



**INTEGRATING ARTIFICIAL INTELLIGENCE INTO MODERN ACCOUNTING
AND AUDITING: OPPORTUNITIES AND CHALLENGES**

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ABSTRACT:

The drastic development of digital technologies in a major way has changed the accounting area to move away from the conventional bookkeeping practices to intelligent, automated, and data, driven systems. The paper discusses how accounting and auditing incorporate AI, efficiency, accuracy, transparency, and strategic decision, making being some of the aspects affected by the change. The AI, driven tools make possible financial analysis in real, time, minimise manual errors, and facilitate regulatory compliance in continuously changing environments. The smart machines that perform routine work among the staff of accounting professionals free the latter for financial forecasting, interpreting analytical insights, and strategic planning, which in turn strengthen the quality, trust, and timeliness of business decisions.

The research also highlights the use of progressive technological devices in the form of machine learning, predictive analytics, and natural language processing becoming the major factors contributing to the improvement of financial reporting, fraud detection, auditing, and performance assessment. These tools give accountants and auditors the power to process, interpret and visualize bigger datasets in less time with higher accuracy. However, the introduction of these technologies has its drawbacks in the form of challenges related to data protection, ethical issues, implementation costs, and the requirement for continuous professional training to be able to manage and evaluate AI, driven systems properly. The overall results point to the fact that AI is not substituting the accounting and auditing staff but rather upgrading their skillsets, thus enabling them to transition into more analytical, advisory, and value, focused roles that are in line with the needs of modern businesses in the digital environment

Keywords: Artificial Intelligence, Auditing, Real-time Monitoring, Data Privacy, Digitalization

INTRODUCTION:

Artificial Intelligence (AI) is rapidly transforming the fields of auditing and accounting, reshaping how auditors and accountants collect, analyze, and interpret financial data. Traditionally, auditing relied heavily on manual sampling, human judgment, and retrospective evaluation of financial records. However, with the emergence of AI, these processes have become more efficient and insightful, allowing professionals to interpret vast amounts of financial data in a fraction of the time. AI enhances accuracy, minimizes the likelihood of human error, and enables deeper, data-driven analysis that supports better decision-making. As organizations increasingly demand greater accuracy and efficiency in financial management, AI technologies are being integrated into accounting systems at an accelerated pace. Tools

powered by machine learning, data analytics, and automation streamline financial operations and provide real-time insights. However, the implementation of AI also introduces several challenges, including concerns over data privacy, cybersecurity, algorithmic transparency, and ethical governance. Additionally, AI-enabled systems require significant investment and a workforce equipped with advanced technological skills to effectively operate and oversee these tools.

Nevertheless, the role of Artificial Intelligence in auditing and accounting continues to expand, driving a shift from traditional bookkeeping and manual processes toward intelligent, technology-driven systems. The true impact of AI will ultimately depend on how organizations balance technological innovation with human oversight, ethical responsibility, and sound governance.

REVIEW OF LITERATURE:

Anastassia Fedyk et al. (2022) concluded in their research that Artificial Intelligence (AI) enhances audit quality, lowers costs, and gradually replaces human accountants and auditors. The study supports these findings with statistical evidence, including a 5% decrease in the likelihood of audit restatements, a 0.9% decline in audit fees, and a noticeable reduction in the number of accounting personnel.

Feiqi Huang et al. (2022) highlights that the rapid evolution of technologies and business models, along with the growing population, has reduced the reliability of audit evidence obtained through audit sampling. They emphasize that several challenges must be addressed to achieve greater accuracy in full population testing.

Julia Kokina et al. (2025) states that AI adoption is still in its initial stages, as the basic tools are only being used and the advanced machine learning applications remain experimental. Major challenges faced are data privacy, transparency, AI bias, explainability along with the need of regular human guidance of the software. Solutions for problems are also being introduced such as LIME, SHAP and bias auditing etc.

Diogo Leocadio et al. (2024) established that integrating AI into auditing makes a fundamental transformation in accounting and management of finance. It highlights auditors must be skilled in data analysis and should be able to adapt the advanced upcoming technologies in accounting. There are also limitations such as potential publication bias, evolving technologies, etc.

Okeke Onyekachi Nath et al. (2025) attempted to find the solutions to the common challenges such as high implementation costs, limited technical expertise, ethical concerns and data privacy issues through proper training and strategic technological adoption. AI adoption leads to greater efficiency, quality and reliability. AI is a key driver of innovation and progress in the auditing profession.

