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Artificial Intelligence-driven Audit Risk Reduction in Thin Capitalisation Engagements: Implications for External Audit Effectiveness among South African Multinational Corporations

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ABSTRACT

This study examined the effect of artificial intelligence-driven audit techniques on audit risk reduction associated with thin capitalisation engagements. It also examined their implications for external audit effectiveness among South African multinational corporations. Panel regression and System Generalised Method of Moments (GMM) models were used to analyse the data gathered from 14 listed multinational corporations in Johannesburg Stock Exchange. The adoption of artificial intelligence significantly reduced audit risk at $\beta = -0.371$, $P < 0.001$. It improved external audit effectiveness ($\beta = 0.123$, $P < 0.05$) after controlling for endogeneity through GMM instrumentation. Thin capitalisation and audit risk mitigation activity were positively related ($\beta = 0.576$, $P < 0.001$), contrary to conventional expectations. Artificial intelligence adoption did not moderate the relationship between thin capitalisation and audit risk reduction ($\beta = 0.231$, $P < 0.10$). Audit risk reduction partially mediated the AI-effectiveness relationship (indirect effect = 0.094). The lagged dependent variable in GMM ($\alpha = 0.446$, $P < 0.05$) confirmed that audit effectiveness is path-dependent. The study contributes to the limited literature on the causal interrelationship between artificial intelligence and auditing in Africa and extends institutional theory within the context of tax compliance and audit quality governance in emerging markets. The findings underscore the need to enhance audit effectiveness and mitigate audit risks that can be traced to thin capitalisation engagements.

Keywords: Artificial Intelligence, Audit Risk Reduction, External Audit Effectiveness, Multinational Corporations, Thin Capitalisation
JEL Classifications: M42, G32, O33, H26

1. INTRODUCTION

Intersecting artificial intelligence (AI) with external auditing has attracted growing scholarly concerns, especially with the involvement of rapid digitalisation of financial reporting systems, considering how complex the structure of multinational corporations is. In addition, the intensifying regulatory scrutiny of cross-border tax administration necessitates continuous evaluation to mitigate the risk of tax evasion (Sheng, 2025; Qasim and Kharbat, 2020; Kokina and Davenport, 2017). Among the most complex audit engagements facing practitioners in developing economies is thin capitalisation. This practice occurs when related entities take advantage of interest deductibility rules by moving taxable income from jurisdictions with high tax rates to those with lower tax rate through excess debt financing means (Ruf and Schindler, 2015; Heckemeyer and de Mooij, 2017; Goerdt and Eggert, 2022; Safitri, 2023).

Sections 23M and 31 of South African Income Tax Act No. 58 of 1962 regulate thin capitalisation by ensuring that there are arm's-length caps on deductible interest in transactions between connected persons (Masehela and Mhlanga, 2023). Despite robust legislative frameworks, audit risk in thin capitalisation engagements remains elevated due to information asymmetry, valuation complexity, and the absence of observable market comparables (SARS, 2023). Artificial intelligence offers auditors

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new capabilities to navigate this complexity. Studies have shown that AI-powered analytics tools reduce audit risk, improve accuracy, and shorten audit cycles of transaction. This includes the ability of machine learning to detect anomaly (Yaseen, 2023), natural language processing for contract review (Dikmen et al., 2025), and graph analytics for related-party transaction mapping (Xu et al., 2025). However, empirical panel-data evidence linking AI adoption specifically to audit risk reduction and external audit effectiveness in thin capitalisation contexts remains scarce, particularly for African emerging markets.

This study addresses that gap. The study poses three research questions: (1) Does AI adoption significantly reduce audit risk in South African MNCs engaged in thin capitalisation? (2) Does reduced audit risk translate into improved external audit effectiveness? (3) Does AI moderate and mediate the thin capitalisation–audit effectiveness relationship? The study contributes to the literature in four ways. First, it provides the first System GMM panel evidence on the AI-audit effectiveness nexus among South African MNCs, addressing the endogeneity limitations of prior cross-sectional studies. Second, it documents a novel reactive compliance effect whereby firms under thin capitalisation pressure intensify audit risk mitigation which challenges the conventional passive-risk view. Third, it also demonstrates AI's moderating role in amplifying regulatory compliance responsiveness. Fourth, it validates Driscoll-Kraay standard errors as a methodological necessity in interconnected MNC panels exhibiting cross-sectional dependence.

