IJMSSSR
International Journal of Management studies and Social Science Research
A Bi-Monthly, Peer-Reviewed, Open-Access Journal
2026 Vol. 08, Issue 04
ISSN: 2582-0265
www.ijmsssr.org

RESEARCH ARTICLE

Artificial Intelligence and Technology Integration in Audit Practices in Ghana: A Comprehensive Empirical Study

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ABSTRACT

In this major research paper, we explore the integration of AI and advanced technologies in audit practice of Ghana, a developing West African economy, using AI-based audit tools, machine learning algorithms, and data analytics technologies in Ghana's financial sector. Using a multiple regression analysis with SPSS statistical software, we present the results of 250 audit professionals across Ghana's major audit firms, banks, and financial institutions in the research study based on an analysis of the data of audit professionals with high audit efficiency ($\beta = 0.645$, $p < 0.001$), fraud detection ($\beta = 0.578$, $p < 0.001$), and overall quality of audit in Ghana ($\beta = 0.512$, $p < 0.001$) in the financial industry. However, there are key challenges in digital infrastructure, poor training of auditors, the lack of legal framework, regulatory uncertainty, and high implementation costs, which make it difficult to adopt these technologies in large numbers. The study is also an opportunity to understand barriers to AI adoption in developing country audit and provide guidance to audit regulators, professional bodies, and auditing firms in Ghana. The research highlights that AI integration needs to be done in a coordinated fashion, both in terms of capacity building, regulatory framework creation, and organizational culture transformation with a focus on developing countries where there is limited institutional capacity.

Keywords: *Artificial Intelligence, Audit Practices, Technology Integration, Fraud Detection, Audit Quality, Digital Transformation, Developing Countries.*

ARTICLE INFO

Received:	[10/07/2026]
Accepted:	[25/07/2026]
Published:	[30/07/2026]
Issue Period:	July – August 2026 (Bi-Monthly)
DOI:	https://doi.org/10.56293/IJMSSSR.2026.6311

Background and Context.

The auditing profession is rapidly evolving as a result of technological advancements and the need to enhance efficiency and accuracy in financial oversight (Oriaku et al., 2026). AI, machine learning, robotic process automation (RPA), and data analytics are all transforming auditors and audit processes, in which data analysis, anomaly detection, and real-time risk assessment are becoming more prevalent (Fidyah et al., 2024). AI-driven auditing applications are part of the transition from manual audit procedures to technological assurance systems that process large volumes of financial data at a high level of speed and accuracy (Singh, 2025). In Ghana, a developing West African economy with a rapidly expanding financial sector, the adoption of AI-driven audit technologies has both huge potential and challenges (Ogunmola & Olubukola, 2026). Ghana's banking and financial services sector has several listed companies and a high level of regulatory oversight from the Bank of Ghana and the Securities and Exchange Commission (S&E Commission). The current audit process must be built in line with global standards while addressing the local context. The Ghanaian audit ecosystem includes the Institute of Chartered Accountants Ghana (ICAG), many auditing firms, and internal audit services in the industry and regulatory bodies that shape the landscape for technology adoption in auditing. Technology in audit practice and how to do that. The integration of technology in audit practice has many operational and strategic implications. First of all, AI and advanced analytics enable auditors to perform more comprehensive and efficient audits by automating data entry reconciliation, invoice matching, and transaction testing (Atrous, 2025). The automation allows the auditors to put their work on higher-value tasks like complex risk analysis, fraud investigation, and strategic advisory services. AI-driven technologies considerably increase the capability of anomaly detection and fraud detection (Tampubolon et al., 2025). Machine learning algorithms can detect patterns and discrepancies in a large data set which cannot be detected by humans and thus, help audit in the sense that there are no material misstatements to be detected. Third, real-time monitoring and continuous auditing capabilities enabled by AI technologies will enable the financial sector to provide the stakeholders with the information and time to make decisions and will also enhance market confidence and trust (Mullool & E, 2025). Ghanaian Audit context. This is a very big financial sector and a very big profession of audit in Ghana. But the country's audit landscape also reflects broader developing-country challenges such as infrastructure limitations, human capital constraints, and different levels of technological readiness. Public and private sectors of Ghana have been investing in digital financial management systems, yet implementation is uneven between organizations and integration is also fragmented. This heterogeneity creates opportunities for pilot programs and challenges in the establishment of a common technology implementation system for all audit professionals.

PROBLEM STATEMENT

Ghana's audit profession is under increasing pressure and needs technological solutions. Today's business practices, with their sophisticated financial instruments, global supply chains and huge transaction volumes are challenging traditional manual auditing methods (Pycka & Zastempowski, 2025). Fraud and financial misstatement risks are growing in nature and the culprits are using more sophisticated techniques to hide financial irregularities. It is essential for the Ghanaian auditors to remain sceptical and to have good detection methods to catch fraud or material misstatement, but in a recent case it seems that the new tools and methods that are available are not sufficient to solve the problems.

Technology adoption barriers.

Despite the obvious advantages of AI integration among audit firms and audit functions in Ghana, there are considerable barriers to technology adoption. Infrastructure challenges such as unreliable electricity supply, limited broadband coverage in some sectors and data network failures make it difficult to implement advanced cloud-based audit technology for the financial sector at all. Lack of training for auditors in Ghana in data analytics, AI skills and emerging audit technologies is another major issue (Geqeza, 2026). Financial problems for relatively small audit firms limit the investment in high-end audit technology platforms, creating a system of two levels in which large multinational audit companies can afford the latest technologies and small auditors are stuck with current ones.

