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HUMAN-AI COLLABORATION IN INTERNAL AUDITING: THE MODERATING ROLE OF FINANCIAL REPORTING QUALITY

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ABSTRACT

This study examines how artificial intelligence (AI) capabilities influence the quality of internal auditing (QIA) within a human-AI collaborative framework. It also investigates whether the quality of financial reports (QFR) moderates this relationship.

The study applies a quantitative, cross-sectional survey design. Data were collected from 150 employees working in accounting and audit-related roles in Jordanian industrial companies listed on the Amman Stock Exchange. The proposed model was tested using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4. AI capabilities were examined through four dimensions: expert systems (ES), algorithms (A), artificial neural networks (ANN), and intelligent agents (IA).

All four AI capability dimensions have positive and statistically significant effects on QIA. Algorithms exert the strongest effect, followed by intelligent agents, expert systems, and artificial neural networks. The interaction between AI capabilities and QFR is also positive and statistically significant. This indicates that AI capabilities contribute more strongly to QIA when financial reports are accurate, complete, timely, and reliable.

The study conceptualises internal auditing as a socio-technical process in which AI capabilities complement rather than replace auditors' professional judgement. It extends the literature by identifying QFR as a contextual condition that shapes the effectiveness of AI-enabled internal auditing.

Organisations should combine investment in AI tools with improvements in financial reporting systems, data governance, auditors' digital competencies, and human-in-the-loop procedures. Reliable financial information and professional oversight are necessary to realise the benefits of AI-enabled internal auditing.

KEY WORDS

artificial intelligence capabilities, human-AI collaboration, internal audit quality, financial reporting quality, audit effectiveness

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INTRODUCTION

Digital technologies, including artificial intelligence (AI), are reshaping organisational processes across industries. In accounting and auditing, AI represents the operationalisation of human knowl-

edge and expertise in intelligent systems capable of performing complex analytical and decision-support tasks (Zaqeeba & Iskandar, 2020a). Auditors therefore need advanced digital, analytical, and cognitive competencies to work effectively in technology-enhanced environments (Lutfi et al., 2024). This change is particularly relevant to internal auditing, where AI is

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redefining traditional audit practices and performance expectations.

Contemporary auditing is better understood as a socio-technical system in which audit outcomes emerge from the interaction between technological capabilities, human expertise, and organisational processes (Singh et al., 2025). AI augments rather than replaces auditors, enabling the automation of routine procedures while preserving the central role of professional judgement, scepticism, and contextual interpretation (Tiron-Tudor & Deliu, 2022; Singh et al., 2025). Auditors and intelligent systems thus operate as interdependent components of decision-making processes. The human-in-the-loop (HITL) approach retains human oversight and validation of algorithmic outputs, supporting transparency, accountability, and audit reliability (Tiron-Tudor & Deliu, 2022). From a management perspective, this interaction represents value co-creation within a hybrid collaboration network: audit quality emerges from the combined use of human judgement and machine-driven analytics.

Financial reporting remains essential to transparency and trust in organisational performance. However, the increasing complexity of global markets and recurring financial crises have exposed the limitations of traditional reporting frameworks in delivering timely, reliable, and decision-relevant information (Zaqeeba & Iskandar, 2020b). Digitalisation has improved access to financial information, yet challenges related to data integrity, security, and reliability persist. Organisations increasingly use advanced technologies, including AI, to improve the quality and timeliness of financial information and support decision-making.

AI capabilities, such as expert systems (ES), algorithms (A), artificial neural networks (ANN), and intelligent agents (IA), can improve the efficiency, accuracy, and scope of auditing activities. They enable auditors to process large volumes of structured and unstructured data, detect anomalies, and support risk assessment, thereby contributing to improved quality of internal auditing (QIA) and reduced audit risk (Almatarnneh et al., 2023). Their effectiveness depends on the quality of the underlying data and reporting systems. Information quality is therefore an enabling condition for AI-enabled auditing.

The quality of financial reports (QFR) shapes the outcomes of AI-enabled auditing processes. Accurate, complete, consistent, and timely reports provide a reliable information base for human judgement and algorithmic analysis. Deficiencies in QFR may under-

mine AI performance and lead to biased or inaccurate audit conclusions. QFR can therefore be conceptualised as a moderating variable that conditions the relationship between AI capabilities and QIA.

Despite the growing adoption of AI in auditing, existing research has focused primarily on technological capabilities and efficiency gains. Less attention has been paid to the conditions under which human-AI collaboration improves internal audit outcomes. In particular, the moderating role of QFR remains underexplored. This study addresses that gap by examining how AI capabilities influence QIA within a socio-technical framework and whether QFR moderates this relationship. It links auditing, information systems, and management perspectives to explain how technological and organisational factors jointly shape audit performance.

The remainder of the article is organised as follows. Section 1 reviews the literature and develops the hypotheses, with particular attention to the socio-technical character of internal auditing, AI capabilities, human-AI collaboration, and the moderating role of QFR. Section 2 outlines the research design, sample, data collection procedure, and PLS-SEM approach. Section 3 reports the empirical results, including the assessment of the measurement and structural models and the moderation analysis. Section 4 discusses the findings in relation to prior research and considers their theoretical and practical implications. The paper concludes by summarising the main findings, acknowledging the study's limitations, and identifying directions for future research.