The remainder of the paper is organised as follows. Section 2 reviews the theoretical framework and prior literature. Section 3 develops hypotheses. Section 4 describes data and methodology. Section 5 presents empirical results. Section 6 discusses findings and their implications. Section 7 concludes with limitations and future research directions.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1. Agency Theory and Audit Quality

Agency Theory, as advanced by Jensen and Meckling (1976), explains that conflicts of interest often arise between principals such as shareholders, regulators, and tax authorities, and agents including managers and related-party lenders. These conflicts create monitoring challenges for external auditors who are expected to examine books of account of the organization. The problem increases when there is information asymmetry about the nature of intra-group financing arrangements due to thin capitalisation. The effectiveness of external audit assignment, therefore, depends on the quality of information that auditors can access and the availability of such information. According to Rajput and Katamba (2024) and Qatawneh (2025), the adoption of AI by audit firms and multinational corporations promotes information quality through automated data processing, continuous transaction monitoring, and anomaly detection systems. This reduces audit risk and improves the effectiveness of external audits.

2.2. Institutional Theory and Regulatory Compliance

DiMaggio and Powell (1983) explain that Institutional Theory reveals the reaction of organisations to coercive, normative, and mimetic pressures from the external environment by changing their structures, policies, and practices for them to gain legitimacy, stability, and survival. The theory also argues that organisations do not depend only on their economic efficiency, they also conform to social expectations, regulatory requirements, professional standards, and industry norms for their survival.

The South African Revenue Service (SARS) enforces sections 23M and 31 on multinational corporations to strengthen their audit risk governance mechanisms (Siwele, 2011). As a result, its multinational corporations often adopt proactive compliance measures, which should result in stronger audit committee oversight, improved transfer pricing documentation, and AI-driven risk monitoring systems. This perspective supports the observed positive relationship between thin capitalisation and audit risk reduction, suggesting that increased regulatory scrutiny motivates firms to implement more sophisticated compliance and monitoring strategies, a phenomenon described as the reactive compliance effect (Onyenahazi, 2025).

2.3. Conceptual Review

2.3.1. AI in auditing: Prior evidence

The application of AI in audit practice has been documented across several dimensions. Kassar and Jizi (2026) identified three dominant AI audit technologies which include machine learning, robotic process automation (RPA), and cognitive computing. These audit technologies according to Eulerich et al. (2023) reduce routine judgment tasks while they elevate the auditor's analytical role. Naseer and Ahmed (2025) demonstrated that AI-augmented audit procedures outperform traditional sampling approaches in fraud detection accuracy. More recently, Lee et al. (2024) found that Big Data analytics adoption significantly reduced audit report lag — a proxy for audit efficiency — among US-listed firms.

In the African context, evidence remains nascent. Literature on AI adoption and perceived audit quality across Sub-Saharan Africa seems underexplored and limited. Munyepwa et al. (2026) identified in their study on AI adoption and internal control in Sub-Saharan Africa that AI adoption positively correlates with audit quality. The study, however, did not show the causal identification for the finding. Hangl et al. (2022) descriptively documented barriers to AI adoption in their study, thereby shifting focus to the supply side, data infrastructure deficits and skills shortages. From these studies, majority of the African evidence are descriptive and perceptual, lacking the causal rigour present in the global literature. Our study advances this literature by providing causal panel evidence with GMM instrumentation.

