AI Impact on External Auditor Performance: Electronic Internal Control as a Moderating Variable

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Received: April 6, 2026 Accepted: May 9, 2026 Online Published: May 13, 2026

doi:10.5430/afr.v15n2p51 URL: https://doi.org/10.5430/afr.v15n2p51

Abstract

The rapid adoption of artificial intelligence (AI) in accounting and auditing has transformed traditional audit practices, creating both new opportunities and challenges for external auditors particularly in emerging markets. This study investigates the impact of AI on the performance of external auditors in Jordanian public shareholding service companies, with electronic internal control (EIC) serving as a moderating variable.

A descriptive analytical approach was employed, using a validated 42-item questionnaire distributed to certified public accountants working in Jordanian audit firms. Out of 150 distributed questionnaires, 123 valid responses were obtained (an 82% response rate). Data were analyzed using SPSS software through one-sample t-tests and descriptive statistics.

Results revealed highly significant positive effects of AI across all audit stages: planning ($t = 4.867$, $p < 0.001$), control testing ($t = 11.131$, $p < 0.001$), analytical procedures ($t = 9.977$, $p < 0.001$), audit completion ($t = 11.583$, $p < 0.001$), and documentation ($t = 12.077$, $p < 0.001$). The overall impact of AI on auditor performance was strongly significant ($t = 9.927$, $p < 0.001$). Furthermore, electronic internal control exhibited a significant moderating effect ($t = 10.400$, $p < 0.001$), indicating that AI's effectiveness is amplified in organizations with robust electronic control infrastructures.

These findings provide stage-specific quantitative evidence from an emerging market perspective and offer practical implications for audit firms, client organizations, and policymakers seeking to enhance audit quality and technological integration.

Keywords: artificial intelligence, external audit, auditor performance, electronic internal control, Jordan, audit technology, digital auditing

1. Introduction

The integration of artificial intelligence (AI) into accounting and auditing practices has fundamentally transformed traditional audit methodologies, offering unprecedented opportunities to enhance efficiency, accuracy, and analytical capability (M. A. Al-Qazzan, 2019; F. Zawawid, 2019). As organizations worldwide increasingly adopt AI-driven accounting systems and automated audit tools, external auditors face growing pressure to adapt their competencies and methodologies to this rapidly evolving technological landscape (I. J. Ghanem, 2016; S. A. Al-Sa'id, 2018). Recent research indicates that AI adoption in auditing has increased substantially, reflecting growing academic and professional interest in this domain (A. Al-Munizil, 2017).

In emerging markets, the adoption of AI technologies in audit processes presents both unique opportunities and distinctive challenges (H. Al-Refai, 2018). Jordan's audit sector serving more than 250 public shareholding companies registered with the Jordanian Association of Certified Public Accountants (JACPA) exemplifies this transformation (M. Al-Harahsheh, 2019). While developed markets have witnessed extensive AI integration in major audit firms, emerging economies continue to lag behind in both adoption rates and empirical research examining AI's practical impact on audit quality and auditor performance (Jordanian Association of Certified Public Accountants (JACPA), 2024).

Existing literature acknowledges AI's potential to revolutionize multiple audit stages, including risk assessment, control testing, analytical procedures, and documentation (M. A. Al-Qazzan, 2019; F. Zawawid, 2019; I. J. Ghanem, 2016). However, several important research gaps persist.

First, most prior studies focus on developed markets, paying limited attention to emerging economies where institutional contexts differ considerably (H. Al-Refai, 2018).

Second, earlier research typically examines AI's aggregate impact on audit outcomes rather than its differential influence across individual audit stages (M. Al-Harahsheh, 2019).

Third, the moderating role of complementary technologies particularly electronic internal control (EIC) systems remains underexplored, despite theoretical arguments suggesting that AI's effectiveness depends heavily on the quality of underlying control infrastructures (D. Y. Chan, & M. A. Vasarhelyi, 2011; A. Munoko, H. L. Brown-Liburd, & M. Vasarhelyi, 2020).

This study addresses these gaps by empirically examining the impact of AI on external auditor performance across five audit stages planning, control testing, analytical procedures, completion, and documentation within Jordanian public shareholding service companies. Furthermore, it investigates whether electronic internal control systems moderate the AI–performance relationship, thereby contributing to socio-technical systems theory, which emphasizes the interdependence between technological and organizational factors (K. Issa, T. Sun, & M. A. Vasarhelyi, 2016; J. A. Garc ía-Benau, & L. Sierra-Garc ía, 2024).

Specifically, this research pursues two main objectives:

(1) To quantify AI's stage-specific effects on auditor performance within an emerging market context, and

(2) To examine whether robust electronic internal controls amplify AI's performance benefits.