1. LITERATURE REVIEW

1.1. INTERNAL AUDITING AS A SOCIO-TECHNICAL SYSTEM

The interaction between digital technologies, human expertise, organisational governance, and information quality shapes internal auditing. Rather than being a purely procedural control activity, internal auditing can be conceptualised as a socio-technical system in which audit outcomes emerge from the joint operation of technological and human components. In this system, AI technologies support data processing, anomaly detection, risk assessment, and continuous monitoring, while internal auditors remain responsible for professional judgement, contextual interpretation, ethical reasoning, and decision

validation (Tiron-Tudor & Deliu, 2022; Singh et al., 2025).

This perspective is particularly relevant to internal auditing because the internal audit function (IAF) is not limited to verifying transactions. It also contributes to risk management, governance, internal control evaluation, and organisational learning. AI can enhance the IAF by reducing manual procedures, enabling broader audit coverage, and supporting value-adding assurance activities (Wassie & Lakatos, 2024). However, the effectiveness of AI in internal auditing depends on how it is embedded in audit workflows, how auditors interact with AI-generated outputs, and whether organisations provide adequate access, skills, governance, and commitment to support AI adoption (Wassie & Lakatos, 2024).

This study therefore treats AI as a complement to, rather than a substitute for, internal auditors. AI capabilities operate within a human-AI collaborative audit framework in which QIA emerges from the combined use of machine-driven analytics and human judgement. This view is consistent with the HITL perspective: algorithmic outputs require continuous monitoring, interpretation, and validation by human experts (Tiron-Tudor & Deliu, 2022).

Research on collaborative auditing further suggests that effective use of AI depends on communication, sensemaking, and users' ability to guide and test AI outputs. Rastogi et al. (2023) show that collaborative auditing tools are most effective when machine-generated suggestions are combined with human strengths such as hypothesis testing and semantic interpretation. For internal auditors, the task is not simply to use AI outputs but to assess their reliability and relevance to governance and control.

1.2. AI CAPABILITIES IN INTERNAL AUDITING

AI capabilities refer to the ability of AI-enabled systems to automate audit tasks, process large volumes of data, detect irregularities, support risk assessment, and generate audit-relevant insights. In this study, AI capabilities are conceptualised as a multidimensional construct comprising expert systems (ES), algorithms (A), artificial neural networks (ANN), and intelligent agents (IA). These capabilities represent different but complementary forms of AI-enabled support within the internal audit process.

Expert systems (ES) are AI-based tools designed to simulate the reasoning processes of human experts. In auditing, they can support compliance assessment, risk classification, control evaluation, and knowledge-

based decision-making. Prior research indicates that ES improve audit precision, enhance irregularity detection, and help auditors apply structured professional knowledge in complex audit environments (O'Leary & Watkins, 1989; Kizmaz et al., 2018; Jebiril et al., 2023). By formalising expert knowledge in rule-based or knowledge-based systems, ES can reduce inconsistency in audit procedures and support more reliable audit judgements.

Algorithms (A), understood in this study as algorithmic analysis, refer to the use of computational procedures to identify patterns, exceptions, and risks in large datasets. Algorithmic tools allow internal auditors to move beyond traditional sampling and towards broader or population-level testing. This enhances the ability to detect unusual transactions, identify control weaknesses, and prioritise audit areas with higher risk exposure (Boskou et al., 2019; Raji et al., 2020). However, algorithmic outputs require human interpretation, as algorithms may reproduce bias, reflect poor data quality, or generate results that are technically accurate but contextually misleading (Tiron-Tudor & Deliu, 2022; Graves & Ratti, 2025).

Artificial neural networks (ANN) are particularly useful for predictive and pattern-recognition tasks. In internal auditing, ANN can support fraud detection, anomaly identification, financial pattern prediction, and risk forecasting. Previous studies suggest that neural networks can reduce human error, increase the reliability of audit results, and improve auditors' ability to detect hidden relationships in financial data (Ali et al., 2022; Qasaimeh et al., 2022b; Ajayi & Akinrinola, 2023; Zaqeeba, 2024). Their value is especially evident in audit environments characterised by complex, high-volume, and non-linear data structures.

Intelligent agents (IA) are AI-enabled systems capable of performing tasks autonomously or semi-autonomously, such as continuous monitoring, automated data collection, exception reporting, and real-time alerts. These systems can improve internal audit efficiency by automating repetitive audit activities and enabling auditors to focus on complex analytical tasks (Qasaimeh et al., 2022a; Ali et al., 2022). IA can also support broader audit scope and timelier risk detection, especially in environments where financial and operational data are generated continuously (Kovanen, 2020; Seethamraju & Hecimovic, 2020).

Taken together, these capabilities can strengthen QIA by widening audit coverage, supporting risk-based planning, and improving audit evidence. Their

value, however, depends on auditors' ability to interpret and validate AI outputs. AI capabilities operate within collaborative audit processes rather than as stand-alone technological assets.