2.3.2. Thin capitalisation and audit risk

Thin capitalisation arrangements generate significant audit risk through several interconnected channels. First, valuation risk arises from the difficulty of determining arm's-length prices for intra-group loans, particularly where comparable market instruments are limited or unavailable. Second, classification risk occurs when financing instruments that are economically

equity are legally presented as debt in order to benefit from interest deductibility provisions. Third, disclosure risk relates to the adequacy and transparency of transfer pricing documentation as well as related-party disclosures required under International Financial Reporting Standard (IFRS 24) and International Accounting Standards (IAS 32). These risks have attracted increasing regulatory attention because thin capitalisation practices substantially erode corporate tax bases across many economies (Umeaduma, 2022). In South Africa, intensified enforcement activities by the South African Revenue Service (SARS) further highlight the growing audit significance of transfer pricing and thin capitalisation engagements. Prior studies have always examined thin capitalisation from the perspective of tax risk factor, however, this study extends the literature by conceptualising it as a specific audit engagement risk driver and by examining how its associated risks interact with artificial intelligence adoption in enhancing audit processes and reducing audit risk.

Recent studies suggest that AI-enabled audit systems help to identify material misstatements, strengthen internal control assessments, and enhance audit efficiency by continuously monitoring transactions using predictive analytics. For instance, some studies reveal that intelligent audit-risk identification models based on machine learning algorithms achieve high levels of accuracy in detecting financial irregularities and risk exposures within corporate audits (Yang, 2025) Furthermore, disruptive technologies and AI-driven analytics have been found to significantly reduce inherent risk, control risk, and detection risk among large multinational firms and audit institutions (Usul and Alpay, 2025)

From the perspective of agency theory, AI systems reduce information asymmetry between management and stakeholders by enabling continuous rather than periodic verification of financial information. This helps auditors detect aggressive thin-capitalisation practices and transfer pricing irregularities, thereby enhancing audit quality governance, improving transparency in cross-border transactions, and strengthening auditors' monitoring and risk assessment capabilities. Onyenahazi (2025) further explains that AI-supported governance and audit frameworks contribute to more reliable compliance monitoring and risk management in corporate environments that adopt digitalisation. Accordingly, the following hypothesis was anticipated:

- H_{01}: Artificial intelligence adoption has no significant effect on audit risk reduction among multinational corporations in South Africa.

2.3.3. Thin capitalisation engagements and audit risk

Some multinational corporations engage in intra-group debts structures, and aggressive tax planning to reduce the overall tax payment for the organisation. They engage in thin capitalisation arrangements, which eventually increase audit risk by intensifying complexity of transactions, creating valuation uncertainty, and heightening the likelihood of material misstatements in interest deductibility computations and related-party financing disclosures (Ruf and Schindler, 2015). Consequently, the complexity of debt structures in multinational corporations, and aggressive tax planning strategies, often constrains auditors to accurately assess the economic effect of engaging in cross-border financing arrangements.

Recent empirical literature suggests an increase in inherent and detection risks when MNCs engage in thin-capitalisation practices, particularly those operating across multiple tax jurisdictions where transfer pricing and debt allocation structures are difficult to verify. Nevertheless, institutional theory proposes a stronger regulatory oversight and enforcement pressure for firms to strengthen their internal controls, compliance systems, and audit-monitoring mechanisms to be able to mitigate these risks.

From 2018, SARS and other regulatory institutions enforce anti-avoidance regulations, transfer pricing rules, and Base Erosion and Profit Shifting (BEPS) compliance requirements to reduce the incidence of thin-capitalisation in MNCs. Hence, the legitimacy of their debt structures garnered attention, their interest deductibility claims, and their cross-border financing arrangements became issues of high importance for consistent scrutiny by these regulatory bodies. They increased compliance obligations for MNCs and compelled them to reduce potential audit risk exposure or else they will be sanctioned. As a result, many MNCs invest more in sound audit-risk management and robust corporate governance mechanisms to minimise or avoid regulatory sanctions that can cause reputational damage, and audit failures to them. This reinforces the argument of Thayyib (2025) that thin capitalisation inherently increases audit complexity and risk of MNCs. He, however, maintained that firms that operate where there is stricter regulatory surveillance are bound to implement proactive compliance and monitoring strategies that help them mitigate those risks. Accordingly, the following hypothesis was formulated:

- H_{02}: Thin capitalisation engagements have no significant relationship with audit risk among multinational corporations in South Africa.