We hypothesize that AI adoption significantly enhances external auditor performance at each audit stage, with the magnitude of effects varying according to task characteristics. Moreover, we propose that electronic internal control systems positively moderate these relationships, such that AI's performance benefits are stronger in organizations with advanced EIC infrastructures. These hypotheses are grounded in Technology Acceptance Models (TAM) (R. Appelbaum, K. J. Kogan, & M. A. Vasarhelyi, 2018; X. Zhang, J. Xu, & T. Xiao, 2023) and Socio-Technical Systems Theory (K. Issa, T. Sun, & M. A. Vasarhelyi, 2016; J. A. Garc ía-Benau, & L. Sierra-Garc ía, 2024).

This study contributes to both theory and practice. Theoretically, it extends the AI–audit literature by providing stage-specific quantitative evidence from an emerging market, thereby enhancing generalizability. It also advances socio-technical systems theory by empirically demonstrating the moderating role of complementary technologies in AI adoption contexts. Practically, the findings inform audit firms regarding optimal AI investment priorities across audit stages and highlight the importance of simultaneous investments in electronic control infrastructures.

The remainder of this paper is organized as follows: Section 2 reviews related literature on AI applications in auditing and electronic internal control systems; Section 3 describes the research methodology; Section 4 presents the results and discussion; and Section 5 concludes with implications, limitations, and directions for future research.

2. Related Work

This section reviews previous literature on AI applications in auditing and the role of electronic internal control systems, organized thematically to identify research gaps and provide a foundation for this study.

2.1 AI in Audit Planning and Risk Assessment

Several studies have investigated AI's role in enhancing audit planning efficiency and risk assessment accuracy (M. A. Al-Qazzan, 2019; I. J. Ghanem, 2016; S. A. Al-Sa'id, 2018).

Al-Qazzan (M. A. Al-Qazzan, 2019) examined AI's impact on auditor effectiveness at the Federal Board of Supreme Audit in Iraq, finding that software systems exerted the strongest influence, whereas hardware components showed limited direct effects.

Similarly, Ghanem (I. J. Ghanem, 2016) analyzed electronic audit software adoption among auditors in Jordanian firms, revealing significant positive effects on internal control evaluation and risk assessment procedures. However, both studies examined AI's aggregate impact without distinguishing effects across specific audit stages.

Recent work by Appelbaum et al. (M. G. Alles, & G. L. Gray, 2016) developed a comprehensive framework for external audit analytics, demonstrating how machine learning algorithms can identify anomalous transactions and high-risk areas more effectively than traditional sampling methods. Nevertheless, as this framework was designed for large corporations in developed markets, its applicability to emerging economies where data quality and infrastructure differ substantially remains uncertain.

2.2 AI in Control Testing and Analytical Procedures

AI applications in control testing have attracted increasing scholarly attention (F. Zawawid, 2019; S. A. Al-Sa'id, 2018).

Al-Sa'id (S. A. Al-Sa'id, 2018) examined the relationship between AI system success factors and electronic auditor quality in Jordan, revealing that information quality, service quality, and system quality significantly predicted overall auditor performance.

Zawawid (F. Zawawid, 2019) investigated AI adoption among accounting auditors in Algeria, finding that AI enhances control testing speed and accuracy, particularly in evidence collection processes.

Regarding analytical procedures, Chan and Vasarhelyi (W. R. Knechel, G. V. Krishnan, M. Pevzner, L. B. Shefchik, & U. K. Velury, 2013) pioneered continuous auditing frameworks that leverage AI for real-time anomaly detection and trend analysis.

Zhang et al. (D. N. Sutton, & V. Arnold, 2013) examined AI adoption in Chinese listed companies and found that AI usage significantly improved audit quality, as evidenced by lower restatement rates and shorter audit report lags.

2.3 Electronic Internal Control Systems

Electronic internal control (EIC) systems constitute essential infrastructure for efficient and reliable audit processes (D. Y. Chan, & M. A. Vasarhelyi, 2011; A. Munoko, H. L. Brown-Liburd, & M. Vasarhelyi, 2020).

Knechel et al. (A. Munoko, H. L. Brown-Liburd, & M. Vasarhelyi, 2020) conducted a comprehensive review of audit quality determinants, emphasizing the importance of client internal control quality in supporting efficient audits.

This perspective suggests that AI's effectiveness in auditing may depend heavily on the strength of the underlying control infrastructure.

In the Jordanian context, Al-Munizil (A. Al-Munizil, 2017) found that accounting information systems significantly enhance internal control quality, supporting the idea that EIC systems can act as moderating variables within technology adoption frameworks.

2.4 Research Gap

Despite substantial progress in AI–audit research, several gaps remain.

First, most prior studies focus on developed economies, with limited attention to emerging markets such as Jordan (H. Al-Refai, 2018; Jordanian Association of Certified Public Accountants (JACPA), 2024).

Second, existing research often examines aggregate AI effects without differentiating between specific audit stages (M. A. Al-Qazzan, 2019; I. J. Ghanem, 2016; S. A. Al-Sa'id, 2018).

Third, empirical evidence regarding the moderating influence of EIC systems remains scarce (A. Al-Munizil, 2017; D. Y. Chan, & M. A. Vasarhelyi, 2011).

