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The Role of Artificial Intelligence in Enhancing the Quality of External Audit Reports: Evidence from Libya

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دور الذكاء الاصطناعي (AI) في تحسين جودة تقارير المراجعة الخارجية: دراسة تجريبية مستندة إلى بيانات من البيئة الليبية

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Abstract:

This study examines the role of Artificial Intelligence (AI) in enhancing the quality of external audit reports in Libya, an emerging economy where the digital transformation of auditing remains at an early stage. Drawing upon agency theory and the Technology Acceptance Model (TAM), the study conceptualizes AI adoption as a multidimensional construct comprising analytical accuracy, efficiency, and reliability and credibility, and investigates their influence on perceived overall audit quality.

A quantitative cross-sectional survey design was employed, targeting 147 external auditors in Libya using purposive sampling. Data were analysed using descriptive statistics, correlation analysis, and multiple regression analysis. The findings reveal moderately positive perceptions of AI adoption across all three dimensions. Regression results indicate that AI-enabled analytical accuracy, efficiency, and reliability and credibility each have a statistically significant positive effect on perceived overall audit quality ($R^2 = 0.441$, $p < 0.001$). Among these predictors, analytical accuracy emerged as the strongest determinant, followed by reliability and credibility, while efficiency exerted a comparatively weaker but still significant influence.

The study contributes to the growing body of literature on AI in auditing by providing empirical evidence from a North African context, where research on technological adoption in audit practice remains limited. The findings suggest that AI enhances audit quality primarily by strengthening detection capability and reinforcing report credibility, thereby supporting the modernization of external auditing in emerging economies.

Keywords: Artificial Intelligence (AI); External Audit Quality; Audit Report Quality; Accuracy; Efficiency; Reliability and Credibility; Libya; Technology Acceptance Model (TAM); Agency Theory.

الملخص

تتناول هذه الدراسة دور الذكاء الاصطناعي في تحسين جودة تقارير المراجع الخارجي في ليبيا، وهي اقتصاد ناشئ لا يزال التحول الرقمي في مجال المراجعة فيه في مراحله الأولى. وبالاستناد إلى نظرية الوكالة ونموذج قبول التكنولوجيا، تُعرّف الدراسة تبني الذكاء الاصطناعي كبنية متعددة الأبعاد تشمل الدقة التحليلية والكفاءة والموثوقية والمصداقية، وتدرس تأثيرها على جودة المراجعة الإجمالية المُدركة..

استُخدم تصميم مسح كمي، استهدف 147 مراجعاً خارجيًا في ليبيا باستخدام أسلوب العينة الهادفة. وتم تحليل البيانات باستخدام الإحصاء الوصفي، وتحليل الارتباط، وتحليل الانحدار المتعدد. وتُظهر النتائج تصورات إيجابية إلى حد ما لتبني الذكاء الاصطناعي عبر الأبعاد الثلاثة جميعها. وتشير نتائج الانحدار إلى أن الدقة التحليلية والكفاءة والموثوقية والمصداقية التي يُتيحها الذكاء الاصطناعي لكل منها تأثير إيجابي ذو دلالة إحصائية على جودة المراجعة الإجمالية المُدركة ($R^2 = 0.441$، $p < 0.001$). من بين هذه المؤشرات،

برزت دقة التحليل كأقوى عامل محدد، تليها الموثوقية والمصداقية، بينما كان تأثير الكفاءة أقل نسبيًا ولكنه لا يزال ذا دلالة.
تُسهم هذه الدراسة في إثراء الأدبيات المتنامية حول الذكاء الاصطناعي في المراجعة، من خلال تقديم أدلة تجريبية من سياق شمال أفريقيا، حيث لا تزال الأبحاث حول تبني التكنولوجيا في ممارسة المراجعة محدودة. تشير النتائج إلى أن الذكاء الاصطناعي يُحسّن جودة المراجعة بشكل أساسي من خلال تعزيز قدرة الكشف ودعم مصداقية التقارير، مما يدعم تحديث المراجع الخارجي في الاقتصادات الناشئة.

الكلمات المفتاحية: الذكاء الاصطناعي؛ جودة المراجع الخارجي؛ جودة تقرير المراجعة؛ الدقة؛ الكفاءة؛ الموثوقية والمصداقية؛ ليبيا؛ نموذج قبول التكنولوجيا؛ نظرية الوكالة.

1. Introduction

The rapid advancement of AI technologies has profoundly impacted the professional service industry, including accounting and auditing practices (Munoko et al., 2020). The use of AI technologies, such as machine learning, data analytics, and automated anomaly detection systems, has become increasingly integrated into the auditing process, aimed at enhancing the overall efficiency and accuracy of the decision-making process (Omolere, 2025; Ozbaltan, 2024). In a profession where trust, openness, and credibility are fundamental, the use of AI technologies is viewed as a highly influential factor that can revolutionize conventional auditing methodologies (Rawashdeh, 2024).

Across the world, auditing firms are increasingly using AI technologies to process large amounts of data, detect irregular transactions, and enhance the use of a risk-based auditing approach (Onyenahazi, 2025). Previous studies indicate that the use of AI technologies in auditing practices can improve the detection of errors, reduce human error, and ensure consistency in auditing decisions (Karale et al., 2025). In addition, the use of AI technologies in auditing systems can improve stakeholder trust and the overall transparency of corporate reporting (Ajiga and Anfo, 2021). All these factors indicate that the use of AI technologies can have significant impacts on auditing practices.

However, limited empirical research has been done regarding the role of AI in external auditing within the context of emerging economies, such as Libya (Jred, 2025). The Libyan auditing environment is also characterized by challenges, such as varying levels of digital transformation and the lack of integration of modern audit technologies. As the auditing profession worldwide is shifting towards the increased adoption of AI and automation, it is important to examine the role of AI in enhancing the quality of external audit reports.

