's contribution to real-time compliance checking, particularly in continuous auditing environments, by embedding AI tools into existing data workflows, organizations can proactively flag potential issues and intervene earlier in the financial cycle. Ichihara pointed to future applications of AI in greenwashing detection and ESG fraud analysis, where auditors will need new tools to assess sustainability claims and identify risks in non-financial disclosure. While these tools are still under development, he stressed that audit firms must begin investing in AI systems that go beyond financial reporting. Ketolainen emphasized that AI has significant potential in planning and reporting, especially within internal audit. She found AI helpful in brainstorming risks during scoping phases and in drafting clear, structured audit reports:

> "Even if AI doesn't replace the whole audit, it already helps us report findings faster and more clearly. That's a big win in terms of efficiency."

In addition, all participants viewed AI as a gateway to more strategic auditing. By removing repetitive tasks and enabling deeper analysis, auditors can focus on higher-level judgment, risk interpretation and strategic recommendations.

4.5 From Results to Reflection: Bridging to the Discussion Chapter

The findings reveal that AI is already transforming key aspects of auditing, particularly in risk assessment and fraud detection, by enabling full data coverage, anomaly detection and predictive analytics. While participants acknowledged technical limitations, regulatory ambiguity and the continued need for human oversight, they also expressed optimism about AI's expanding role. These insights, drawn from professionals across internal, IT, and external audit functions, demonstrate how AI is not merely enhancing audit procedures but prompting a strategic shift in the profession's focus. This evolving landscape invites deeper reflection on the implications, limitations and figure potential of AI in auditing, topics that will be critically explored in the following chapter.

5 Discussion

This chapter reflects on the key findings presented in the previous section and interprets their implications within the broader context of auditing theory, practice and ethics. It integrates insights from the literature review and expert interviews, assess the reliability of the results, address ethical concerns and anticipates future developments in AI-driven auditing.

5.1 Key Findings and their Interpretations

The findings show that AI has brought measurable improvements to auditing, especially in risk assessment and fraud detection. All interviewees confirmed that AI-driven tools are helping auditors analyse full data populations, reduce time spent on manual review and increase the accuracy of detecting anomalies. A clear distinction also emerged between internal and external auditors' perspectives. Internal auditors highlighted AI's value in compliance monitoring, operational efficiency and ESG alignment. External auditors, on the other hand, focused on assurance quality, data-driven sampling and fraud detection reliability. These differences suggest that organizational roles influence how AI is adopted and what benefits are emphasized.

Insights from Fonseca further clarified the technical feasibility and current limitations of AI tools, especially in high-complexity environments. External auditors praised machine learning models like EY's GLAD for identifying high-risk journal entries, while internal auditors valued AI for supporting audit planning and ESG risk identification. Participants reported that AI enables comprehensive analysis of entire data populations, reducing reliance on traditional sampling. These findings align with prior research emphasizing AI's potential to enhance efficiency and audit coverage (Rozario & Vasarhelyi 2018; Fedyk et al. 2022).

However, practical constraints remain, including incompatible systems across business units and difficulty interpreting AI-generated insights. These concerns echo existing literature on "black box" algorithms and the importance of Explainable AI (Ferreira 2024; CPAB 2024). Importantly, auditors continue to act as decision makers and validators, using AI to support rather than replace their professional judgment. The findings also highlight AI's emerging relevance in ESG auditing and greenwashing detection. While adoption is still evolving, AI's ability to process both structured and unstructured data positions it as a key enabler of real-time sustainability assurance, confirming theoretical perspectives on transparency and ethical compliance (KPMG 2024a; Litvinets & Pijselman 2024).

Table 3 Comparison of Traditional and AI-Driven Auditing

Aspect	Traditional Audit	AI-Driven Audit
Speed	Manual sampling and review; time intensive	Real-time or near-instant analysis of full datasets
Accuracy	Prone to human error and sample bias	High accuracy using anomaly detection across entire datasets
Transparency	Easily documented and explained	Often opaque (“black box”) unless XAI techniques are implemented
Oversight	Full human oversight and decision-making	Human oversight remains essential; Ai just assists
Scope	Limited to sampled transactions	Comprehensive, analyses entire data population
Fraud Detection	Based on predefined rules; reactive focused on known red flags	Predictive and adaptive, using ML and NLP to detect evolving and subtle fraud patterns

5.2 Reliability and Validity of the Research

The research was designed to ensure credibility through purposeful participant selection, thematic analysis and triangulation with recent literature. By interviewing experts from external, internal and IT auditing roles, the study offers a diverse and grounded understanding of AI implementation. The semi-structured format allowed for consistency across interviews while enabling personalized insights. However, certain limitations must be acknowledged. The small sample size, while appropriate for qualitative research, may limit generalizability. Moreover, findings are time-sensitive, as AI tools and standards evolve rapidly. Nevertheless, the strong alignment between empirical results and literature enhances both the reliability and relevance of the findings. The research remains highly applicable for understanding current and near-future trends in AI adoption within the auditing field.

5.3 Suggestion for Future Research

Future studies should explore how AI impacts audit quality and independence across different jurisdictions and regulatory environments. Comparative studies between countries or audit firm tiers (e.g., Big Four vs. mid-sized firms) could yield insights into the scalability and accessibility of AI tools. Furthermore, deeper exploration of AI in ESG audits, particularly in detecting greenwashing, represents an important area for further research. Quantitative studies measuring cost savings, error rates or audit quality post-AI adoption would complement these qualitative findings. In addition, longitudinal research could track how auditors' roles and skill requirements evolve with the increasing integration of AI.