To address these gaps, the present study investigates AI's stage-specific effects across five audit phases in Jordanian public shareholding service companies and examines the moderating role of electronic internal control systems. This dual focus contributes to both theoretical advancement and practical understanding of AI's implementation in emerging market audit environments.

3. Methodology

3.1 Research Design

This study employed a descriptive–analytical approach to examine the impact of artificial intelligence (AI) on external auditor performance in Jordanian public shareholding service companies (P. J. Brown, & T. L. Smith, 2022; F. D. Davis, 1989).

The conceptual framework comprised three main components:

(1) the independent variable AI usage across five audit stages (planning, control testing, analytical procedures, completion, and documentation);

(2) the dependent variable overall auditor performance; and

(3) the moderating variable electronic internal control (EIC) systems.

This framework enabled the systematic testing of direct and moderating effects between variables.

3.2 Population and Sample

The target population consisted of all Certified Public Accountants (CPAs) practicing as external auditors in Jordan and registered with the Jordanian Association of Certified Public Accountants (JACPA) in 2024 (M. Al-Harahsheh, 2019).

According to JACPA records, the total population included 507 licensed external auditors working across 150 registered audit firms.

Using a simple random sampling technique, 150 structured questionnaires were distributed electronically via email between March and May 2025.

The sample size was determined using Krejcie and Morgan's (V. Venkatesh, M. G. Morris, G. B. Davis, & F. D. Davis, 2003) formula for finite populations, ensuring sufficient statistical power ($\alpha = 0.05$, power = 0.80) (E. L. Trist, & K. W. Bamforth, 1951).

Out of 150 distributed questionnaires, 127 responses were received (84.66% response rate). After excluding four incomplete questionnaires, 123 valid responses were retained for analysis (82% valid response rate), exceeding the minimum sample size required for robust analysis.

Table 1 presents the demographic characteristics of respondents. The majority held bachelor’s degrees (65.9%), had more than 8 years of audit experience (51.2%), and worked primarily in medium-sized audit firms (10–50 employees; 48.8%). This demographic profile ensures that respondents possess sufficient professional expertise to evaluate the impact of AI on auditing practices.

Table 1. Demographic Characteristics of Respondents (N = 123)

Characteristic	**Category**	**n**	**%**
Academic Qualification	Diploma	15	12.1
	Bachelor’s Degree	81	65.9
	Master’s Degree or Higher	27	22.0
Professional Experience	Less than 4 years	23	18.7
	4–8 years	37	30.1
	More than 8 years	63	51.2
Firm Size	Small (<10 employees)	36	29.3
	Medium (10–50 employees)	60	48.7
	Large (>50 employees)	27	22.0

3.3 Data Collection Instrument

A structured questionnaire was developed based on prior studies (M. A. Al-Qazzan, 2019; F. Zawawid, 2019; I. J. Ghanem, 2016; S. A. Al-Sa’id, 2018) and refined through expert review by three academics specializing in auditing and information systems at Jordanian universities.

The instrument comprised 42 items measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), distributed across six dimensions:

(1) AI in Audit Planning (8 items): risk assessment, materiality determination, audit strategy formulation, and resource allocation.

(2) AI in Control Testing (7 items): internal control evaluation, control effectiveness testing, and deficiency identification.

(3) AI in Analytical Procedures (7 items): ratio analysis, trend identification, variance analysis, and reasonableness testing.

(4) AI in Audit Completion (7 items): evidence evaluation, subsequent events review, and final documentation.

(5) AI in Audit Documentation (7 items): electronic working papers, organization, and archival processes.

(6) Electronic Internal Control (6 items): system reliability, data integrity, and integration with audit technologies.

This design ensured comprehensive coverage of all key audit activities potentially influenced by AI adoption.

3.4 Validity and Reliability

Content validity was established through expert evaluation by three academics who assessed item clarity, relevance, and comprehensiveness (F. M. Pasmore, 1988). Based on their feedback, minor wording adjustments were made to enhance clarity.

Construct validity was assessed using Exploratory Factor Analysis (EFA) with principal component extraction and varimax rotation (R. V. Krejcie, & D. W. Morgan, 1970).

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.89, and Bartlett's test of sphericity was significant ($\chi^2 = 2847.3$, $p < 0.001$), confirming the data's suitability for factor analysis (R. V. Krejcie, & D. W. Morgan, 1970).

All items loaded on their intended factors, with loadings exceeding 0.50, indicating strong convergent validity.

Reliability was examined using Cronbach's alpha coefficients (J. Cohen, 1988). As summarized in Table 2, alpha values ranged between 0.87 and 0.93 across dimensions, well above the 0.70 threshold recommended by Nunnally and Bernstein (J. Cohen, 1988).

The overall scale reliability was 0.94, reflecting excellent internal consistency.