1.3. HUMAN-AI COLLABORATION AND THE QUALITY OF INTERNAL AUDITING (QIA)

QIA refers to the extent to which the internal audit function provides reliable, timely, independent, and value-adding assurance and advisory services. High-quality internal auditing supports effective governance, risk management, internal control, and organisational decision-making. In AI-enabled environments, QIA is shaped by both the technical capabilities of AI tools and auditors' professional capabilities.

More broadly, human-AI collaboration can be understood as a hybrid collaborative network in which human actors, AI tools, data infrastructures, and governance arrangements interact to produce context-dependent outcomes. Jurczuk et al. (2026) showed that the effectiveness of such networks depends on the alignment between technological capabilities, human-centred practices, and the surrounding context. Applied to internal auditing, this perspective suggests that QIA depends not only on the availability of AI tools but also on how effectively they are integrated with auditors' expertise, reporting systems, and governance mechanisms.

AI can enhance QIA by automating repetitive and rule-based activities, allowing auditors to devote more attention to judgement-intensive tasks. It also enables the analysis of larger datasets, improves anomaly detection, and supports continuous auditing and real-time risk monitoring (Alhazmi et al., 2025; Singh et al., 2025; Wassie & Lakatos, 2024).

AI-enabled internal auditing also creates risks, including algorithmic opacity, bias, limited explainability, overreliance on automated outputs, and concerns about data use and accountability (Tiron-Tudor & Deliu, 2022; Graves & Ratti, 2025). These risks increase the importance of the auditor's role. Internal auditors must validate AI-generated evidence, assess the reasonableness of algorithmic recommendations, and ensure that audit conclusions remain aligned with organisational objectives, professional standards, and ethical requirements.

HITL provides a useful lens for understanding this relationship. AI generates insights, detects irregularities, and accelerates analysis, while auditors retain responsibility for oversight, interpretation, and final

judgement (Tiron-Tudor & Deliu, 2022). QIA is therefore expected to improve when AI capabilities and auditor expertise are integrated effectively. Accordingly, the following hypothesis is proposed:

H1: AI capability dimensions positively influence the quality of internal auditing (QIA) within a human-AI collaborative framework.

Because AI capabilities are multidimensional, H1 is examined through the following sub-hypotheses:

H1a: Expert systems (ES) positively influence the quality of internal auditing (QIA) within a human-AI collaborative framework.

H1b: Algorithms (A) positively influence the quality of internal auditing (QIA) within a human-AI collaborative framework.

H1c: Artificial neural networks (ANN) positively influence the quality of internal auditing (QIA) within a human-AI collaborative framework.

H1d: Intelligent agents (IA) positively influence the quality of internal auditing (QIA) within a human-AI collaborative framework.

1.4. QUALITY OF FINANCIAL REPORTS (QFR) AS A MODERATOR

QFR reflects the extent to which financial reports provide accurate, relevant, complete, timely, comparable, and faithfully represented information. High-quality financial reports reduce information asymmetry, support stakeholder decision-making, and strengthen organisational transparency (Alassuli et al., 2025; Wang & Liang, 2025). In the context of internal auditing, QFR is particularly important because audit procedures rely on the quality of underlying accounting data, financial disclosures, and reporting systems.

Prior research suggests that AI can improve financial reporting quality by enhancing data processing, reducing human error, improving anomaly detection, supporting real-time reporting, and strengthening compliance with financial standards (Alhazmi et al., 2025; Alassuli et al., 2025). Alassuli et al. (2025) found that AI improves the quality of financial reports directly and indirectly through the development of accountants' skills, while Alhazmi et al. (2025) emphasise that AI adoption can improve reporting accuracy, audit efficiency, and regulatory compliance. These findings suggest that AI and QFR are closely interconnected.

QFR also shapes the effectiveness of AI-enabled internal auditing. AI systems depend on the quality of their input data. Accurate, complete, consistent, and

timely reports support more reliable audit insights and make validation easier. Poor reporting quality can weaken the value of AI capabilities by introducing incomplete data, inconsistent classifications, unreliable disclosures, or biased patterns. This is the familiar “garbage in, garbage out” problem associated with data-driven systems.

Governance-related literature provides further support for this argument. Wang and Liang (2025) showed that internal audit independence enhances financial reporting quality by reducing managerial interference and improving transparency. High-quality reporting environments provide a stronger information base for internal audit activities. In such settings, AI capabilities are more likely to improve QIA because auditors can rely on more credible and decision-useful information.

QFR therefore conditions the strength of the relationship between AI capabilities and QIA. When QFR is high, AI systems and auditors work with more reliable information. When QFR is low, data integrity problems and reporting deficiencies constrain AI-generated insights. The positive effect of AI capabilities on QIA is therefore expected to be stronger when QFR is higher. Accordingly, the following hypothesis is proposed:

H2: Quality of financial reports (QFR) positively moderates the relationship between AI capabilities and the quality of internal auditing (QIA).