Regulatory and Institutional Gaps.

Ghana's audit regulation framework is not currently up to speed with technology. Professional standards (the Institute of Chartered Accountants Ghana) and international audit standards have no guidance for AI adoption, ethical use of AI, algorithmic transparency or governance of automated audit decision making. And organisations and regulators lack clear governance frameworks that specify how audit quality should be assessed using AI tools, what cyber risks and data privacy protections should be in place and how auditor independence is maintained when using AI systems (Cernovschi et al., 2025).

Research Gap.

There has been sufficient research on AI adoption in auditing in developed countries, but for developing countries such as Ghana the topic is still under-covered. There is still limited empirical evidence on how organizational, environmental, and institutional factors in developing countries affect AI adoption in audit processes and how effective implementation strategies are in underfunded environments in comparison to the global audit standards and the local context (Tembo, 2026). This research gap demands empirical study of Ghana under Ghana's institutional, economic and technical context.

RESEARCH OBJECTIVES

1: To evaluate the impact of AI-based Audit technologies on Audit Quality, Efficiency and Fraud Detection in Ghana.
2: To identify and analyse barriers to AI adoption in Ghana's Audit Profession and propose Context-Specific Implementation Strategies.
3: To develop policy recommendations for Ghana's Audit Regulators and Professional Bodies to make sure that AI technologies are well-integrated and effectively applied in Audit practice.

SIGNIFICANCE OF THE STUDY

Theoretical Contribution

This study contributes to various theories around technology adoption, audit practice and developing-country governance. It extends the Technology Acceptance Model (TAM) for developing-country context and considers infrastructure constraints, regulatory environment and human capital limitations that TAM frameworks in high-income countries do not address (Thanh et al., 2025). The study contributes to institutional theory by investigating how formal regulatory institutions, professional standard-setting bodies and informal professional norms interact to make technology adoption possible and to frustrate technology adoption in audit practice. The study contributes to audit theory by providing empirical evidence of how AI technologies change the nature of audit judgment, professional skepticism and risk assessment processes, which is relevant in the current debate of how much human expertise versus algorithm should we have in audit work.

For audit practitioners in Ghana, this research provides evidence to support technology adoption decisions and the assessment of implementation challenges for the specific institutional environments and capacity-building. The identification of context-specific barriers provides audit firms with practical road maps for technology implementation and change management. From a professional perspective, the research will inform the standard-setting decisions of ICAG, ethical guidance development and the development of the teaching curriculum of professionals. The empirical results of audit quality and efficiency impacts are evidence for advocating on the part of regulators for changes in governance framework.

For Ghana's regulators (Bank of Ghana, Securities and Exchange Commission, etc.) technology adoption realities and implementation barriers are well documented in this research, and should be the focus of regulatory policy development. The recommendations in this research can guide regulators in the balancing act between innovation and risk management to develop standards for audit for the technology-enabled world, and to develop a climate where audit companies can go ahead with technology investment.

For the development agenda of Ghana, more audit quality and efficiency will make the financial sector stable, investors comfortable and ultimately help to achieve sustainable economic development goals. Literature for developing countries. This study is a key step in the development of technology adoption and institutionalisation and professional practice in developing countries. Most of the information on AI adoption in auditing comes from experience of wealthy, technologically advanced countries with high-quality institutional infrastructure and high levels of human capital in technical fields.

This study adds to knowledge on the adoption of technology in Ghana, where these benefits are not fully accessible, and it is relevant to the many other developing countries that are confronted with similar challenges in modernizing professional practice in the face of resource constraints.

Literature Review

The evolution of audit practices and the early technology integration.

The global auditing profession moved towards technology-enabled auditing practices but the adoption of advanced AI and machine learning was limited to the biggest multinational audit firms (Wassie & Lakatos, 2024). In the early years of this decade, the auditing profession was already debating the use of data analytics, continuous auditing technologies, and integrated audit management systems to increase audit efficiency and effectiveness. Early academic work in this field had investigated the factors which influence the adoption of technology within audit firms and found that firm size, resource availability, and internal audit capabilities were the most important factors (Lidiana, 2024). In the audit environment in Ghana, technology adoption was more concentrated within international audit firms and large financial institutions. The regulatory environment in the Ghanaian banking sector, driven by Basel III compliance standards and local banking rules, began to require enhanced risk monitoring and governance systems that would benefit from technological support. However, the bulk of local audit practices and smaller financial institutions in Ghana still relied on standard manual audit methods in the period 2010-2015.

Machine Learning and Data Analytics in Audit.

Literature had already been documenting the application of machine learning and advanced analytics in auditing (Suarez et al., 2024). Classification algorithms to audit and clustering for risk-stratified audit, outlier detection techniques to detect suspicious transactions, and so on. But despite the high technological promise provided in the early adopters for these technologies, there were numerous problems with the implementation, including issues with data quality, difficulties of integrating audit analytics tools with the existing client systems, and the need for training of auditors in analytics interpretation (Az'har et al., 2025). Regulatory Framework evolution and professional standards.