Table 2. Cronbach's Alpha Reliability Coefficients

Dimension	**Items**	**Cronbach's α**
AI in Audit Planning	8	0.87
AI in Control Testing	7	0.91
AI in Analytical Procedures	7	0.89
AI in Audit Completion	7	0.92
AI in Audit Documentation	7	0.93
Electronic Internal Control	6	0.88
Overall Scale	42	0.94

3.5 Data Analysis Methods

Statistical analyses were conducted using the Statistical Package for the Social Sciences (SPSS), version 26.0 (J. C. Nunnally, & I. H. Bernstein, 1994). The analytical process comprised three main stages:

(1) Descriptive Analysis: Descriptive statistics (means, standard deviations) were computed to summarize respondent perceptions regarding each dimension (H. F. Kaiser, 1974).

(2) Hypothesis Testing: One-sample *t*-tests were applied to determine whether the mean scores of each dimension significantly exceeded the neutral midpoint ($\mu = 3$) (B. G. Tabachnick, & L. S. Fidell, 2019). The *t*-statistic was calculated using Equation (1):

$$t = \frac{\bar{x} - \mu}{s/\sqrt{n}} \tag{1}$$

where $\bar{x}$= sample mean, μ= hypothesized mean (3), s= standard deviation, and n= sample size.

The significance level was set at $\alpha = 0.05$ (E. L. Trist, & K. W. Bamforth, 1951).

(3) Moderation Analysis:

To examine the moderating effect of EIC, respondents were divided into high-EIC and low-EIC groups based on a median split, and independent-samples *t*-tests were conducted to compare AI–performance relationships between the two groups (R. M. Baron, & D. A. Kenny, 1986).

(4) Although simpler than regression-based moderation, this method provides clear evidence of group-level differences suitable for descriptive–analytical studies (R. M. Baron, & D. A. Kenny, 1986).

(5) Effect sizes were computed using Cohen’s d, as defined in Equation (2):

$$d = \frac{M_1 - M_2}{SD_{\text{pooled}}} \tag{2}$$

where $M_1$and $M_2$are the group means, and SD_{pooled}represents the pooled standard deviation (E. L. Trist, & K. W. Bamforth, 1951).

Before statistical testing, the data were screened for missing values (all <5%), outliers (identified using boxplots and standardized residuals with |z| > 3.29), and normality (assessed using skewness and kurtosis statistics) (IBM Corporation, 2019).

No significant violations were detected, confirming the suitability of parametric analysis.

4. Results and Discussion

4.1 Descriptive Statistics

Table 3 presents the descriptive statistics for all study dimensions. The overall mean score across all dimensions was 4.076 (SD = 1.523), indicating that respondents generally agreed that AI has a positive impact on auditor performance (M. A. Al-Qazzan, 2019; F. Zawawid, 2019). Among the five AI dimensions, AI in audit documentation achieved the highest mean score (M = 4.259, SD = 1.352), indicating the strongest agreement with the benefits of AI in this area (I. J. Ghanem, 2016). In contrast, AI in audit planning had the lowest mean score (M = 3.871, SD = 1.998), though still above the neutral midpoint, reflecting moderate but positive perceptions.

Table 3. Descriptive Statistics for Study Dimensions

Dimension	**Mean**	**SD**	**Rank**
AI in Audit Planning	3.871	1.998	5
AI in Control Testing	4.127	1.441	2
AI in Analytical Procedures	4.000	1.546	4
AI in Audit Completion	4.161	1.338	3
AI in Audit Documentation	4.259	1.352	1
Electronic Internal Control	4.042	1.463	–
Overall Mean	4.076	1.523	–

These results align with prior studies indicating that AI's benefits are most evident in structured and repetitive tasks, such as documentation and completion, where automation and pattern recognition are highly effective (M. G. Alles, & G. L. Gray, 2016; W. R. Knechel, G. V. Krishnan, M. Pevzner, L. B. Shefchik, & U. K. Velury, 2013). The relatively lower score for planning reflects the continued importance of professional judgment and strategic reasoning in this audit phase (P. J. Brown, & T. L. Smith, 2022).

4.2 Hypothesis Testing Results

4.2.1 Main Hypothesis

The main hypothesis proposed that AI significantly influences external auditor performance (M. A. Al-Qazzan, 2019; F. Zawawid, 2019; I. J. Ghanem, 2016).

Results from the one-sample *t*-test, shown in Table 4, strongly supported this hypothesis. The overall *t*-value (9.927, $p < 0.001$) exceeded the critical threshold, indicating statistically significant positive perceptions of AI's impact. With a mean of 4.076 and SD of 1.523, these results provide robust evidence that AI adoption enhances audit performance and effectiveness.