5.4 Self-Assessment and Reflection on Learning

Throughout this thesis process, I gained a deep understanding of the intersection between technology and auditing. Initially, I approached AI as a tool primarily focused on efficiency, but through research and expert interviews, I realized that its role is far more transformative and strategic. I learned how ethical concerns; data governance and human oversight must evolve in parallel with technological advancement. Academically, this project strengthened my ability to critically engage with literature, synthesize diverse viewpoints and conduct structured qualitative research. Professionally, it sharpened my understanding of how digital tools are redefining financial roles and taught me the importance of adaptability in a rapidly evolving field. It emphasizes the importance of maintaining professional oversight alongside technological tools, a principle that remains vital in ethical auditing practices.

6 Conclusion

This thesis is set out to explore how AI is transforming the audit profession, particularly in the domains of risk assessment and fraud detection. The research shows that AI technologies are not only optimizing audit workflows but are also reshaping the role of the auditor. The expert interviews confirmed that AI enhances audit precision through real-time risk flagging and complete data population analysis, surpassing traditional sampling methods. One of the most significant implications of these findings is the shift from manual sampling to automated, data-driven audits. This change enhances transparency and responsiveness in auditing practices, particularly relevant in the growing field of ESG assurance. However, the findings also highlight the limitations of AI systems, such as their dependency on high-quality data, the risk of bias and the challenges posed by the lack of regulatory standards for AI integration in audits. For auditors, this transformation requires a dual focus: embracing AI tools while reinforcing human oversight. Skills in data governance, algorithmic interpretation and ethical analysis are becoming indispensable. For regulators, the findings point to the need for updated standards and oversight mechanisms that account for the use of AI in audit procedures. This study contributes to both academic and practical discussions on AI in auditing, demonstrating that while technology plays a central role, human expertise remains essential. By navigating the opportunities and challenges of AI adoption, the audit profession can evolve to meet the increasing complexity and accountability demands of modern financial environments.

6.1 Implications for Practice

For auditing professionals, this research emphasizes the need to invest in AI-related skills, including data analytics, model interpretation and ethical reasoning. Auditors must continue to apply skepticism and professional judgment when interpreting AI outputs, ensuring that automation enhances rather than overrides their role. Internal auditors may increasingly use AI to monitor ESG compliance and perform real-time risk assessments, while external auditors must ensure the transparency and auditability of AI-based procedures. For regulators, the findings support the development of frameworks that formally recognize AI-generated audit evidence, promote Explainable AI standards and set boundaries for ethical data use. Clearer guidance is needed to balance innovation with reliability and public trust.

6.2 Final Thoughts

Artificial Intelligence is not merely a technological trend; it’s a catalyst for reshaping the auditing profession. As auditors transition from procedural checkers to strategic advisors, AI becomes a powerful partner, but not a substitute, for professional skepticism, ethical reasoning and human judgment. The future of auditing lies not in choosing between human or machine but in mastering the synergy between them.

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Appendices

Appendix 1. Interview Questions

Interview Questions – Lídia Fonseca and Naoto Ichihara

1. How has AI transformed auditing in the past 5 years?
2. How has AI changed risk assessment and fraud detection in auditing compared to traditional methods?
3. What specific AI tools or technologies have you used (or considered using) for auditing? Can you provide any specific examples or metrics?
4. To what extent has AI improved accuracy in risk assessment and fraud detection? Reduction in false positives/negatives?
5. How AI influenced decision-making in your audit work? Do auditors rely on AI recommendations or is human oversight still essential?
6. What are the biggest challenges in using AI for risk assessment and fraud detection? examples lack of transparency, or over-reliance on automation?
7. Do you think AI can contribute to more sustainable auditing practices, such as enhancing ESG reporting and compliance monitoring?
8. How do you see AI evolving in auditing over the next 5 years? What opportunities, challenges and/or limitations for the future of risk assessment and fraud detection?
9. what advice would you give to firms looking to integrate AI into their auditing processes?
10. What skills do you think auditors will need to effectively work with AI-driven tools in the future?

Interview Questions – Arla Ketolainen

a. How has AI transformed internal auditing in your organization in the past 5 years?
b. Compared to traditional internal audit methods, how has AI changed how you approach risk assessment and fraud prevention?
c. Have you used or considered using any AI or digital tools in your internal audit work? Can you share examples or results?
d. To what extent has AI improved accuracy in risk assessment and fraud detection? Reduction in false positives/negatives?
e. How has AI influenced your decision-making in internal audit? Do you use AI insights directly or rely more on human judgment?
f. What are the biggest challenges in using AI for risk assessment and fraud detection? examples lack of transparency, or over-reliance on automation?

g. Do you think AI can support sustainable internal audit practices, like ESG compliance monitoring or better risk reporting?
h. How do you see AI evolving in internal auditing over the next 5 years, and what future opportunities or risks do you anticipate?
i. What advice would you give to internal audit teams preparing to adopt AI in their processes?
j. What new skills do internal auditors need to effectively work with AI-driven tools in the coming years?