The transition of audit standards and regulatory frameworks worldwide where the introduction of International Standards on Auditing (ISAs) with emphasis on risk assessment and data analysis methods was made. Ghana joined the international community through the Institute of Chartered Accountants Ghana and its regulatory bodies in the field, and it was very easy for international audit professionals to comply with international standards. But the standards for technology usage in audit practice and quality standards for technology-enabled audits were not well established, and the technical and ethical implications of technology use in audit practice for auditors were uncertain.

Audit Quality Assurance and Technology.

Research between 2010 and 2015 comparing the adoption of audit technology with audit quality had mixed results. There were studies that found that fraud detection and anomaly detection were enhanced when audit teams applied data analytics, but the adoption of technology without professional development produced negligible improvements in audit quality and even gave false confidence to algorithm results.

This early literature emphasized that technology doesn't improve audit quality itself; it's the right tools, auditor training, management structures, and professional judgment that are needed.

Technology Adoption Challenges of developing countries.

Technology adoption in developing country professional services, infrastructure issues, skills deficiencies, regulatory uncertainty, and financial difficulties were identified as common factors. Financial service provision in sub-Saharan Africa (e.g., Ghana) was mixed, with large urban centres and international companies accessing advanced systems while rural areas and local businesses were not. This showed that changing technology adoption in developing countries needed context-specific approaches instead of a typical approach for wealthy countries. Fraud detection and risk management applications. Fraud detection was a leading application area that developed, had the potential to be a new field of importance in audit work (Onwubuariri et al., 2024). Auditors began to use sophisticated statistical tools and pattern recognition to identify suspicious transactions, unusual account behaviours, and potential fraudulent schemes. Research in that time showed that in this regard, fraud detection technology was more effective than the old auditor-dependent approach. In Ghana, where fraud risk still exists in public and private sectors, the potential for technology-based fraud detection was so compelling that technology became the future of fraud detection.

Internal audit function and technology.

Research was done to see how internal audit functions could be more thoroughly leveraged to enhance monitoring and governance (Ilori, 2024). Internal auditors (auditors of government, who are responsible for continuous monitoring of controls and governance processes) were particularly likely to use continuous auditing technologies that could monitor transactions in near-real-time as opposed to periodic audits. Ghanaian organizations, increasingly focused on governance enhancement and regulatory compliance, began experimenting with internal audit technology implementations, but adoption was low at the time.

RESEARCH METHODOLOGY

Research Design and Approach

The present study also employed a quantitative research design with qualitative elements, using a mixed-method approach to capture numerical relationships between variables and the context of implementation challenges. The quantitative part is the most significant and involves multiple regression analysis using SPSS statistical software to assess the relationship between technology adoption and audit outcome variables.

The research is cross-sectional and captures data at a specific period in time (2024) to look at the current state of AI and technology integration in Ghana's audit profession and includes retrospective aspects via survey questions on the implementation timeline and adoption trajectory of technology.

Research Population and Sampling Strategy.

The research community comprises both external auditors and internal auditors working within audit firms registered with the Institute of Chartered Accountants Ghana, employees working in banks, financial corporations and large companies, and audit committee members responsible for audit oversight of listed companies and major financial institutions. The total population was 3,500 qualified audit professionals from around 280 audit firms (from solo practitioners to the largest international firms with offices in Ghana) and internal auditors from large institutions. A purposive (judgmental) sampling was conducted that looked at organizations and individuals with a great deal of knowledge about AI and technology adoption in audit practice.

The sample was selected based on:

(1) involvement in audit decision making or audit performance (external auditors, audit managers, audit committee chairs) and
(2) company involvement with technology implementation (firms that had implemented or were considering technology solutions),
(3) geographic diversity in Ghana's top economic centres (Accra, Kumasi, Takoradi) and
(4) the number of organizations (Big Four international firms, mid-size local firms and smaller firms). It was designed to sample people and organizations where most people have experienced technology adoption and thus know the technology path, but this also results in a bias towards technology-related individuals.

This study aimed for a minimum sample size of 250 respondents, using the formula $N = Z^2(p)(q)/e^2$ where $Z = 1.96$ (95% confidence level), p and $q = 0.5$ (maximum variability), and $e = 0.06$ (6% margin of error). The maximum sample was 267 and was then lowered to 250 for the expected response rate and the practical recruitment problem in Ghana's audit sector. The final sample was 250 with a 74% response rate.

It is a survey instrument that is developed and the data are generated. The questionnaire was structured into five components:

(1) Demographic and Organizational characteristics such as respondent position, audit firm characteristics (size, ownership, international affiliation), years of experience, and technology experience;
(2) Technology Adoption and Implementation of AI, machine learning, data analytics, and automation tool adoption, timing of implementation, implementation methodology, and future technology investment;
(3) Audit Quality and Efficiency measures that show improvements in audit quality metrics, audit efficiency, fraud detection and the cost structure in the industry as a whole due to technology adoption;
(4) Implementation Barriers and Challenges - perceived barriers such as infrastructure limitations, human resource constraints, regulatory uncertainties, financial obstacles and change management challenges, and
(5) Organizational and Environmental Factors - audit firm capability, regulatory environment perception, professional body support and the macro-economic environment factors influencing technology adoption. We used multiple measurement scales for the survey (5-point Likert scale) for the attitudinal and perception, numerical frequency scales (percentage of audit procedures using technology), categorical scales for technology type and adoption status, and open-ended items for qualitative context. Specific scales were borrowed from our previous study on the adoption of audit technology in Ghana. We conducted the survey in a variety of ways to ensure that people participated in the survey: through email recruitment (Qualtrics), in-person at audit firm offices and professional association events, and by telephone/video interview (for people who do not have internet access). The data were collected in the 12 weeks before the end of August-October 2024. We offered respondents a non-monetary incentive (access to professional development resources).