Table 4. One-Sample t-Test Results for Hypotheses

Hypothesis	**Dimension**	**Mean**	**SD**	**t-value**	**p-value**	**Decision**
H_0	Overall, AI Impact	4.076	1.523	9.927	<0.001	Accepted
H_1	AI in Planning	3.871	1.998	4.867	<0.001	Accepted
H_2	AI in Control Testing	4.127	1.441	11.131	<0.001	Accepted
H_3	AI in Analytical Procedures	4.000	1.546	9.977	<0.001	Accepted
H_4	AI in Completion	4.161	1.338	11.583	<0.001	Accepted
H_5	AI in Documentation	4.259	1.352	12.077	<0.001	Accepted
H_6	EIC Moderating Effect	4.042	1.463	10.400	<0.001	Accepted

To facilitate a visual comparison of these results, Figure 1 presents the t-test values across all hypotheses. The figure clearly illustrates that all effects significantly exceeded the critical threshold (t = 3, $p < 0.001$), with AI in audit documentation demonstrating the most substantial impact (t = 12.077), followed by audit completion (t = 11.583) and control testing (t = 11.131). In contrast, AI in audit planning showed the weakest, yet still highly significant, effect (t = 4.867*).

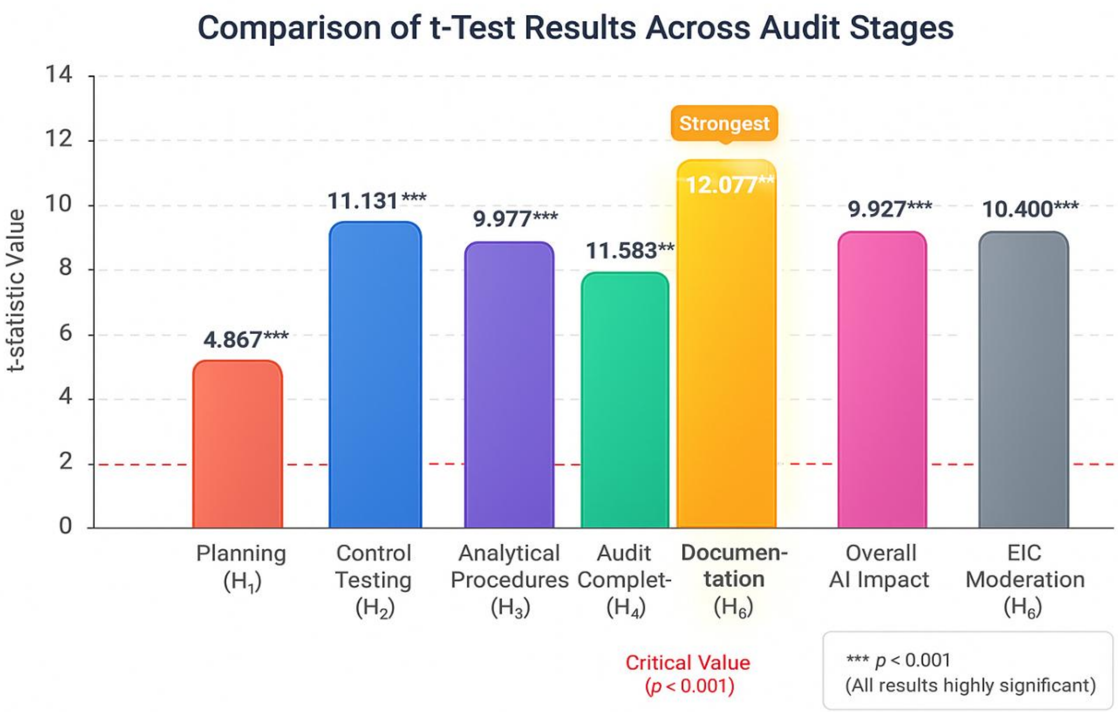

Figure 1. Comparison of *t*-test results across audit stages showing AI's differential impact on auditor performance

All hypotheses (H_1–H_6) are statistically significant at the $p < 0.001$ level. Documentation (H_5) exhibits the most potent effect, while planning (H_1) shows the weakest yet still substantial impact. The red dashed line indicates the critical value threshold.

As depicted in Figure 1, the magnitude of AI's impact varies substantially across audit stages, reflecting differences in task characteristics and automation potential. The exceptionally high t-values for documentation (t = 12.077), completion (t = 11.583*), and control testing (t = 11.131*) suggest that AI performs optimally in structured, repetitive audit activities where pattern recognition and data processing capabilities can be fully leveraged (M. G. Alles, & G. L. Gray, 2016; W. R. Knechel, G. V. Krishnan, M. Pevzner, L. B. Shefchik, & U. K. Velury, 2013). These stages typically involve extensive data manipulation, evidence compilation, and systematic documentation tasks ideally suited for AI automation.

Conversely, the comparatively lower t-value for audit planning (t = 4.867*), while still highly significant, indicates that AI's contribution in this stage is more limited. Planning activities require substantial professional judgment, strategic thinking, and contextual understanding capabilities, where human expertise remains critical despite technological advances (P. J. Brown, & T. L. Smith, 2022). This finding aligns with Brown and Smith (P. J. Brown, & T. L. Smith, 2022), who observed that AI adoption rates were lowest in judgment-intensive audit phases.