1.5. RESEARCH MODEL SUMMARY

Based on these arguments, this study proposes a socio-technical model of AI-enabled internal auditing. The model assumes that AI capabilities improve QIA when they operate within a human-AI collaborative system. AI provides analytical, predictive, and automation capabilities, while internal auditors contribute professional judgement, interpretation, ethical oversight, and decision validation. QFR is expected to strengthen this relationship by providing reliable information for both AI systems and auditors.

The model extends the literature by framing AI adoption as a collaboration issue rather than a substitution issue, treating AI capabilities as multidimensional technological resources, and identifying QFR as a condition that shapes their effect on QIA.

The study employed partial least squares structural equation modelling (PLS-SEM) using SmartPLS 4. PLS-SEM was considered appropriate because the study tests a prediction-oriented model involving multiple latent constructs and a moderating relationship. The analysis was conducted in three stages. The first stage presents the demographic characteristics of the respondents. The second stage evaluates the measurement model, including indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The third stage examines

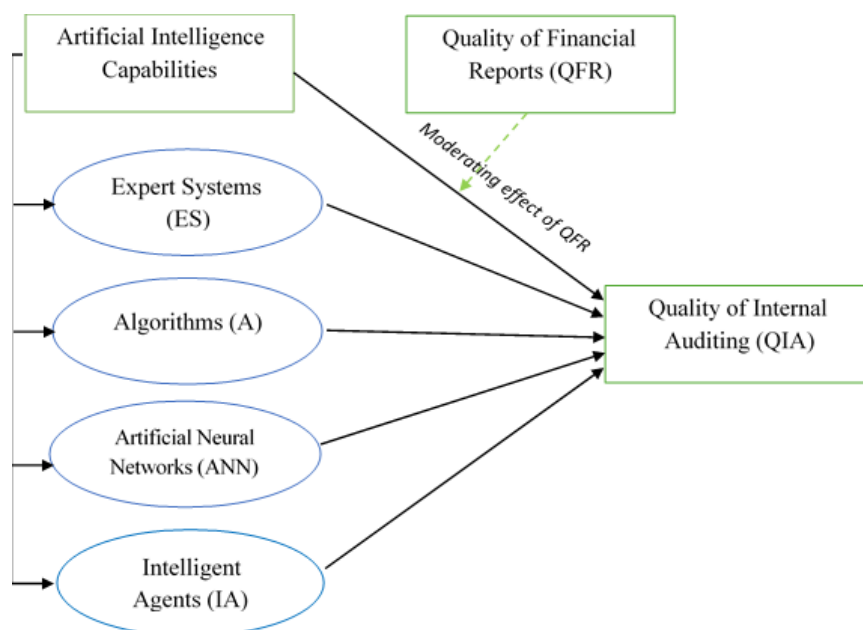


Fig. 1. Conceptual model of the study
Source: author's elaboration.

the structural model, direct hypothesis testing, and the moderating effect of QFR.

To examine the moderating role of QFR, the study tested the interaction effect between AI capabilities and QFR on QIA. AI capabilities were conceptualised as a higher-order construct composed of four lower-order dimensions: ES, A, ANN, and IA. The direct effects were assessed at the dimensional level, whereas the moderating effect was assessed using the higher-order AI capabilities construct. This specification is consistent with the socio-technical perspective adopted in this study, where AI capabilities represent the technological component of human-AI collaboration in internal auditing.

The moderating effect was assessed using the two-stage PLS-SEM approach. In the first stage, latent variable scores were obtained for the lower-order AI capability dimensions. In the second stage, these scores were used to form the higher-order AI capabilities construct, and an interaction term between AI capabilities and QFR was created. Bootstrapping procedures in SmartPLS 4 evaluated the significance of the moderating effect. A statistically significant interaction term indicates that QFR changes the strength of the relationship between AI capabilities and QIA.

Note. AI capabilities are conceptualised as a higher-order construct comprising expert systems (ES), algorithms (A), artificial neural networks (ANN), and intelligent agents (IA). Direct effects are assessed at the dimensional level, whereas the moderating effect of QFR is examined at the higher-order AI capabilities level.

Fig. 1 illustrates the proposed conceptual model. The model assumes that AI capabilities, represented by ES, A, ANN, and IA, influence QIA. In addition, QFR is expected to moderate this relationship by strengthening or weakening the effect of AI capabilities on QIA. This structure reflects the study's socio-technical perspective, in which AI capabilities operate as technological components of human-AI collaboration, while QFR provides an informational condition shaping internal audit outcomes. The direct effects are assessed at the dimensional level, whereas the moderating effect of QFR is examined at the higher-order AI capabilities level. The following section presents the empirical results, beginning with the demographic profile of respondents, followed by the measurement model evaluation, structural model assessment, and moderation analysis.

2. RESEARCH METHODS

This study adopted a quantitative, cross-sectional, explanatory survey design to examine the effect of AI capabilities on QIA and the moderating role of QFR. AI capabilities comprise four dimensions: ES, A, ANN, and IA. These dimensions are conceptualised as technological components of a human-AI collaborative audit framework in which AI supports internal audit processes while auditors remain responsible for interpretation, professional judgement, and decision validation.