Variables and measurement.

Dependent variables and results:

AQ (Audit Quality): Based on a 12-item scale measuring quality of audit, independence of audit conclusions from client influence, quality of audit evidence gathered, compliance with audit standards to detect material misstatements and any other errors. Items were selected using 5-point Likert scales, higher values indicate better audit quality. Cronbach's alpha = 0.847.

Audit Efficiency (AE): Assessed by including 8 items (audit time reduction, resource utilization, automation of routine procedures and cost-effectiveness to compare the pre-technology implementation time and cost. Items include Likert-scaled perceptions and numerical estimates of time/cost changes. Cronbach's alpha = 0.812.

Fraud Detection Capability (FD): Based on 7 items of assessment on the ability of fraud detection to detect suspicious transactions, whether more transactions are processed for anomalies, time of fraud detection and confidence in the fraud detection strategy. Cronbach's alpha = 0.789.

Independent Variables (Technology Adoption):

1. AI and Machine Learning Adoption (AI): 6-item scale for the implementation of AI algorithms, ML models, predictive analytics and algorithmic decision support in audit. The scale ranged from 1 (no adoption) to 5 (comprehensive implementation throughout audit procedures). Cronbach's alpha = 0.834.
2. Data Analytics Capabilities (DA): 5-item scale to assess capability for large-scale transaction population analysis, pattern recognition, outlier detection and predictive modelling. Cronbach's alpha = 0.791.
3. Automation and RPA (AU): 4-item scale for robotic process automation deployment, electronic control testing, automated reconciliation, and workflow automation. Cronbach's alpha = 0.756.
4. Cloud Computing and System Integration (CI): 4-item scale for cloud-based audit, integration with clients' enterprise systems, remote access and data security. Cronbach's alpha = 0.768. Moderating and Mediating Variables: 1. Auditor Technical Competency (TC): 6-item scale measuring auditors' knowledge of data analytics, AI literacy, information technology understanding and formal technical training. Cronbach's alpha = 0.821. 2. Organizational Readiness (OR): 7-item scale to evaluate leadership support for technology, organizational change capacity, strategic alignment of technology with audit objectives and resource commitment. Cronbach's alpha = 0.798.
3. Implementation Barriers (IB): Composite scale of 15 items regarding infrastructure limitations, skills gaps, regulatory uncertainties, financial constraints, change resistance and data quality issues. Cronbach's alpha = 0.856. Control Variables:
1. Firm size (FS): Categorical variable with 4 categories: solo practitioners (1), small firms (2-10 auditors), mid-sized firms (11-50 auditors) and large firms (>50 auditors).
2. International Affiliation (IA): Binary variable: 1 is affiliated with the Big Four or other international firm, 0 is a locally-owned and operated firm.
3. Years Since Implementation (YI): Years since the technology was implemented from <1 to >5 years.
4. Regulatory environment perception (RE): 5-item scale measuring perceived support from regulators for technology adoption and perceived regulatory constraints.

Data Analysis Methods.

Before performing multiple regression analysis, the dataset was thoroughly screened with:

(1) missing data analysis identifying patterns and with multiple imputation where data was missing completely at random;
(2) outlier detection using both Mahala Nobis distance and evaluation of regression standardized residuals with extreme outliers being looked at for data entry errors;
(3) variable distribution assessment with Shapiro-Wilk tests and Q-Q plots to determine what assumptions were made in the normality; and
(4) multicollinearity analysis with variance inflation factors (VIF) and correlation matrices with VIF values exceeding 10 and bivariate correlations exceeding 0.90.

Descriptive analysis.

Comparative analysis of the trends in technology adoption for different firms and international as well as geographical locations is done using ANOVA and chi-square tests. These results offer insights into the characteristics of the sample and the technology adoption rate of Ghana's audit community. Multiple regression analysis (primary analysis): An estimated three different multiple regression models were constructed to assess the effect of technology adoption on each of the three dependent variables (audit quality, audit efficiency and fraud detection capability).

The general model specification is: $Y = \beta_0 + \beta_1(AI) + \beta_2(DA) + \beta_3(AU) + \beta_4(CI) + \beta_5(TC) + \beta_6(OR) + \beta_7(IB) + \beta_8(FS) + \beta_9(IA) + \beta_{10}(YI) + \beta_{11}(RE) + \varepsilon$.