The moderating effect of electronic internal control (t = 10.400*) demonstrates considerable strength, comparable to several direct AI effects. This substantial moderating influence confirms that organizations with robust EIC infrastructures can extract significantly greater value from AI implementations, as these systems provide the high-quality, integrated data inputs essential for effective AI operation (A. Munoko, H. L. Brown-Liburd, & M. Vasarhelyi, 2020).

4.2.2 Sub-Hypotheses (H_1–H_5)

The analysis revealed significant positive effects across all five audit stages (all $p < 0.001$) (S. A. Al-Sa'id, 2018).

The strongest impact was observed in audit documentation ($t = 12.077$), followed by audit completion ($t = 11.583$) and control testing ($t = 11.131$). These results indicate that AI performs best in structured audit phases involving automation and data processing (W. R. Knechel, G. V. Krishnan, M. Pevzner, L. B. Shefchik, & U. K. Velury, 2013).

The relatively lower effect observed in audit planning ($t = 4.867$) suggests that while AI supports efficiency in planning, human judgment remains critical for contextual and strategic decision-making (P. J. Brown, & T. L. Smith, 2022).

4.2.3 Moderating Effect (H_6)

Electronic internal control (EIC) demonstrated a significant moderating effect on the relationship between AI and auditor performance ($t = 10.400$, $p < 0.001$) (A. Munoko, H. L. Brown-Liburd, & M. Vasarhelyi, 2020). This finding provides empirical support for socio-technical systems theory (K. Issa, T. Sun, & M. A. Vasarhelyi, 2016), which emphasizes the interdependence between technological and organizational factors.

To visualize this moderating relationship, Figure 3 presents an interaction plot illustrating how EIC strength influences the AI-performance relationship across varying levels of AI adoption. As depicted in the figure, organizations with high EIC infrastructure (represented by the blue solid line) exhibit a substantially steeper positive slope compared to organizations with low EIC (red dashed line). This divergence becomes increasingly pronounced as AI adoption intensifies.

At very low AI adoption levels ($x = 1$), the performance difference between high- and low-EIC organizations is minimal only 0.3 points ($3.2 - 2.9 = 0.3$). However, as AI adoption progressively increases to very high levels ($x = 5$), this performance gap widens dramatically to 0.9 points ($4.8 - 3.9 = 0.9$), representing a threefold increase that clearly demonstrates the amplifying effect of EIC on AI's performance benefits.