A structured questionnaire was designed to measure the main study variables: AI capabilities as the independent variable, QIA as the dependent variable, and QFR as the moderating variable. The questionnaire was used to examine the relationships among these constructs and to generate empirical evidence on how AI capabilities contribute to internal audit outcomes within a human-AI collaborative framework.

The measurement items used in this study were adopted from scales used in prior literature on the use of AI (Ali et al., 2022; Ajayi & Akinrinola, 2023), QIA (Jebril et al., 2023), and financial reporting quality (Kizmaz et al., 2018). Each construct was rated on a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Subject-matter experts and academic researchers reviewed and refined the questionnaire to ensure content validity and measurement quality. A pre-test was administered to assess item clarity, relevance, and comprehensibility. The questionnaire was revised before final administration to minimise potential measurement error. Data screening was also used to ensure response completeness and verify the accuracy and reliability of the collected responses.

The study population consisted of all 33 Jordanian industrial companies listed on the Amman Stock Exchange in 2023. Data were collected through a structured questionnaire distributed to employees working in accounting and audit-related roles. A total of 175 questionnaires were distributed, of which 162 were returned. Data collection was completed in January 2026. The responses were subsequently screened and prepared for analysis. After 12 invalid responses had been excluded due to response bias or incompleteness, 150 valid questionnaires were retained for analysis, yielding a usable response rate of 85.7%. The unit of analysis was the individual respondent.

3. RESEARCH RESULTS

3.1. DEMOGRAPHIC PROFILE OF RESPONDENTS

The demographic characteristics of the valid respondents were analysed to assess the sample's suitability for examining AI-enabled internal auditing. Table 1 presents the respondents' profiles by gender, years of experience, academic qualifications, and job positions.

As shown in Table 1, male respondents accounted for 75% of the sample, while female respondents accounted for 25%. In terms of professional experience, 66% of respondents had more than ten years of experience, indicating that the sample consisted mainly of experienced professionals. Regarding academic qualifications, 78% of respondents held at least a bachelor's degree, while 17% had postgraduate qualifications. In addition, 65% of respondents held audit-related positions, whereas 35% were accountants.

Given the study's focus on human-AI collaboration, the respondents' professional experience and job roles are particularly important, as evaluating AI-enabled audit practices requires both accounting knowledge and practical familiarity with audit processes.

3.2. MEASUREMENT MODEL EVALUATION

Following the two-step approach recommended for PLS-SEM, the measurement model was assessed

before the structural model. The assessment included indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The outer loadings are displayed in Fig. 2.

Indicator reliability was examined using the outer loadings of all measurement items. As shown in Fig. 2, most items exceeded the recommended threshold of 0.70. However, five items (ES1, IA1, IA3, QIA4, and QIA7) displayed loadings below the acceptable threshold and were therefore removed from further analysis. After item deletion, all retained indicators had outer loadings of 0.70 or above, confirming adequate indicator reliability (Hair et al., 2017). Fig. 3 presents the outer loadings after deleting items that did not meet the recommended threshold.

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR). Convergent validity was evaluated using average variance extracted (AVE). Table 2 presents the results.

As shown in Table 2, all Cronbach's alpha and CR values exceeded the recommended threshold of 0.70, confirming internal consistency reliability. In addition, all AVE values exceeded 0.50, confirming convergent validity.

Discriminant validity was assessed using the Fornell-Larcker criterion. As shown in Table 3, the square root of AVE exceeded the correlations with other constructs for most construct pairs. However, the correlation between IA and QIA (0.813) exceeded the square root of AVE for IA (0.796), indicating a potential discriminant validity concern for this pair of constructs. This relationship should be examined

Tab. 1. Demographic characteristics

FACTOR	CATEGORY	FREQUENCY	PERCENTAGE
Gender	Male	112	75%
	Female	38	25%
Years of experience	Less than 6 years	20	13%
	6-10 years	31	21%
	11-15 years	39	26%
	More than 15 years	60	40%
Academic qualification	Diploma	32	22%
	Bachelor's degree	92	61%
	Master's degree	17	11%
	PhD	9	6%
Job	Accountants	52	35%
	Audit staff	98	65%
TOTAL		150	100%

Source: author's elaboration.