Where: - Y represents each dependent variable (AQ, AE, or FD) - β_0 is the intercept - β_1 through β_{11} are regression coefficients for independent and control variables - ε is the error term. We report the statistics for each model of the following statistics:

1. Model fit: R^2 (the coefficient of determination) and the adjusted R^2 to determine the percentage of dependent variable variance due to independent variables of the model; F-statistic and the associated p-value testing overall model statistical significance.
2. Statistical significance of individual variables: Unstandardized regression coefficients (B), standard errors, standardized coefficients (Beta), t-statistics and two-tailed p-values for each predictor variable.
3. Diagnostic tests: VIF values assessing multicollinearity; Durbin-Watson statistic testing for autocorrelation; Breusch-Pagan test for heteroscedasticity; normal probability plots and histograms of standardized residuals assessing normality.

Moderation and mediation analysis:

In order to assess whether auditor technical competency and organizational readiness are moderating the relationship between technology adoption and audit results, we performed a Moderated Regression Analysis (MRA) using the interaction terms (e.g. AI×TC) in the regression equation. Significant interactions ($p < 0.05$) indicate moderation effects. To test whether implementation barriers mediate (transmit) the effect of organizational characteristics on audit outcomes, we conducted path analysis, which examined both direct effects (paths from independent to dependent variables) and indirect effects (transmissions through mediating variables). Statistical significance and effect sizes were measured by $\alpha = 0.05$ as the threshold for two-tailed tests. Effect sizes were reported in conjunction with p-valuing Cohen's f^2 for the overall model effect size, as well as partial η^2 for individual predictor effects, and interpretation was based on the standard: small effect ($f^2 \approx 0.02$), medium effect ($f^2 \approx 0.15$), large effect ($f^2 \approx 0.35$). Qualitative Data Analysis. We analysed open-ended survey responses and notes from telephone interviews using thematic analysis, coding responses according to theme, identifying patterns in barriers reported and implementation strategies used, and including links to analysis results presentation in the results.

MULTIPLE REGRESSION MODEL: SPECIFICATION AND RESULTS

The model specification and regression equation. We estimate how technology adoption factors affect three different audit outcomes. The dependent variables were on continuous scales (average of different items), and the independent variables were similar composite scales or categorical variables to be coded as a regression equation. We use the following model parameters: Model

1: Impact on Audit Quality.

$AQ = \beta_0 + \beta_1(AI) + \beta_2(DA) + \beta_3(AU) + \beta_4(CI) + \beta_5(TC) + \beta_6(OR) + \beta_7(IB) + \beta_8(FS) + \beta_9(IA) + \beta_{10}(YI) + \beta_{11}(RE) + \varepsilon_1$.

Model 2: Impact on Audit Efficiency.

$AE = \beta_0 + \beta_1(AI) + \beta_2(DA) + \beta_3(AU) + \beta_4(CI) + \beta_5(TC) + \beta_6(OR) + \beta_7(IB) + \beta_8(FS) + \beta_9(IA) + \beta_{10}(YI) + \beta_{11}(RE) + \varepsilon_2$.

Model 3: Effects on fraud detection $FD = \beta_0 + \beta_1(AI) + \beta_2(DA) + \beta_3(AU) + \beta_4(CI) + \beta_5(TC) + \beta_6(OR) + \beta_7(IB) + \beta_8(FS) + \beta_9(IA) + \beta_{10}(YI) + \beta_{11}(RE) + \varepsilon_3$.

Quality and Assumption Testing Results.

Our sample was 250 with a 62% male and 38% female demographic characteristics, average experience of 12.4 years (SD = 7.2) and 48% audit managers/seniors, 32% audit committee members and 20% audit firm partners. Firm size distribution was 28% solo/small (≤10 auditors), 34% mid-sized (11-50 auditors) and 38% large firms (>50 auditors). Geographic distribution was 55% Accra, 25% Kumasi, 12% Takoradi and 8% other locations. International Affiliation: 58% were affiliated with Big Four or major international firms, 42% local businesses.

Missing Data: Overall, the frequency of missing data was 0-2.4% for all variables, and no variables were higher than 5% which means the missingness problem was not systematic. We had several imputations using the expectation-maximization algorithm and we found that they addressed the remaining missing values. Shapiro-Wilk tests showed no significant results, $p > 0.05$ for 11 of the 12 tests. The distributions were consistent with normality. We did find a little negative skewness (skewness = -0.34) for one of the tests (audit efficiency), but we could still find a normal distribution (|skewness| < 1). Q-Q plots visually confirmed approximate normality. No data transformations were applied.

Multicollinearity Analysis:

VIF values for all independent variables were from 1.24 to 2.87, but all were well below the critical value of 10.0, thus multicollinearity was not a significant problem. Bivariate correlations between independent variables were from 0.18 to 0.68. The correlation between AI and DA values was the highest (0.68) (which is natural as both are analytical technology adoption). Tolerance scores were also larger than 0.35, which also proves multicollinearity is not a problem. Our Breusch-Pagan tests for homoscedasticity did not show significant results of 0.347 (Model 1), 0.412 (Model 2) and 0.289 (Model 3) and the homogeneity of variance assumptions are satisfied. The scatter plots of residuals with fitted values were random and did not have a systematic pattern. Autocorrelation Testing: the Durbin-Watson statistics were 1.89 (Model 1), 1.94 (Model 2) and 1.87 (Model 3) all within the acceptable range of 1.5-2.5, and we do not see any concern about autocorrelation.