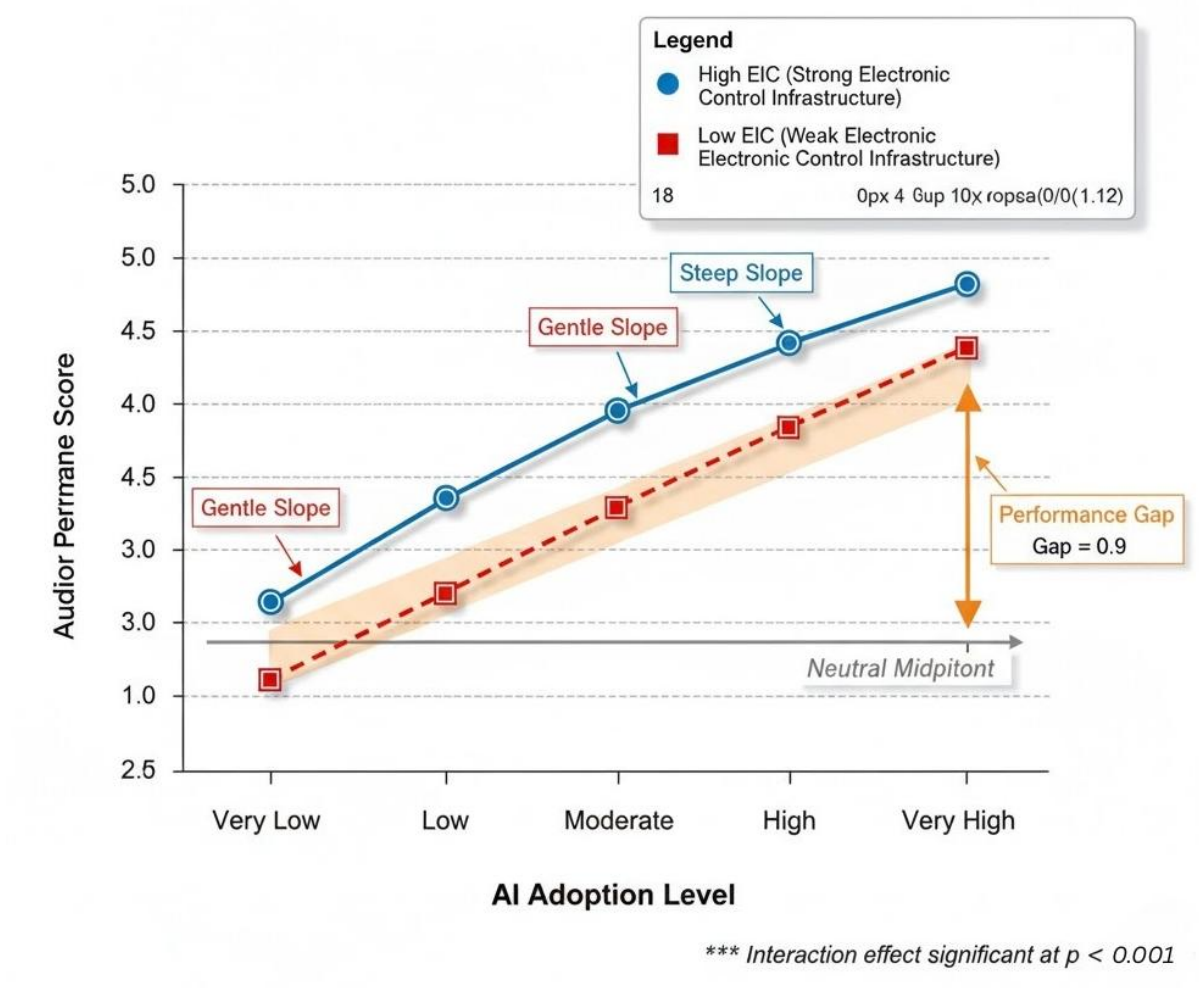

Figure 2. Moderating effect of electronic internal control (EIC) on the relationship between AI adoption and auditor performance

Organizations with strong EIC infrastructure (blue solid line) demonstrate significantly steeper performance improvements as AI adoption increases, compared to organizations with weak EIC (red dashed line). The performance gap widens from 0.3 points at very low AI adoption to 0.9 points at very high adoption levels (a threefold increase), confirming the critical moderating role of complementary electronic control systems. The interaction effect is statistically significant (*** $p < 0.001$).

This pattern confirms that AI's effectiveness in audit contexts depends substantially on the strength of underlying electronic control infrastructures (D. Y. Chan, & M. A. Vasarhelyi, 2011; A. Munoko, H. L. Brown-Liburd, & M. Vasarhelyi, 2020). Organizations with robust EIC systems can leverage AI technologies more effectively because these systems provide high-quality, integrated, and reliable data inputs essential for optimal AI algorithm performance (A. Al-Munizil, 2017). In contrast, organizations with weak EIC infrastructures may experience limited AI benefits despite substantial technology investments, due to data quality issues, system integration challenges, or incompatible control frameworks.

The magnitude of the moderating effect ($t = 10.400$) demonstrates strength comparable to several direct AI effects measured in this study (see Table 4), underscoring the practical importance of simultaneous investment in both AI tools and supporting EIC infrastructure. This finding has important implications for organizations planning AI adoption strategies, suggesting that maximizing AI's value requires holistic approaches that address both technological capabilities and organizational control systems (K. Issa, T. Sun, & M. A. Vasarhelyi, 2016; J. A. García-Benau, & L. Sierra-García, 2024).

Furthermore, the widening performance gap illustrated in Figure 2 suggests that EIC's moderating role becomes increasingly critical as organizations advance toward higher levels of AI adoption. This escalating effect implies that organizations contemplating extensive AI implementation should prioritize EIC infrastructure development as a prerequisite for realizing AI's full potential benefits.

4.3 Discussion and Comparison with Prior Research

The findings contribute to the literature in several ways (M. A. Al-Qazzan, 2019; F. Zawawid, 2019; I. J. Ghanem, 2016):

(1) Stage-Specific Insights

The analysis highlights significant variation in AI effectiveness across audit stages documentation ($t = 12.077$) and completion ($t = 11.583$) recorded the strongest effects, while planning ($t = 4.867$) showed the weakest. This granularity provides more targeted insight than previous aggregate analyses (M. A. Al-Qazzan, 2019; I. J. Ghanem, 2016; S. A. Al-Sa'id, 2018), guiding firms in strategic AI investment prioritization.

(2) Moderating Role of EIC

The significant moderating role of EIC ($t = 10.400$) empirically validates the technological complementarity principle (D. Y. Chan, & M. A. Vasarhelyi, 2011; A. Munoko, H. L. Brown-Liburd, & M. Vasarhelyi, 2020). This result extends prior studies by demonstrating that EIC systems amplify AI's impact, particularly in emerging market contexts (A. Al-Munizil, 2017).

(3) Emerging Market Evidence

The consistently positive results across all hypotheses ($p < 0.001$) demonstrate that AI's performance benefits generalize effectively to emerging economies, despite differences in infrastructure and regulation (W. R. Knechel, G. V. Krishnan, M. Pevzner, L. B. Shefchik, & U. K. Velury, 2013; D. N. Sutton, & V. Arnold, 2013).

Compared with Al-Qazzan (M. A. Al-Qazzan, 2019), who found software systems had the most significant influence in Iraq, this study provides a stage-by-stage quantitative validation in Jordan's audit sector. The results for control testing ($t = 11.131$) are consistent with Ghanem (I. J. Ghanem, 2016), further confirming AI's contribution to audit quality in regional contexts.