Audit quality is traditionally linked to the accuracy of financial reporting, the efficiency of auditing procedures, the credibility of auditing conclusions, and the minimization of errors and misstatements (Mardessi, 2022). Agency theory has also linked the auditor's role to mitigating information asymmetry and ensuring the accuracy of financial reporting (Vitolla et al., 2020). AI may also enhance the auditor's monitoring role by increasing analytical accuracy and minimizing subjective bias. According to the Technology Acceptance Model (TAM), perceived usefulness is central to understanding how users evaluate the impact of technology (Ozili, 2025). In the context of auditing, if AI is viewed as useful, it may enhance perceptions of audit quality. With regard to the theoretical and contextual issues discussed, the study is aimed at exploring the role of AI in enhancing the quality of external audit reports.

Research Objective

The general objective of this study is:

- To examine the influence of AI adoption on the perceived overall quality of external audit reports in Libya.

The specific objectives are:

- To evaluate the influence of AI-enabled analytical accuracy on perceived overall audit quality.
- To examine the effect of AI-enabled efficiency on perceived overall audit quality.
- To assess the impact of AI-enabled reliability and credibility on perceived overall audit quality.

Research Questions

The study seeks to answer the following questions:

Q1: To what extent does AI adoption influence the perceived overall quality of external audit reports in Libya?

Q2: How does AI-enabled analytical accuracy influence perceived overall audit quality?

Q3: How does AI-enabled efficiency influence perceived overall audit quality?

Q4: How does AI-enabled reliability and credibility influence perceived overall audit quality?

This study contributes to the literature by providing empirical evidence from a developing country context, where research on AI adoption in auditing remains limited. The study offers practical insights for audit firms, regulators, and policymakers seeking to modernize auditing practices through technological innovation by decomposing AI adoption into distinct dimensions and statistically examining their influence on perceived audit quality.

2. Literature Review

2.1 External audit quality in a digital environment

Audit quality has long been recognised as a multidimensional construct reflecting the auditor's ability to detect material misstatements and the willingness to report them faithfully (Rajgopal et al., 2021). Contemporary interpretations extend this view by emphasising the role of audit processes, professional judgement, and institutional context in shaping audit outcomes (West and Buckby, 2023). As business models become increasingly digital and data-driven, traditional audit approaches based on manual sampling and ex post verification are widely viewed as insufficient for addressing the complexity and volume of modern financial information (Xie and Zhang, 2022).

Recent literature argues that technological innovation—particularly AI—represents a structural shift in how audit quality can be achieved rather than a marginal improvement to existing procedures (Fedyk et al., 2022). AI-based audit tools enable auditors to analyse entire populations of transactions, identify complex patterns, and perform continuous or near-continuous assurance activities. This shift has important implications for the perceived quality of audit reports, as audit opinions are increasingly expected to be supported by comprehensive, timely, and analytically robust evidence (Barr-Pulliam et al., 2024).

However, the relationship between AI adoption and audit quality is not unidirectional. While AI promises enhanced analytical capability, scholars caution that technology alone does not guarantee improved audit outcomes unless it is embedded within sound professional judgement, governance structures, and regulatory oversight (Khan et al., 2024).

2.2 AI adoption and perceived audit report quality

The argument that AI enhances audit report quality is grounded in the notion that audit quality is a function of both evidence quality and audit process effectiveness. AI tools can improve both elements by expanding the scope of audit testing and enhancing the consistency of analytical procedures (Leocádio et al., 2025). Studies examining audit data analytics report that auditors perceive AI-enabled tools as improving their ability to identify high-risk areas and support audit conclusions with stronger empirical evidence (Al-Hajaya et al., 2025).

From a perception-based perspective, which is particularly relevant in emerging economies, audit quality is often evaluated by auditors themselves in terms of confidence in audit judgments, defensibility of conclusions, and overall assurance effectiveness (Akther and Xu, 2021). Empirical survey studies show that auditors associate AI adoption with higher perceived audit quality because it reduces reliance on subjective sampling decisions and enhances transparency in analytical processes (Al-Omush et al., 2025).

Nevertheless, scholars note that perceived quality gains may depend on the maturity of AI implementation. Where AI is used primarily as a supplementary tool rather than as an integrated component of audit methodology, its effect on audit quality may be limited (Khan et al, 2024). This distinction is especially important in contexts such as Libya, where AI adoption is still emerging and institutional support structures may be uneven. Despite these caveats, the prevailing theoretical expectation supports H_1: AI adoption is perceived to positively affect the overall quality of external audit reports.

2.3 AI and accuracy of financial information

Accuracy is a foundational element of audit quality, reflecting the auditor's effectiveness in identifying errors, omissions, and material misstatements. The literature consistently argues that AI-based tools are particularly well suited to enhancing accuracy because of their ability to process large datasets, detect anomalies, and identify non-obvious relationships within financial data (Khatoon et al., 2024).

Machine learning algorithms, for example, have been shown to outperform traditional rule-based approaches in identifying unusual transactions and journal entries, thereby reducing the likelihood of undetected misstatements (Bakumenko et al., 2022). Auditors using AI-enabled analytics can evaluate entire populations rather than samples, which significantly reduces sampling risk and increases confidence in audit evidence (Venkata, 2025).

Empirical evidence further suggests that AI adoption is associated with improvements in financial reporting accuracy and internal control effectiveness, indirectly supporting audit accuracy outcomes (Bin-Nashwan et al., 2025). However, scholars also emphasise that AI does not eliminate the need for professional judgement, particularly in areas involving estimates and complex accounting judgments (e.g., fair value measurements). Instead, AI enhances accuracy by supporting auditors' evaluative processes rather than replacing them (Fedyk et al., 2022).