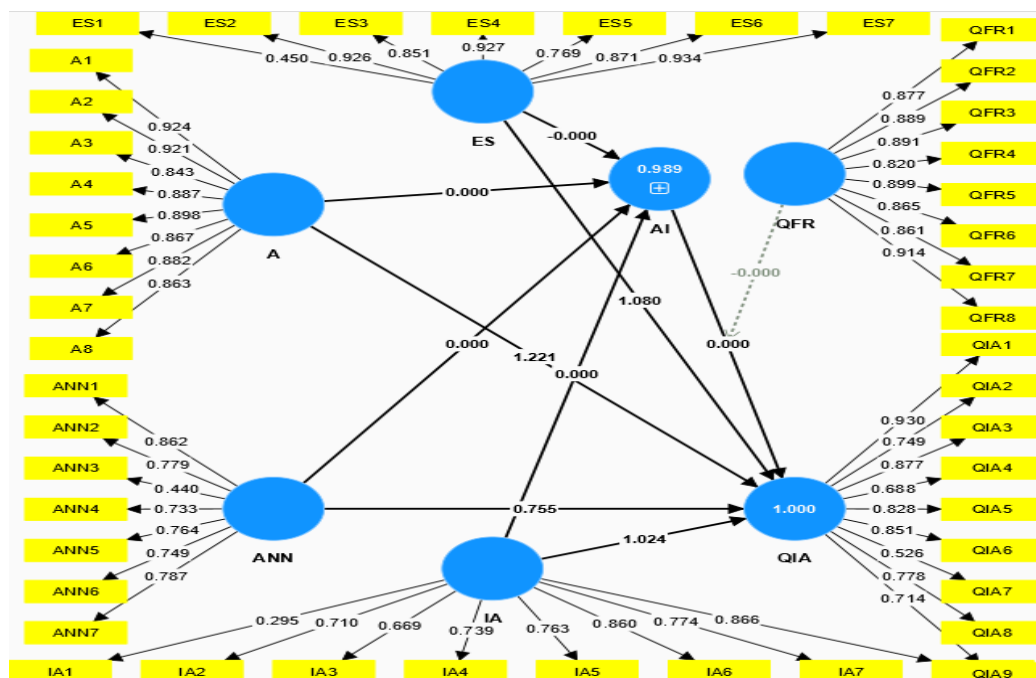


Fig. 2. Outer loadings before item deletion

Source: elaborated by the author.

Note. Intelligent agents (IA), artificial neural networks (ANN), algorithms (A), expert systems (ES), quality of internal auditing (QIA), and quality of financial reports (QFR).

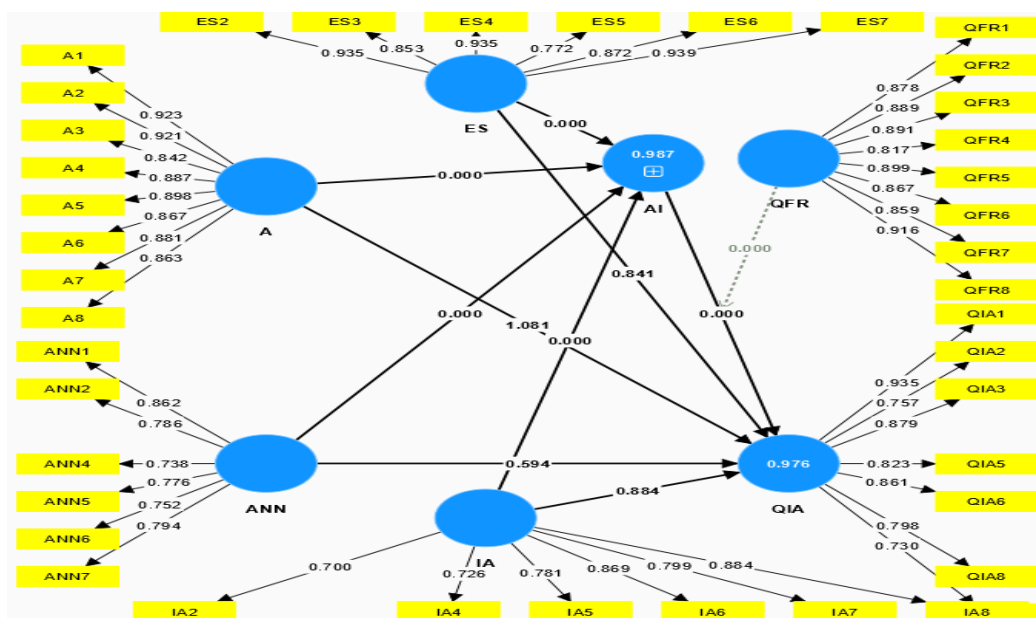


Fig. 3. Outer loadings after item deletion

Source: elaborated by the author.

Note. Intelligent agents (IA), artificial neural networks (ANN), algorithms (A), expert systems (ES), quality of internal auditing (QIA), and quality of financial reports (QFR).

Tab. 2. Reliability and convergent validity of constructs

	ITEM		CRONBACH'S ALPHA >0.7	CR >0.7	AVE >0.5
A	A1	0.923	0.961	0.962	0.785
	A2	0.921			
	A3	0.842			
	A4	0.887			
	A5	0.898			
	A6	0.867			
	A7	0.881			
	A8	0.863			
ANN	ANN1	0.862	0.876	0.881	0.617
	ANN2	0.786			
	ANN4	0.738			
	ANN5	0.776			
	ANN6	0.752			
	ANN7	0.794			
ES	ES2	0.935	0.944	0.953	0.786
	ES3	0.853			
	ES4	0.935			
	ES5	0.772			
	ES6	0.872			
	ES7	0.939			
IA	IA2	0.700	0.882	0.894	0.634
	IA4	0.726			
	IA5	0.781			
	IA6	0.869			
	IA7	0.799			
	IA8	0.884			
QFR	QFR1	0.878	0.957	0.959	0.770
	QFR2	0.889			
	QFR3	0.891			
	QFR4	0.817			
	QFR5	0.899			
	QFR6	0.867			
	QFR7	0.859			
	QFR8	0.916			
QIA	QIA1	0.935	0.923	0.929	0.687
	QIA2	0.757			
	QIA3	0.879			
	QIA5	0.823			
	QIA6	0.861			
	QIA8	0.798			
	QIA9	0.730			

Source: elaborated by the author.