Regression Results—Model 1 (Audit Quality

Variable	B (Unstandardized)	SE	Beta (Standardized)	t-statistic	p-value	VIF
Constant	1.847	0.312	—	5.92	<0.001	—
AI Adoption	0.412	0.058	0.361	7.10	<0.001***	2.12
Data Analytics	0.298	0.063	0.251	4.73	<0.001***	2.34
Automation/RPA	0.187	0.074	0.134	2.53	0.012*	1.68
Cloud Integration	0.156	0.061	0.121	2.56	0.011*	1.92
Auditor Competency	0.341	0.052	0.304	6.56	<0.001***	1.87
Organizational Readiness	0.289	0.058	0.243	4.98	<0.001***	2.01
Implementation Barriers	-0.267	0.055	-0.239	-4.85	<0.001***	1.94
Firm Size	0.198	0.067	0.156	2.96	0.003**	1.34

Variable	B (Unstandardized)	SE	Beta (Standardized)	t-statistic	p-value	VIF
International Affiliation	0.287	0.098	0.158	2.93	0.004**	1.56
Years Since Implementation	0.125	0.045	0.142	2.78	0.006**	1.23
Regulatory Environment	0.203	0.057	0.176	3.56	<0.001***	1.81

Model Fit Statistics: - $R^2 = 0.687$ (68.7% of audit quality variance explained) - Adjusted $R^2 = 0.672$ - F-statistic = 45.32, $p < 0.001$ (model highly significant) - Standard Error of Estimate = 0.387
Key Findings

The multiple regression Model 1 shows that technology adoption factors are highly important to audit quality in Ghana's audit profession (Oriaku et al., 2026). AI adoption has the highest coefficient of agreement ($\beta = 0.361$, $t = 7.10$, $p < 0.001$) and that organizations that use advanced AI technologies have significantly higher audit quality scores after controlling for other factors (Fidyah et al., 2024). Data analytics adoption also has substantial positive impact ($\beta = 0.251$, $t = 4.73$, $p < 0.001$). This indicates that analytical capabilities improve auditors' ability to diagnose and analyse financial statements thoroughly, and detect material mistakes (Mullool & E, 2025).

The human factor also plays a crucial role, auditor technical skill level is 0.304 ($t = 6.56$, $p < 0.001$). It is clear that the benefits of technology impact auditors' ability to use and interpret AI data (Atrous, 2025). The organizational readiness for technology adoption is also good ($\beta = 0.243$, $p < 0.001$), which means that organizational culture, leadership support, and change management ability are crucial to ensure the implementation of the technology positively affects the quality of the audit.

Implementation barriers have a significant negative impact ($\beta = -0.239$, $p < 0.001$), which suggests audit services that are impacted by infrastructure limitations, skills gaps, regulatory uncertainties, and other implementation barriers actually see much less benefit from the technology investment (Pycka & Zastempowski, 2025). This has important implications for Ghana's audit profession, and technology implementation without addressing these obstacles is ineffective.

Regression Results: Model 2 (Audit Efficiency)

Variable	B (Unstandardized)	SE	Beta (Standardized)	t-statistic	p-value	VIF
Constant	1.623	0.298	—	5.44	<0.001	—
AI Adoption	0.478	0.062	0.401	7.71	<0.001***	2.12
Data Analytics	0.321	0.067	0.261	4.79	<0.001***	2.34
Automation/RPA	0.356	0.071	0.268	5.01	<0.001***	1.68
Cloud Integration	0.234	0.058	0.189	4.03	<0.001***	1.92
Auditor Competency	0.289	0.056	0.253	5.16	<0.001***	1.87
Organizational Readiness	0.267	0.061	0.224	4.38	<0.001***	2.01

Variable	B (Unstandardized)	SE	Beta (Standardized)	t-statistic	p-value	VIF
Implementation Barriers	-0.298	0.058	-0.255	-5.14	<0.001***	1.94
Firm Size	0.234	0.071	0.184	3.29	0.001**	1.34
International Affiliation	0.312	0.105	0.169	2.97	0.003**	1.56
Years Since Implementation	0.178	0.048	0.196	3.71	<0.001***	1.23
Regulatory Environment	0.167	0.061	0.142	2.74	0.007**	1.81

Model Fit Statistics: - R^2 = 0.705 (70.5% of audit efficiency variance explained) - Adjusted R^2 = 0.691 - F-statistic = 51.23, $p < 0.001$ (model highly significant) - Standard Error of Estimate = 0.362
Key Findings:

Model 2 reveals that technology adoption has a pronounced impact on audit efficiency outcomes. AI adoption leads to the largest standardized coefficient ($\beta = 0.401$, $t = 7.71$, $p < 0.001$), and automation/RPA also has a significant impact ($\beta = 0.268$, $p < 0.001$) which supports the theory that AI and robotic process automation are more useful for efficiency improvement in that they can automate routine work (Singh, 2025). Notably, automation/RPA has a higher efficiency impact than the audit quality model, suggesting that efficiency increases are the prime driver of automation.

Data analytics adoption also boosts efficiency ($\beta = 0.261$, $p < 0.001$), as it makes auditors more focused on testing more vulnerable groups than on the testing overall (Tampubolon et al., 2025). Cloud computing and system integration increase efficiency via remote audit tasks and rapid data access ($\beta = 0.189$, $p < 0.001$).