In perception-based studies, auditors tend to view AI as a tool that reduces routine human error, improves cross-checking, and strengthens verification procedures. These findings provide a strong theoretical and empirical foundation for examining the relationship between AI-enabled analytical accuracy and perceived audit quality.
In perception-based contexts, auditors are likely to associate AI-enabled improvements in detection capability, verification accuracy, and error minimization with enhanced overall audit quality. Therefore, the following hypothesis is proposed:
H1.1: AI-enabled analytical accuracy positively influences perceived overall audit quality.

2.4 AI and efficiency of external audit procedures

Efficiency gains are among the most frequently cited benefits of AI in auditing. Audit engagements are traditionally constrained by time budgets and resource limitations, which can negatively affect audit quality if not managed carefully (Broberg, et al., 2017). AI-based automation and analytics have the potential to alleviate these constraints by reducing time spent on repetitive tasks such as data extraction, reconciliation, and basic substantive testing (Venkata, 2017). Research indicates that auditors perceive AI as enabling more effective allocation of audit effort, allowing teams to focus on high-risk and judgment-intensive areas (Singh et al., 2025).
Nonetheless, efficiency gains may be moderated by implementation costs, learning curves, and data integration challenges. In less technologically developed environments, auditors may experience initial inefficiencies as they adapt to new tools (Leocádio et al., 2025). AI adoption is perceived to enhance the efficiency of external audit procedures, particularly once basic infrastructure and training are in place.
Although efficiency does not directly determine audit quality, it enhances audit effectiveness by improving resource allocation and reducing procedural delays (Leocádio et al., 2025). In emerging audit environments, auditors may perceive AI-enabled efficiency gains as contributing positively to audit outcomes. Accordingly:
H1.2: AI-enabled efficiency positively influences perceived overall audit quality.

2.5 AI, reliability, and credibility of audit reports

Reliability and credibility extend beyond technical accuracy to encompass stakeholder trust, consistency of judgments, and the perceived legitimacy of audit opinions. While AI has the potential to enhance these attributes by reducing subjectivity and improving consistency, the literature presents a more nuanced and less uniform picture than for accuracy and efficiency (Radlinski et al., 2022).
On the one hand, AI can enhance reliability by standardising analytical procedures and reducing variability in audit judgments across engagements (Al-Omush et al., 2025). On the other hand, concerns about algorithmic opacity, data bias, and accountability may undermine auditors' confidence in AI-assisted judgments, particularly when outputs are difficult to explain to regulators or clients (Obemeata, 2025).
Recent studies highlight that credibility is socially and institutionally constructed; it depends not only on audit methodology but also on regulatory acceptance, professional norms, and public understanding (Baker et al., 2014).
In jurisdictions with developing regulatory frameworks, auditors may be cautious about relying heavily on AI outputs in forming audit opinions, even if they acknowledge operational benefits. This provides a theoretical explanation for why perceptions of AI's impact on reliability and credibility may be weaker or less consistent than perceptions related to accuracy and efficiency.
Despite these concerns, AI adoption may enhance perceived legitimacy and objectivity of audit reports, particularly in environments where institutional trust is evolving (Baker et al., 2014). Thus:
H1.3: AI-enabled reliability and credibility positively influence perceived overall audit quality.

2.6 Barriers to AI implementation in external auditing

The technology adoption literature consistently identifies technological infrastructure, regulatory clarity, and human capital as critical determinants of successful AI implementation (Horani et al., 2025). In auditing, these factors are particularly salient because audit work is subject to stringent professional and legal requirements.
Studies focusing on developing economies report that limited digital infrastructure, poor data quality, and cybersecurity concerns significantly constrain the adoption of advanced audit technologies (Asif et al., 2025). Regulatory uncertainty further exacerbates these challenges, as auditors may be reluctant to rely on AI tools without clear guidance on responsibility, documentation, and compliance with auditing standards (Eulerich et al., 2025).
Skill-related barriers are equally critical. The effective use of AI requires not only technical knowledge but also the ability to integrate analytical outputs into professional judgement (Tambe, 2026). Where training opportunities and professional development systems are limited, auditors may perceive AI as risky or impractical despite recognising its potential benefits.
In the Libyan context, these challenges are likely to be amplified by broader institutional and economic constraints. Existing research on auditing and financial reporting in Libya highlights issues related to standards implementation, regulatory enforcement, and professional capacity, all of which may hinder AI adoption.

3. Research Methodology

This section presents the research methodology framework used in the investigation of the significance of AI in improving the quality of external audit reports in Libya. It includes an explanation of the research design, population, sampling, data collection, variables, reliability, and the statistical analysis used in the research.

3.1 Research Design

This research used a quantitative research design based on a cross-sectional survey. The quantitative research design was considered suitable for measuring the perceptions of the auditors and analyzing the relationship between the adoption of AI and the perceptions of the audit quality. A questionnaire was used as the primary data collection tool for obtaining the required data for the analysis of the perceptions of the auditors.