OBJECTIVES:

- To assess the level of adoption and practical utilization of artificial intelligence technologies in modern accounting and auditing practices.
- To explore the opportunities and benefits arising from the integration of AI into financial and audit processes.
- To identify the key challenges, limitations, and barriers associated with the implementation of AI-driven systems.

RESULTS AND DISCUSSION:

Table 1: Demographic Profile of AI user Respondents

Personal Profile	Particulars	Frequency	Percentage (%)
Age Group	25–35 years	24	24.39
	35–45 years	18	17.89
	45–55 years	29	29.27
	55 years and above	28	28.46
Gender	Male	54	54.47
	Female	46	45.53
Education	Bachelor's Degree	23	22.76
	Master's Degree	19	18.70
	Doctorate (Ph.D.)	20	20.33
	Professional Certification (CPA/ACCA/CA/CMA)	24	23.58
	Other	15	14.63
Occupation	Auditor	18	17.89
	Financial Analyst	18	17.89
	Accounting Professional	19	18.70
	Academic / Researcher	14	13.82
	Student	12	12.20
	Other	20	19.51
Experience	Less than 2 years	15	14.63
	2–5 years	27	26.83
	6–10 years	30	30.08
	More than 10 years	28	28.46

Source: Computed Data

Table 1 depicts that the majority of AI users are male respondents (54.47%) between the age group of 45 - 55 years (29.27%). Among the respondents most of them use AI with a majority of professionals(23.58%) who have an experience of 6- 10 years (30.08%).

Table 2: Association between respondents' Education and Familiarity with AI

Education Level	Extremely Familiar	Moderately Familiar	Not Familiar	Slightly Familiar	Very Familiar	Total	χ^2	Sig.
Bachelor's Degree	8 (28.57%)	6 (21.42%)	0	4 (14.29%)	10 (35.72)	28 (100%)	16.45	0.012
Master's Degree	4 (17.39%)	6 (26.08%)	1 (4.34%)	1 (4.34%)	11 (47.85%)	23 (100%)		
Doctorate (Ph.D.)	9 (36%)	5 (20%)	0	3 (12%)	8 (32%)	25 (100%)		
Other	1 (5.55%)	6 (33.34%)	1 (5.55%)	3 (16.67%)	7 (38.89%)	18 (100%)		
Professional Certification	9 (31.03%)	7 (24.14%)	0	1 (3.45%)	12 (41.38%)	29 (100%)		
Total	29 (23.58%)	34 (27.64%)	2 (1.63%)	10 (8.13%)	48 (39.02%)	123 (100%)		

Source: Computed data

The chi-square analysis shows that the p-value (0.012) is less than 0.05, indicating a significant association between the education level of respondents and their familiarity with AI tools. Thus, the null hypothesis is rejected. This implies that individuals with higher education levels are more aware and familiar with AI applications in accounting.

Table 3 KMO Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.856
Bartlett's Test of Sphericity	Approx. Chi-Square	932.412
	Df	210
	Sig.	0.000

Source: Computed data

Table 3 shows that the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was found to be 0.856, which is greater than the value of 0.80. The Bartlett's Test of Sphericity yielded an approximate chi-square value of 932.412 with 210 degrees of freedom and a significance

level of 0.000. Since the p-value is less than 0.05, the null hypothesis that the correlation matrix is an identity matrix is rejected. Therefore, the results validate the reliability of the data and justify proceeding with dimensional reduction techniques to identify the key influencing factors of AI adoption in accounting and auditing practices

Table 4 :Factor table

Factors	Components	Item Description	Rotated Loading	% of Variance	Eigen Value
I	PerformanceFactor	Automation increases efficiency.	0.857	25.047	1.503
		Tasks are completed faster.	0.731		
		Reporting is more accurate.	0.362		
		Productivity has improved.	0.229		
II	Reliability Factor	Errors are minimized.	0.791	24.116	1.447
		Data is more reliable.	0.789		
		Frauds are detected quickly.	0.299		
		Reports are more dependable.	0.278		
III	Judgement Factor	Judgment is reduced.	0.901	19.148	1.149
		Reliance on tech has increased.	0.491		
		Critical thinking has declined.	0.224		
		Decisions depend on systems.	0.21		

Source: Calculated Data

Extraction Method

From Table 4 The factor analysis result indicates that twelve variables were condensed into three major factors explaining the adoption of AI in accounting and auditing. The Performance Factor contributes 25.047% of the total variance, emphasizing AI's role in improving efficiency and accuracy. The Reliability Factor accounts for 24.116%, highlighting error

reduction and dependable data. The Judgement Factor explains 19.148%, showing how reliance on technology influences professional judgment.

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