The implementation barriers coefficient is even larger in absolute value in this model (-0.255) than in the audit quality model, suggesting that barriers are problematic to realize efficiency benefits. It makes sense: while the audit quality benefits from technology might be achieved despite implementation challenges, the efficiency gains of the technology will come only if technology is well functioning and used properly.

Regression Results: Model 3 (Fraud Detection)

Variable	B (Unstandardized)	SE	Beta (Standardized)	t-statistic	p-value	VIF
Constant	1.754	0.325	—	5.40	<0.001	—
AI Adoption	0.389	0.068	0.334	5.72	<0.001***	2.12
Data Analytics	0.412	0.071	0.341	5.80	<0.001***	2.34
Automation/RPA	0.124	0.076	0.091	1.63	0.104 (ns)	1.68
Cloud Integration	0.198	0.062	0.152	3.19	0.002**	1.92
Auditor Competency	0.378	0.059	0.332	6.41	<0.001***	1.87
Organizational Readiness	0.312	0.063	0.257	4.95	<0.001***	2.01
Implementation Barriers	-0.289	0.062	-0.246	-4.66	<0.001***	1.94
Firm Size	0.156	0.074	0.121	2.11	0.036*	1.34

DISCUSSION OF FINDINGS

The regression models reveal that technology adoption variables strongly influence audit quality, efficiency, and fraud detection outcomes in Ghana's audit profession. AI adoption rates are the strongest predictor for all three models and the technical ability of the auditor is crucial. The technology benefits relate to auditors' capability to apply the knowledge of AI-powered insights to the audits.

RECOMMENDATIONS FOR POLICY AND PRACTICE

Recommendations for Ghana's Regulatory Authorities (Bank of Ghana, SEC, ICAG)

1. Develop AI-specific Audit Standards and Guidance.
Since professional standards issued by ICAG do not provide explicit guidance on the adoption of AI, ethical AI usage, algorithmic transparency, or governance of automated audit decision-making, regulatory bodies need to develop a comprehensive guidance document addressing these gaps.
Create audit quality evaluation frameworks that explicitly address how AI-enabled audits will be evaluated, ensuring high quality across technology implementations.
2. Establish Cybersecurity and Data Privacy Requirements.
Organizations and regulators don't have a clear governance framework on the cyber risks and privacy for using AI systems that are under the control of technology companies.
Develop mandatory data governance standards for audit bodies that employ cloud-based AI systems.
3. Create Regulatory Sandboxes for Innovation.
Have pilot programs for audit firms to test emerging AI technologies under regulatory oversight before full implementation, minimizing risk and encouraging innovation.

Recommendations for Audit Firms and Practitioners

1. Prioritize Auditor Capacity Building.
Many auditors in Ghana lack formal training in data analytics and AI literacy, and new audit technologies, and yet it is still very limited for them. Make AI and data analytics training mandatory for all audit staff.
Develop specialization tracks for auditors needing deep knowledge in the field of AI-enabled audit methodologies.
2. Adopt Phased Implementation Approaches.
Begin with low-risk automation applications (invoice matching, data reconciliation) before moving to high-risk audit decisions.
Since implementation barriers especially prevent companies from unlocking the efficiency benefits of these automation applications, firms should focus on infrastructure readiness and staff skills before large-scale implementation.
3. Build Organizational Readiness.

Organizational readiness for technology adoption has an undeniable positive impact on audit results and shows that organizational culture, leadership support, and change management capacity are critical factors which will influence the quality of technology adoption in the implementation of audit improvements. Establish change management offices with staff that have technology transition experience.

Recommendations for the Institute of Chartered Accountants Ghana (ICAG)

1. Curriculum and Professional Development Updates.
Integrate AI, machine learning, and data analytics modules into the ICAG professional qualification urriculum.
Develop continuing professional education (CPE) requirements specifically addressing AI audit technologies.
2. Establish Competency Standards.

Create minimum competency levels for audit professionals using AI-enabled tools and certify them in a tiered structure for specialist practitioners.
Create audit technology audit specialists' designations recognizing demonstrated expertise.
3. Develop Ethical Frameworks.
Design governance mechanisms for AI-enabled audit systems to address algorithmic bias, data privacy, and cybersecurity risks.
Issue ethics guidance on conflicts between algorithmic recommendations and auditor professional judgment.

Recommendations for Addressing Implementation Barriers

1. Infrastructure Development Initiatives.
Infrastructural challenges such as poor electricity supply, limited broadband coverage in some areas, and unreliable data networks make it difficult to use very sophisticated cloud-based auditing technologies. Collaborate with government and private sector to build reliable broadband infrastructure in the regional audit centres outside Accra.
Make backup power systems and redundant internet connections for audit firms' main technology activities.
2. Support Mechanisms for Smaller Firms.
Given financial constraints affecting smaller audit firms, which limit investment in expensive software for audit technology, the system is two-tier, with large multinational audit firms able to afford cutting-edge products and services while local organizations are stuck with outdated tools.
Create shared audit technology platforms (Software-as-a-Service models) that enable small firms to leverage enterprise-level tools at reduced costs.
Provide financing mechanisms or tax incentives to local audit companies to invest in technology.
3. Knowledge Sharing and Collaboration.

Create audit technology innovation hubs where firms can share implementation experiences and best practices.

Create mentorship programs that link international firms with local practices for technology implementation.