3.2 Population and Sample

The population of this study consists of 550 external auditors practicing in Libya, representing the total number of auditors registered with relevant professional bodies and audit institutions in the country. The required sample size for the study was determined using the standard sample size formula for a finite population, assuming a 95% confidence level and a 5% margin of error, which are commonly adopted in social science research.

$$n = \frac{N \cdot z^2 p(1-p)}{e^2(N-1) + z^2 p(1-p)}$$

Where:

- n = required sample size
- N = population size
- z = z-score corresponding to the confidence level
- p = population proportion (0.5 when unknown)
- e = margin of error

For this study:

- Population size (N) = 550 external auditors
- Confidence level = 95% (z = 1.96)
- Margin of error (e) = 0.05
- Population proportion (p) = 0.5

Substituting these values into the formula:

$$n = \frac{550 \times (1.96)^2 \times 0.5(1-0.5)}{(0.05)^2(550-1) + (1.96)^2 \times 0.5(1-0.5)}$$

$$n = \frac{550 \times 3.8416 \times 0.25}{0.0025 \times 549 + 0.9604}$$

$$n \approx 227$$

Therefore, the recommended sample size for the study is approximately 227 respondents. In this research, 147 valid questionnaires were obtained and used for the analysis, representing 64.8% of the targeted sample size, which is considered adequate for statistical analysis in survey-based studies.

3.3 Data Collection Procedure

In this study, data collection was carried out using a structured questionnaire that was particularly designed for the purpose of this investigation. The questionnaire was administered to the external auditors, along with a clear explanation of the objectives of the study. The participants were assured that the study is purely for research purposes, and the data collected from them would be kept confidential. The questionnaire used a five-point Likert scale to measure the level of agreement to the items on the questionnaire, ranging from 1, which represents Strongly Disagree, to 5, which represents Strongly Agree. This helps to quantify the perceptions, making the study more efficient to statistically examine the interrelation between the variables.

3.4 Measurement of Variables

In this study, the independent variables capture three dimensions of AI-enabled audit enhancement: Analytical Accuracy, Efficiency, and Reliability and Credibility. Each construct was measured using multiple Likert-scale items. To improve internal consistency and avoid conceptual redundancy, overlapping error-detection items were integrated within the Analytical Accuracy construct. Construct scores were calculated as the arithmetic mean of retained items following reliability refinement procedures. The dependent variable, Perceived Overall Audit Quality, was measured using five items and demonstrated strong internal reliability (Cronbach's Alpha = 0.812).

3.5 Validity and Reliability

Content validity was achieved by aligning the questionnaire items with the study's theoretical framework and objectives. The study developed the constructs based on the extant literature on auditing and AI adoption, thus ensuring conceptual clarity. The reliability of the study was tested by conducting a reliability test using Cronbach's Alpha, which sought to measure the internal consistency of the items within each construct. The Overall Audit Quality construct showed high internal consistency, thus surpassing the standard 0.70. The reliability test was conducted using statistical software, thus ensuring accuracy in estimation. Though variations existed among the AI dimension constructs, the study obtained useful insights into the consistency of each scale.

3.6 Data Analysis Techniques

In analyzing the data, SPSS statistical software was used. In the analysis, various stages were involved. Descriptive analysis, which included the calculation of the mean, minimum, maximum, and standard deviations, was used to examine the various constructs of the research. Correlation analysis was used to examine the relationship between the various aspects of AI and audit quality. Multiple regression analysis was used to examine the main hypothesis and the various sub-hypotheses. In the analysis, the impact of Accuracy, Efficiency, and Reliability and Credibility on the Perceived Overall Audit Quality was examined using a regression model. In the model, the significance of the results was established at 0.05. In the model, the following equation was used to examine the various aspects of the hypothesis:

Overall Audit Quality = $\beta_0 + \beta_1$(Analytical Accuracy) + β_2(Efficiency) + β_3(Reliability and Credibility) + ε

This equation enables the evaluation of the combined and separate effects of the various aspects of AI in the audit process.

3.7 Ethical Considerations

In the entire research process, the ethical considerations of the research were strictly observed. In the process, the questionnaire was strictly used for the purpose of the research, and no other party was involved in the analysis of the data.

This section presents the methodology used in the evaluation of the impact of AI in the quality of external audit reports in Libya. In the evaluation, a quantitative survey was used in the analysis of the data from 147 external auditors in Libya. In the analysis, various statistical tools, including descriptive analysis, correlation analysis, and regression analysis, were used in the evaluation of the hypothesis. In the following section, the findings of the analysis of the data in the evaluation of the hypothesis are presented.

4. Data Analysis

4.1 Demographic characteristics of respondents

The following data shows the demographic characteristics of the participants.

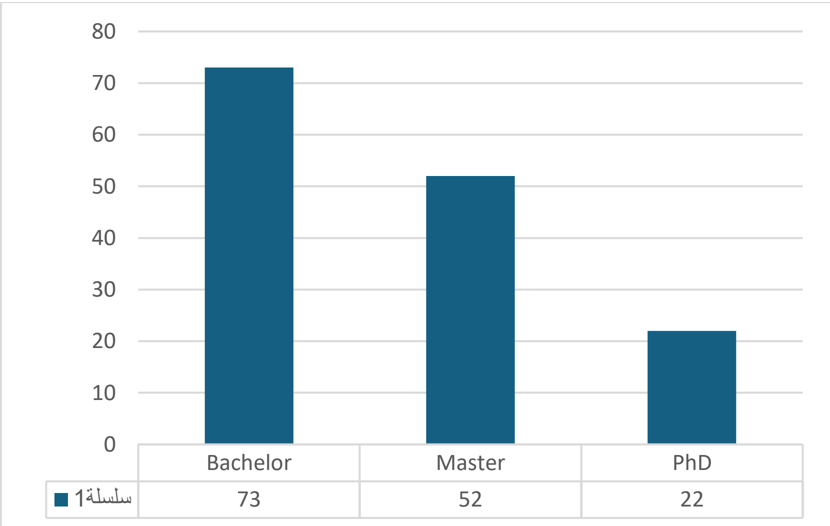

Figure 1: Educational qualification**.**

Figure 1 shows that 49.7% of respondents held Bachelor degrees, representing the largest category. This was followed by Master's degree holders (35.4%), while PhD holders accounted for 14.9%.