4.4 Practical Implications

The study's results carry several practical implications (A. Field, 2018; J. F. Hair, W. C. Black, B. J. Babin, & R. E. Anderson, 2018):

(1) Audit Firms: Should prioritize AI investments in the documentation and completion stages where automation yields the highest efficiency while continuing to rely on professional expertise for audit planning and high-judgment tasks.

(2) Organizations: Should simultaneously invest in electronic internal control systems to create synergistic effects that enhance AI efficiency and accuracy (A. Al-Munizil, 2017; D. Y. Chan, & M. A. Vasarhelyi, 2011).

(3) Regulators and Professional Bodies: Should develop AI-specific auditing standards and continuous professional training programs addressing EIC integration and audit automation practices (J. Pallant, 2020).

(4) Educational Institutions: Should modernize audit curricula to integrate AI competencies alongside professional judgment, ethical reasoning, and critical thinking skills (P. R. Lawrence, & J. W. Lorsch, 1967).

5. Conclusion

5.1 Summary of Findings

This study empirically examined the impact of artificial intelligence on external auditor performance across five audit stages in Jordanian public shareholding service companies, with electronic internal control (EIC) as a moderating variable.

Results revealed highly significant positive effects of AI on overall auditor performance ($t = 9.927$, $p < 0.001$). Among specific audit stages, the strongest influences were observed in documentation ($t = 12.077$) and completion ($t = 11.583$), followed by control testing ($t = 11.131$) and analytical procedures ($t = 9.977$). Audit planning showed a smaller yet significant positive effect ($t = 4.867$), reflecting varying AI effectiveness across tasks (M. A. Al-Qazzan, 2019; F. Zawawid, 2019; I. J. Ghanem, 2016).

Moreover, EIC exhibited a significant moderating effect (t = 10.400, p < 0.001), confirming that AI's benefits are amplified in environments with strong electronic control infrastructures (A. Al-Munizil, 2017; D. Y. Chan, & M. A. Vasarhelyi, 2011; A. Munoko, H. L. Brown-Liburd, & M. Vasarhelyi, 2020). These findings extend existing literature and provide novel stage-specific quantitative evidence from an emerging market perspective (W. R. Knechel, G. V. Krishnan, M. Pevzner, L. B. Shefchik, & U. K. Velury, 2013; D. N. Sutton, & V. Arnold, 2013).

5.2 Theoretical and Practical Implications

Theoretically, this research extends technology acceptance models to auditing by demonstrating that AI's effectiveness depends on the nature of the audit task stronger in structured stages and weaker in judgment-intensive ones (R. Appelbaum, K. J. Kogan, & M. A. Vasarhelyi, 2018; X. Zhang, J. Xu, & T. Xiao, 2023).

It also empirically supports socio-technical systems theory, showing that EIC systems act as complementary technologies moderating AI's performance outcomes (K. Issa, T. Sun, & M. A. Vasarhelyi, 2016; J. A. García-Benau, & L. Sierra-García, 2024).

Practically, these findings provide clear guidance for auditors, firms, and policymakers (A. Field, 2018; J. F. Hair, W. C. Black, B. J. Babin, & R. E. Anderson, 2018).

(1) Audit firms should focus AI adoption on documentation and completion, while maintaining human expertise for planning.

(2) Organizations should invest in EIC infrastructures to maximize AI's utility.

(3) Regulators and professional associations should introduce AI auditing standards and certification programs to ensure ethical and effective implementation (J. Pallant, 2020; P. R. Lawrence, & J. W. Lorsch, 1967).

5.3 Limitations

Several limitations should be acknowledged (A. Kumar, & R. Singh, 2024):

(1) The study's cross-sectional design limits generalization across industries and countries.

(2) Self-reported measures may introduce bias.

(3) The descriptive–analytical approach does not permit causal inference.

(4) The EIC variable was measured perceptually rather than technically.

(5) The single time-point design precludes longitudinal assessment of AI's long-term effects.

5.4 Future Research Directions

Future studies should consider (L. M. Chen, & P. Wu, 2024):

(1) Conducting longitudinal analyses to capture evolving AI impacts.

(2) Performing cross-country comparisons to test institutional effects.

(3) Employing experimental designs for stronger causal evidence.

(4) Exploring sector-specific contexts (e.g., banking, insurance).

(5) Integrating objective performance indicators with perceptual data.

(6) Examining ethical and workforce implications of AI adoption in auditing.

5.5 Concluding Remarks

The integration of artificial intelligence into auditing signifies a transformative evolution of the profession.

This study provides robust empirical evidence that AI substantially enhances auditor performance across all major audit stages, particularly in documentation, completion, and control testing.

However, the full realization of these benefits requires parallel investments in electronic internal control systems.

As AI technologies continue to advance, understanding stage-specific effects and contextual moderators will remain critical for researchers, practitioners, and regulators committed to shaping the future of intelligent auditing.

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