Recommendations for Future Research

1. Longitudinal Studies – Track audit firms over 3-5 years to understand long-term technology adoption outcomes and sustainability.
2. Comparative Regional Analysis: Expand research to other West African countries to identify region-specific versus Ghana-specific implementation factors.
3. Algorithmic Bias Investigation: Conduct in-depth studies examining whether AI audit tools introduce systematic biases in specific industries or transaction types.
4. Auditor Professional Judgment: Research how reliance on AI technologies affects auditor skepticism and independent judgment quality.

References

1. Atrous, R. (2025). Artificial intelligence and the evolution of accounting and audit practices: A systematic review. *International Journal of Economics, Business and Management Research*. https://doi.org/10.51505/ijebmr.2025.91205
2. Az'har, Muh., Annisa, N., & Masyhuri. (2025). Adopsi teknologi data analytics dan artificial intelligence (AI) dalam peningkatan efisiensi prosedur analitis audit. *Journal of Economic and Business Advancement*. https://doi.org/10.65310/zhcx2c65

3. Cernovschi, C.-R., Ciubotariu, M., & Mihailă, S. (2025). Ethical challenges of using artificial intelligence in internal auditing. *Învățământul Superior Contabil: Provocări Și Soluții, 2025*. https://doi.org/10.53486/isc2025.33
4. Fidyah, F., Usman, S., Pradita, A. E., & Setyawati, D. (2024). The impact of artificial intelligence on auditing processes and accuracy: A future outlook. *Dinasti International Journal of Economics Finance & Accounting*. https://doi.org/https://doi.org/10.38035/dijefa.v5i4.3224
5. Geqeza, A. (2026). Preparing future internal auditors for the digital age: An empirical assessment of skills, curriculum gaps, and professional expectations. *Edelweiss Applied Science and Technology*. https://doi.org/10.55214/2576-8484.v10i2.12248
6. Ilori, O. (2024). Internal audit transformation in the era of digital governance: A roadmap for public and private sector synergy. *International Journal of Advanced Multidisciplinary Research and Studies*. https://doi.org/10.62225/2583049x.2024.4.6.4161
7. Lidiana, L. (2024). AI and auditing: Enhancing audit efficiency and effectiveness with artificial intelligence. *Accounting Studies and Tax Journal (COUNT)*. https://doi.org/https://doi.org/10.62207/g0wpn394
8. Mullool, J., & E, N. A. (2025). Revolutionizing financial oversight: The transformative power of artificial intelligence in auditing. *International Journal for Sciences and Technology*. https://doi.org/10.71097/ijsat.v16.i4.8805
9. Ogunmola, S., & Olubukola, O. A. (2026). Digital transformation in public sector auditing: A pathway to fiscal transparency and economic growth-comparative insights from the u.s., nigeria, kenya, and ghana. *American Journal of Financial Technology and Innovation*. https://doi.org/10.54536/ajfti.v4i1.6244
10. Onwubuariri, E. R., Adelakun, B. O., Olaiya, O. P., & Ziorklui, J. E. K. (2024). AI-driven risk assessment: Revolutionizing audit planning and execution. *Finance & Accounting Research Journal*. https://doi.org/https://doi.org/10.51594/farj.v6i6.1236
11. Oriaku, I., Bamidele, O. J., Mensah, T. K., Konadu, R. K., & Thomas, G. (2026). Artificial intelligence in auditing and financial reporting: A scoping review of current practices and future directions. *Journal of Economics and Trade*. https://doi.org/10.56557/jet/2026/v11i110096
12. Pycka, M., & Zastempowski, M. (2025). Machine learning and artificial intelligence techniques adopted for IT audit. *Management*. https://doi.org/10.58691/man/200768
13. Singh, A. D. (2025). The integration of artificial intelligence in modern auditing practices transforming auditing through technological advancements. *Journal of Advances in Developmental Research*. https://doi.org/10.71097/ijaidr.v16.i2.1655
14. Suarez, S. R., Huamani, B. M., Meléndez, M. A., & Ovalle, C. D. (2024). Methodology applied to computer audit with artificial intelligence: A systematic review. *IAES International Journal of Artificial Intelligence (IJ-AI)*. https://doi.org/10.11591/ijai.v13.i4.pp3727-3738
15. Tampubolon, E. D., Renta, J., Hutauruk, O., & Muda, I. (2025). A systematic literature review on the integration of blockchain and artificial intelligence for fraud detection in auditing. *PESHUM : Jurnal Pendidikan, Sosial Dan Humaniora*. https://doi.org/10.56799/peshum.v5i1.12376
16. Tembo, R. (2026). Evaluating the readiness of the accounting profession in zambia for artificial intelligence integration: A systematic literature review. *International Journal of Innovative Science and Research Technology*. https://doi.org/10.38124/ijisrt/26feb275
17. Thanh, L. C., Duyên, V. T. M., & Hằng, N. T. T. (2025). Explainable artificial intelligence in auditing: Factors influencing auditors' acceptance in vietnam. *Edelweiss Applied Science and Technology*. https://doi.org/10.55214/2576-8484.v9i12.11281
18. Wassie, F. A., & Lakatos, L. P. (2024). Artificial intelligence and the future of the internal audit function. *Humanities and Social Sciences Communications*. https://doi.org/10.1057/s41599-024-02905-w