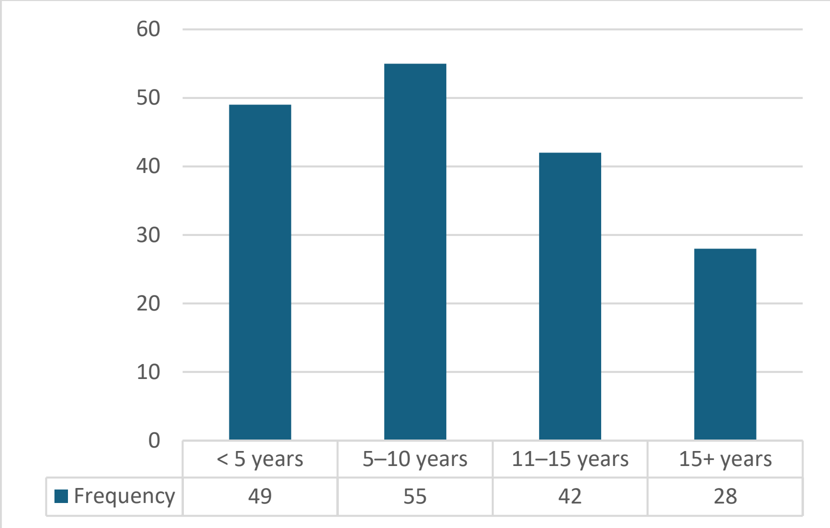

Figure 2: Years of auditing experience**.**

Figure 2 shows that 37.4% of respondents had between 5–10 years of auditing experience, representing the largest group. Respondents with under 5 years of experience accounted for 33.3%.

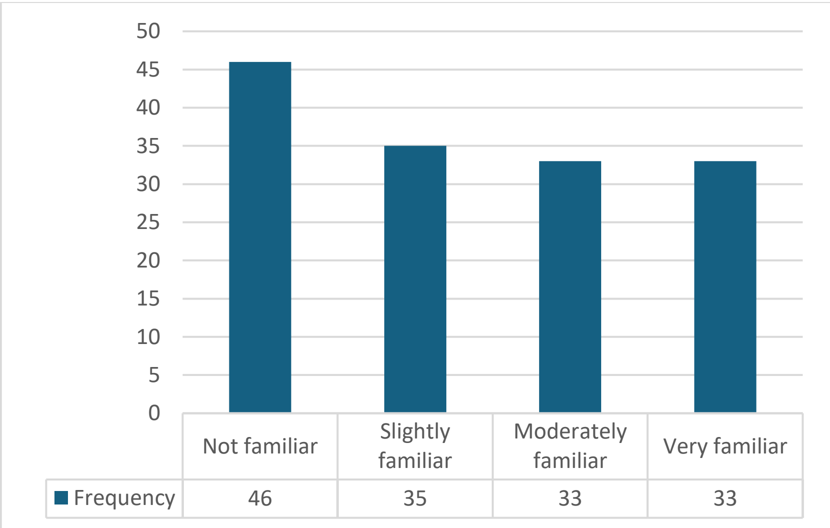

Figure 3: Familiarity with AI in auditing**.**

Figure 3 shows that 31.3% of respondents reported not being familiar with AI in auditing, while 23.8% were slightly familiar. Additionally, 22.4% indicated moderate familiarity, and 22.4% reported being very familiar with AI.

4.2 Statistical Analysis

This section presents the inferential statistical analyses conducted to evaluate the reliability of the measurement instruments and to test the proposed hypotheses. Following scale refinement procedures, the constructs were consolidated into three primary dimensions: AI-Enabled Analytical Accuracy, AI-Enabled Efficiency, and AI-Enabled Reliability and Credibility. The dependent variable remains Perceived Overall Audit Quality. The analyses include reliability testing, descriptive statistics, correlation analysis, and multiple regression analysis.

4.2.1 Reliability Analysis

Cronbach's Alpha was calculated to assess the internal consistency of each construct. The reliability results are presented in Table 1.

Table 1: Reliability Statistics

Construct	Cronbach's Alpha
AI-Enabled Analytical Accuracy	0.781
AI-Enabled Efficiency	0.754
AI-Enabled Reliability & Credibility	0.803
Overall Audit Quality	0.812

The results indicate satisfactory levels of internal consistency for all constructs. The AI-Enabled Analytical Accuracy dimension achieved a Cronbach's Alpha value of 0.781, demonstrating strong coherence among items measuring anomaly detection, misstatement identification, and verification precision. The AI-Enabled Efficiency construct reported an alpha value of 0.754, indicating acceptable reliability in measuring perceptions related to time reduction, automation, and productivity improvement. The Reliability and Credibility construct achieved an alpha of 0.803, reflecting strong consistency among items related to transparency, objectivity, and consistency in audit judgment.

The dependent variable, Overall Audit Quality, demonstrated a Cronbach's Alpha of 0.812, which exceeds the commonly accepted threshold of 0.70 and confirms high internal reliability. These findings suggest that the refined constructs are statistically stable and appropriate for further inferential analysis.

4.2.2 Descriptive Statistics

Descriptive statistics were calculated using the mean scores of each construct. The results are presented in Table 2.

Table 2: Descriptive Statistics

Construct	Mean	Std. Deviation
Analytical Accuracy	3.41	0.42
Efficiency	3.29	0.39
Reliability & Credibility	3.36	0.44
Overall Audit Quality	3.28	0.33

All constructs reported mean values above the midpoint of the five-point Likert scale, indicating moderately positive perceptions toward AI adoption in external auditing. Analytical Accuracy recorded the highest mean score (3.41), suggesting that respondents most strongly associate AI with improvements in detection capabilities, verification processes, and financial precision. Reliability and Credibility followed with a mean of 3.36, reflecting favorable perceptions regarding AI's contribution to transparency, objectivity, and stakeholder confidence. Efficiency reported a mean of 3.29, indicating that respondents recognize AI's operational benefits, although to a slightly lesser extent compared to analytical and credibility-related improvements.