Note. Intelligent agents (IA), artificial neural networks (ANN), algorithms (A), expert systems (ES), quality of internal auditing (QIA), and quality of financial reports (QFR).

Tab. 3. Fornell-Larcker criterion

CRITERION	A	ANN	ES	IA	QFR	QIA
A	0.886					
ANN	0.599	0.786				
ES	0.625	0.565	0.886			
IA	0.527	0.744	0.594	0.796		
QFR	0.506	0.541	0.541	0.667	0.877	
QIA	0.762	0.761	0.782	0.813	0.738	0.829

Source: elaborated by the author.

Note. Diagonal values represent the square root of AVE.

further using the heterotrait-monotrait ratio of correlations (HTMT).

Overall, the measurement model demonstrated satisfactory indicator reliability, internal consistency reliability, and convergent validity. Discriminant validity was supported for most construct pairs, although the distinction between IA and QIA requires further verification. The analysis therefore proceeded to the structural model assessment.

3.3. STRUCTURAL MODEL AND HYPOTHESIS TESTING

After confirming the adequacy of the measurement model, the structural model was assessed to test the direct effects of AI capability dimensions on QIA. The model includes four direct paths from ES, A, ANN, and IA to QIA. QFR is specified as a moderating variable and is therefore examined separately in Section 3.4.

The explanatory power of the direct-effects model was evaluated using the coefficient of determination (R^2). As shown in Table 4, the R^2 value for QIA was 0.687. This indicates that the four AI capability dimensions collectively explain 68.7% of the variance in QIA. The direct-effects model therefore demonstrates strong explanatory power.

The direct effects were assessed using bootstrapping procedures in SmartPLS 4. Table 5 presents the results of hypothesis testing.

The results indicate that all four AI capability dimensions have positive and statistically significant effects on QIA. Algorithms (A) show the strongest effect on QIA ($\beta = 0.376$, $T = 9.736$, $p < 0.001$), followed by intelligent agents (IA) ($\beta = 0.308$, $T = 8.752$, $p < 0.001$) and expert systems (ES) ($\beta = 0.293$, $T = 6.717$, $p < 0.001$). ANN also have a positive and statistically significant effect on QIA ($\beta = 0.207$, $T = 5.771$, $p < 0.001$), although the effect is comparatively weaker.

Tab. 4. Coefficient of determination (R^2) for the direct-effects model

ENDOGENOUS CONSTRUCT	R^2
QUALITY OF INTERNAL AUDITING (QIA)	0.687

Source: author's elaboration.

Tab. 5. Direct effects of AI capability dimensions on the quality of internal auditing

HYPOTHESIS	PATH	β	T-VALUE	P-VALUE	DECISION
H1a	ES $\rightarrow$ QIA	0.293	6.717	$p < 0.001$	Supported
H1b	A $\rightarrow$ QIA	0.376	9.736	$p < 0.001$	Supported
H1c	ANN $\rightarrow$ QIA	0.207	5.771	$p < 0.001$	Supported
H1d	IA $\rightarrow$ QIA	0.308	8.752	$p < 0.001$	Supported

Source: author's elaboration.

Note. Intelligent agents (IA), artificial neural networks (ANN), algorithms (A), expert systems (ES), quality of internal auditing (QIA), and quality of financial reports (QFR).

Therefore, H1a, H1b, H1c, and H1d are supported. These findings suggest that AI capabilities contribute positively to QIA within a human-AI collaborative framework. The strongest effect of algorithms highlights the importance of data-driven pattern identification, anomaly detection, and risk analysis. The substantial effects of IA and ES further highlight the importance of continuous monitoring, automation, and knowledge-based decision support.

3.4. MODERATION ANALYSIS

The moderating role of QFR was examined by testing the interaction effect between AI capabilities and QFR on QIA. A statistically significant interaction term indicates that QFR changes the strength of the relationship between AI capabilities and QIA. Table 6 presents the results of the moderation analysis.

The interaction between AI capabilities and QFR has a positive and statistically significant effect on QIA ($\beta = 0.454$, $T = 8.059$, $p < 0.001$). This result supports H2 and indicates that QFR strengthens the relationship between AI capabilities and QIA.

4. DISCUSSION OF THE RESULTS

The results show that all four AI capability dimensions are positively associated with QIA in Jordanian industrial companies. Their effects differ, suggesting that the contribution of AI is not reducible to automation alone. Audit quality emerges from the use of analytical tools within processes that still require professional judgement, contextual interpretation, and accountability. This pattern supports the socio-technical perspective adopted in the study.

Algorithms exert the strongest effect on QIA. This result confirms the value of data-driven analysis in identifying patterns, irregularities, and risk indicators in large datasets, including anomalies that traditional procedures may overlook (Boskou et al., 2019). The benefit is substantial, but it depends on explainability. Algorithmic outputs should remain auditable

and subject to human oversight because opaque systems may reproduce bias or obscure accountability (Raji et al., 2020; Sandu et al., 2022).