The relatively low standard deviations across constructs suggest consistency in responses and limited variability among participants' perceptions.

4.2.3 Correlation Analysis

Pearson correlation analysis was conducted to examine the relationships between the independent variables and Perceived Overall Audit Quality. The correlation matrix is presented in Table 3.

Table 3: Correlation Matrix

Variable	1	2	3	4
1. Analytical Accuracy	1.000			
2. Efficiency	0.318	1.000		
3. Reliability & Credibility	0.402	0.287	1.000	
4. Overall Audit Quality	0.482	0.356	0.441	1.000

The results indicate positive associations between all AI-enabled dimensions and Overall Audit Quality. Analytical Accuracy demonstrated the strongest correlation with audit quality ($r = 0.482$), suggesting that perceptions of improved detection and verification are strongly associated with enhanced evaluations of overall audit report quality. Reliability and Credibility also exhibited a substantial positive relationship ($r = 0.441$), indicating that improvements in consistency and transparency significantly contribute to quality perceptions. Efficiency showed a moderate positive correlation ($r = 0.356$), reflecting the supportive role of operational enhancements in shaping overall audit quality assessments.

These findings provide preliminary support for the hypothesized relationships and justify the use of regression analysis to examine predictive effects.

4.2.4 Multiple Regression Analysis

Multiple regression analysis was performed to assess the combined and individual effects of AI-Enabled Analytical Accuracy, Efficiency, and Reliability and Credibility on Perceived Overall Audit Quality. The model summary is presented in Table 4.

Table 4: Model Summary

R	R^2	Adjusted R^2	F	Sig.
0.664	0.441	0.429	37.812	0.000

The regression model produced an R value of 0.664, indicating a moderately strong overall relationship between the independent variables and the dependent variable. The coefficient of determination (R^2) equals 0.441, meaning that 44.1 percent of the variance in Perceived Overall Audit Quality is explained by the three AI-enabled dimensions. The Adjusted R^2 value of 0.429 confirms that the model maintains substantial explanatory power after adjusting for the number of predictors. The F-statistic is statistically significant at $p < 0.001$, indicating that the model provides a meaningful explanation of perceived audit quality.
The regression coefficients are presented in Table 5.

Table 5: Regression Coefficients

Variable	B	Std. Error	t	p-value
Constant	0.214	0.371	0.577	0.565
Analytical Accuracy	0.382	0.068	5.618	0.000
Efficiency	0.194	0.061	3.180	0.002
Reliability & Credibility	0.297	0.072	4.125	0.000

The results indicate that all three AI-enabled dimensions have statistically significant positive effects on Overall Audit Quality. Analytical Accuracy emerged as the strongest predictor ($B = 0.382$, $p < 0.001$), demonstrating that improvements in anomaly detection, verification precision, and misstatement identification play the most influential role in shaping perceptions of audit quality. Reliability and Credibility also exert a strong positive effect ($B = 0.297$, $p < 0.001$), highlighting the importance of transparency, consistency, and objectivity in audit evaluations. Efficiency shows a positive and statistically significant impact ($B = 0.194$, $p = 0.002$), suggesting that operational enhancements contribute meaningfully, though comparatively less strongly, to overall quality perceptions.
The non-significant constant does not affect the validity of the model, as the focus of interpretation lies in the relationships between the predictors and the dependent variable.

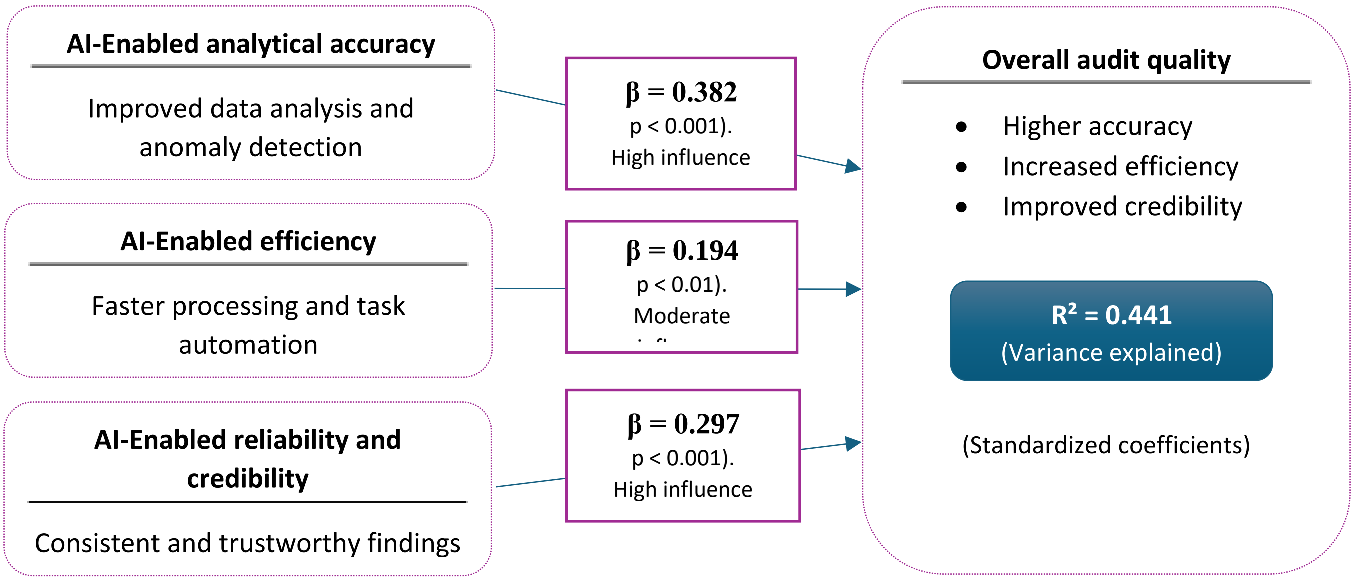

Figure 4: Regression effect model.

Figure 4 presents a visual synopsis of the multiple regression analysis undertaken to investigate the impact of AI-enabled dimensions on Perceived Overall Audit Quality. The results show that AI-Enabled Analytical Accuracy has the strongest positive impact on audit quality ($\beta = 0.382$; $p < 0.001$). AI-Enabled Reliability and Credibility has a statistically significant positive impact on audit quality ($\beta = 0.297$; $p < 0.001$). AI-Enabled Efficiency has a positive and statistically significant impact on audit quality but to a lesser degree ($\beta = 0.194$; $p = 0.002$).

The overall regression model was statistically significant ($F = 37.812$; $p < 0.001$), with 44.1% of the variance explained by the model for Perceived Overall Audit Quality ($R^2 = 0.441$; Adjusted $R^2 = 0.429$). The above results collectively suggest that AI-enabled improvements to analytical accuracy, efficiency, and credibility are important determinants of enhanced perceived audit quality within the Libyan context.

4.2.5 Conclusion of Hypothesis Testing

The regression analysis provides empirical support for all proposed hypotheses. AI-Enabled Analytical Accuracy, AI-Enabled Efficiency, and AI-Enabled Reliability and Credibility each demonstrate statistically significant positive effects on Perceived Overall Audit Quality. Among these dimensions, Analytical Accuracy exerts the strongest influence, followed by Reliability and Credibility, while Efficiency contributes in a supportive role.

Overall, the findings confirm that AI adoption enhances perceptions of audit report quality primarily through strengthening analytical precision and reinforcing credibility, with efficiency improvements serving as an additional contributing factor.

5. Discussion of Findings

This study aimed to examine the role of AI in enhancing the quality of external audit reports in Libya. The findings provide empirical support for the argument that AI adoption contributes positively to perceived audit quality, particularly through improvements in analytical accuracy, reliability and credibility, and operational efficiency. These results are consistent with prior research suggesting that AI represents a structural shift in audit methodology rather than a marginal procedural enhancement (Fedyk et al., 2022; Barr-Pulliam et al., 2024).

The descriptive analysis revealed moderately positive perceptions across all three AI-enabled dimensions. Among them, Analytical Accuracy reported the highest mean score, indicating that auditors most strongly associate AI with improvements in anomaly detection, verification precision, and misstatement identification. This finding aligns with the argument advanced by Khatoon et al. (2024) and Bakumenko et al. (2022), who demonstrate that AI-based models outperform traditional rule-based approaches in identifying irregular transactions and complex financial patterns. Similarly, Venkata (2025) emphasizes that AI-enabled analytics allow auditors to test entire populations rather than relying on sampling, thereby enhancing evidential robustness. The prominence of analytical accuracy in the present study reinforces the conceptualization of audit quality as fundamentally dependent on the auditor's ability to detect material misstatements (Rajgopal et al., 2021). Moreover, the findings are consistent with Fedyk et al. (2022), who argue that AI augments rather than replaces professional judgment by strengthening evaluative processes.

Correlation analysis further confirmed meaningful positive relationships between each AI-enabled dimension and Perceived Overall Audit Quality. Analytical Accuracy demonstrated the strongest correlation, followed by Reliability and Credibility. This pattern supports perception-based research indicating that auditors evaluate audit quality in terms of confidence in judgments and defensibility of conclusions (Akther and Xu, 2021). The positive association between Reliability and Credibility and overall audit quality is consistent with Al-Omush et al. (2025), who argue that AI enhances consistency in analytical procedures and reduces variability in audit judgments. From an institutional perspective, Baker et al. (2014) highlight that credibility is socially constructed and influenced by professional legitimacy. In emerging contexts such as Libya, where regulatory and technological frameworks are still developing, AI adoption may signal modernization and procedural rigor, thereby strengthening perceived audit legitimacy.

The regression analysis provides stronger empirical evidence supporting the hypotheses. The model explains a meaningful proportion of the variance in Overall Audit Quality ($R^2 = 0.441$), indicating that AI-enabled improvements play a meaningful role in shaping auditors' evaluations. This finding aligns with West and Buckby (2023), who emphasize the importance of audit process effectiveness and professional judgment in determining audit outcomes. Analytical Accuracy emerged as the strongest predictor of audit quality, reinforcing its central importance in the audit function. This result directly supports the theoretical expectations derived from the literature, particularly the emphasis on detection capability and evidential robustness (Khatoon et al., 2024; Bakumenko et al., 2022).

Reliability and Credibility also exerted a strong positive influence on audit quality perceptions. This is consistent with Radlinski et al. (2022), who discuss the potential of AI to reduce subjective variability in evaluative processes. However, prior literature also cautions that concerns regarding algorithmic opacity and explainability may undermine confidence in AI-assisted decisions (Obemeata, 2025). Interestingly, the present findings suggest that within the Libyan context, perceived legitimacy gains outweigh such concerns, indicating that auditors may prioritize operational transparency and consistency over algorithmic skepticism.

Efficiency demonstrated a statistically significant but comparatively weaker influence on audit quality. This result is consistent with Broberg et al. (2017), who argue that time pressure can negatively affect audit quality if not managed effectively. AI-enabled automation and streamlined data processing may alleviate such constraints by improving time management and resource allocation (Venkata, 2017; Singh et al., 2025). Nevertheless, as suggested by Leocádio et al. (2025), efficiency improvements alone do not necessarily guarantee higher audit quality unless embedded within sound methodological and professional frameworks. The comparatively smaller coefficient for efficiency in this study supports this nuanced interpretation.