IA and ES contribute through different mechanisms. IA supports continuous monitoring, automated data collection, and real-time responses, allowing auditors to devote more attention to complex tasks (Ali et al., 2022; Kovanen, 2020; Zaqeeba et al., 2024b). ES formalise expert knowledge and increase procedural consistency, particularly in structured decision-making (Jordan, 2024; Qader & Cek, 2024). Their long-standing relevance to audit decision support is well established (O'Leary & Watkins, 1989). Neither technology removes the need for professional judgement, especially in non-routine situations that require contextual interpretation (Lee et al., 2011; Seethamraju & Hecimovic, 2020).

ANN show the weakest of the four effects, but their contribution to QIA remains statistically significant. They support predictive analysis, anomaly detection, and early risk identification (Ali et al., 2022; Ajayi & Akinrinola, 2023). Their effective use requires technical proficiency and careful validation of model-generated outputs (Ajayi & Akinrinola, 2023; Qasaimeh et al., 2022b). The comparatively weaker effect may reflect the greater demands that ANN place on data quality, expertise, and interpretability (Singh et al., 2025; Wassie & Lakatos, 2024).

The moderation analysis adds an important qualification. The positive interaction effect between AI capabilities and QFR on QIA ($\beta = 0.454$, $T = 8.059$, $p < 0.001$) supports H2. AI capabilities contribute more strongly to audit quality when financial reports are accurate, complete, timely, and reliable. High-quality reports provide a more dependable basis for algorithmic analysis and professional judgement, making AI-generated insights easier to interpret and validate. This result is consistent with studies emphasising the importance of reliable financial information in AI-enabled auditing (Alhazmi et al., 2025; Alassuli et al., 2025) and with evidence linking governance mechanisms to financial reporting quality (Wang & Liang, 2025).

Tab. 6. Moderating effect of the quality of financial reports

HYPOTHESIS	PATH	PATH COEFFICIENT (B)	T-VALUE	P-VALUE	DECISION
H2	AI capabilities × QFR → QIA	0.454	8.059	$p < 0.001$	Supported

Source: author's elaboration.

These findings favour a HITL approach to internal auditing. AI capabilities can increase the speed, scope, and analytical depth of audit procedures, but auditors remain responsible for interpreting outputs, exercising professional scepticism, and ensuring accountability. This reflects the complementary relationship between human expertise and AI systems described by Tiron-Tudor and Deliu (2022) and Rastogi et al. (2023). It also raises governance questions. Organisations need transparent system design, procedures for reviewing automated outputs, and clear accountability mechanisms to manage risks related to opacity, bias, and overreliance on automation (Graves & Ratti, 2025; Singh et al., 2025).

The practical implication is straightforward. Organisations should combine investment in AI with improvements in financial reporting systems, auditors' digital competencies, and governance arrangements. AI-enabled internal auditing is most effective when reliable data, appropriate tools, and professional oversight are developed together.

CONCLUSIONS

This study examined how AI capabilities influence QIA within a human-AI collaborative framework and whether QFR strengthens this relationship. The analysis covered employees working in accounting and audit-related roles in Jordanian industrial companies listed on the Amman Stock Exchange. The findings support a socio-technical view of internal auditing: audit outcomes depend on the interaction between AI-enabled tools, auditors' professional judgement, and the quality of financial information.

All four AI capability dimensions have positive and statistically significant effects on QIA. Algorithms exert the strongest effect, followed by IA, ES, and ANN. The results indicate that data-driven analysis, continuous monitoring, structured decision support, and predictive methods each contribute to internal audit quality, although their relative importance differs.

The findings also support the moderating role of QFR. AI capabilities contribute more strongly to QIA when financial reports are accurate, complete, timely, and reliable. The effectiveness of AI-enabled auditing therefore depends not only on the tools deployed but also on the quality of the information used by auditors and AI systems.

The study extends the literature by framing AI adoption in internal auditing as a collaboration issue

rather than a substitution issue. It also treats AI capabilities as multidimensional technological resources and identifies QFR as a condition that shapes their contribution to QIA. For managers and internal audit functions, the implication is clear: investment in AI should be accompanied by improvements in financial reporting systems, data governance, auditors' digital competencies, and HITL procedures.

The study has several limitations. It focuses on listed industrial companies in Jordan, uses a cross-sectional survey, and relies on respondents' perceptions rather than objective audit-performance indicators. Human-AI collaboration is used as an interpretive framework but is not measured as a separate latent construct. Moreover, QFR is examined as a moderator of the higher-order AI capabilities construct rather than of each capability dimension separately.

Future research could compare sectors and national contexts, use longitudinal designs and objective measures of audit performance, and test separate moderating effects for ES, A, ANN, and IA. Additional research should also examine organisational readiness, data governance maturity, cybersecurity, explainability, trust in AI systems, and ethical oversight.

Effective AI-enabled internal auditing depends on the alignment of technological capabilities, reliable financial information, and professional oversight. The findings therefore support a collaborative model of internal auditing rather than a narrow focus on automation.

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