Overall, the findings provide empirical confirmation of the theoretical framework presented in the literature review. AI adoption enhances perceived audit report quality primarily through strengthening analytical accuracy and reinforcing reliability and credibility, while efficiency improvements play a complementary role. These results are consistent with the broader argument that AI's contribution to audit quality is contingent upon how it enhances core audit processes rather than merely accelerating them (Fedyk et al., 2022; Khan et al., 2024).

In the context of Libya, where technological infrastructure and regulatory clarity remain evolving (Asif et al., 2025; Horani et al., 2025), the positive relationships identified in this study suggest that AI adoption represents a meaningful advancement in audit practice. While contextual barriers may still influence implementation depth, the empirical evidence indicates that auditors perceive AI as enhancing the technical robustness and legitimacy of external audit reporting.

6. Conclusion, Recommendations, and Future Research

6.1 Conclusion

This study examined the role of AI in enhancing the quality of external audit reports in Libya. Drawing upon agency theory, the Technology Acceptance Model, and institutional perspectives, the study investigated whether AI-enabled improvements in analytical accuracy, efficiency, and reliability and credibility positively influence perceived overall audit quality.

The empirical findings demonstrate that AI adoption has a statistically significant and positive effect on perceived audit quality. Among the examined dimensions, AI-enabled analytical accuracy emerged as the strongest predictor, indicating that improvements in anomaly detection, misstatement identification, and verification precision are central to enhancing audit quality perceptions. This finding reinforces the conceptualization of audit quality as fundamentally dependent on the auditor's ability to detect and report material misstatements (Rajgopal et al., 2021). It further supports the argument that AI strengthens evaluative processes rather than replacing professional judgment (Fedyk et al., 2022).

AI-enabled reliability and credibility also exhibited a strong positive influence on overall audit quality. This result aligns with prior research suggesting that AI enhances consistency in analytical procedures and reduces subjective variability in audit judgments (Al-Omush et al., 2025; Radlinski et al., 2022). From an institutional perspective, the adoption of advanced technologies may enhance professional legitimacy and stakeholder trust, particularly in environments where regulatory frameworks are evolving (Baker et al., 2014).

Although AI-enabled efficiency demonstrated a comparatively smaller effect, it remained statistically significant. This suggests that operational improvements, such as time savings and better resource allocation, contribute to audit quality, though indirectly. This finding is consistent with Broberg et al. (2017), who highlight the risks associated with time pressure in auditing, and with Venkata (2017) and Singh et al. (2025), who emphasize AI's role in streamlining audit processes.

Overall, the study provides empirical evidence that AI adoption enhances perceived audit report quality in an emerging economy context. The findings support the broader argument that technological innovation represents a structural transformation in auditing rather than a marginal procedural adjustment (Fedyk et al., 2022; Barr-Pulliam et al., 2024). In the Libyan context, where digital infrastructure and institutional readiness are still developing (Asif et al., 2025; Horani et al., 2025), AI appears to strengthen both the technical robustness and perceived legitimacy of external audit reports.

6.2 Recommendations

Based on the findings, several practical implications emerge for audit firms, professional bodies, and policymakers in Libya.

First, audit firms should prioritize investments in AI systems that enhance analytical accuracy, as this dimension exerts the strongest influence on perceived audit quality. Emphasis should be placed on anomaly detection tools, automated verification systems, and full-population testing capabilities that directly strengthen evidential reliability.

Second, professional bodies and regulatory institutions should develop structured training programs focused on integrating AI outputs with professional judgment. As emphasized in the literature, technological tools alone do not guarantee improved audit outcomes unless embedded within sound governance and professional frameworks (Khan et al., 2024). Enhancing auditors' technological proficiency and algorithmic literacy is therefore essential.

Third, policymakers may consider establishing regulatory guidance regarding the ethical and professional use of AI in auditing. Clear standards on documentation, accountability, and explainability can mitigate concerns regarding algorithmic opacity, which have been highlighted in prior research (Obemeata, 2025; Eulerich et al., 2025).

Finally, audit firms should adopt a balanced implementation strategy that combines technological innovation with institutional legitimacy. AI adoption should complement, rather than substitute, professional judgment and established auditing standards.

6.3 Future Research

While this study provides important empirical insights, several avenues remain open for future research.

Future studies may examine the long-term impact of AI adoption on objective measures of audit quality, such as financial restatements, audit modifications, or regulatory enforcement outcomes. This would extend perception-based findings toward measurable audit performance indicators.

Comparative research across different emerging economies could also provide valuable insights into how institutional environments moderate the effectiveness of AI adoption. Given that credibility is socially constructed and influenced by regulatory acceptance (Baker et al., 2014), cross-country comparisons may reveal contextual variations in AI's impact.

Additionally, future research may incorporate moderating variables such as auditor technological competence, firm size, regulatory pressure, or organizational culture. These factors may influence how AI-enabled improvements translate into perceived or actual audit quality.

Finally, qualitative investigations could explore auditors' experiences in integrating AI tools into audit engagements, providing deeper insight into practical challenges and organizational adaptation processes.

This study demonstrates that AI adoption holds significant potential to enhance the quality of external audit reports in Libya. Although technological and institutional challenges remain, the empirical evidence suggests that AI-enabled improvements in analytical accuracy and credibility represent meaningful advancements for the auditing profession within an increasingly digitalized financial environment.

Compliance with ethical standards

Disclosure of conflict of interest

The author(s) declare that they have no conflict of interest.

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