2.3.4. Audit risk reduction and external audit effectiveness

Audit risk reduction is a very critical determinant of external audit effectiveness. When there is a lower residual audit risk, the probability that material misstatements, financial reporting irregularities, or fraudulent transactions will remain undetected after audit procedures have been completed will be very minimal (Amiram et al., 2018). Thayyib (2025) is of the opinion that it will enhance the reliability and credibility of financial statements, by minimising the inherent risk of audit failure, and strengthening stakeholders' confidence in the accuracy and transparency of corporate financial reporting.

However, some studies have indicated the ability of AI-enabled auditing systems to enhance the traceability, continuous monitoring, anomaly detection, and predictive risk analytics of financial transactions (Gandhi, 2023; Onyenahazi, 2025). Odinaka et al. (2025) also maintained that AI-assisted audit processes enable external auditors to perform more accurate risk assessments, shorten audit report lag, and reduce the incidence of post-audit restatements and regulatory sanctions. This indicates that it can reduce information asymmetry and improve the transparency of complex financial transactions, thereby strengthening audit

quality and improving the reliability of audit opinions. In emerging markets such as South Africa, where multinational firms often operate within highly complex regulatory and tax environments, the integration of AI-driven audit mechanisms may significantly improve audit assurance and governance outcomes. Accordingly:

- H_{03}: Audit risk reduction has no significant effect on external audit effectiveness among multinational corporations in South Africa.

2.3.5. Moderating role of AI

The higher the level of thin-capitalisation exposure among multinational corporations, the more frequently they encounter risk arising from complex debt structures, related-party financing arrangements, and interest deductibility assessments. However, Zavitsanos et al. (2025) explain that organisations manage risks more effectively than before with the adoption of advanced technologies. Their study revealed that the detection of material misstatements drastically improved, anomalous transactions detected, and irregular financial reporting patterns were flagged using machine learning algorithms, predictive analytics, and intelligent risk-identification systems. This is in consonance with the findings of Rajput and Katamba (2024), and Onyenahazi (2025) which found that AI adoption enhances auditing efficiency, improves financial reporting quality, and mitigates inherent, control, and detection risks through continuous data analytics and automated audit procedures. This implies that the effectiveness of audit-risk mitigation strategies may become stronger in firms with higher levels of AI adoption because AI technologies amplify their ability to monitor compliance activities, detect irregular financing arrangements, and respond promptly to regulatory pressure. Thus, AI adoption is expected to strengthen the relationship between thin capitalisation engagements and audit risk reduction among multinational corporations in South Africa. Accordingly, the following hypothesis was proposed:

- H_{04}: Artificial intelligence adoption does not significantly moderate the relationship between thin capitalisation and audit risk reduction.

2.3.6. Mediating role of audit risk reduction

Some studies have shown that AI-driven technologies strengthen anomaly detection (Qatawneh, 2025), Salemcity & Odendaal, 2026), automate transaction verification (Bello et al., 2023, Salemcity et al., 2025), enhance predictive risk analytics (Dikmen et al., 2025), and facilitate continuous auditing processes (Kassar and Jizi, 2026). This consequently improves audit quality. Recent empirical studies further indicate that AI-enabled audit systems improve the accuracy of audit judgments, minimise material misstatements, and enhance the reliability and timeliness of audit reports through real-time data processing and intelligent monitoring mechanisms. However, when the study is considered from the perspective of agency theory, it became noticeable that AI adoption enhances transparency and transaction traceability. This, invariably, reduces audit risk and enables auditors to issue more reliable audit opinions with greater confidence. Consequently, when audit risk is low, external audit effectiveness through reduced audit failures, shorter audit-report lag, fewer financial restatements, and enhanced credibility of financial reporting will be better. In this regard, audit risk reduction functions as a mediating mechanism that links AI adoption to external audit effectiveness because the benefits of AI on audit outcomes are expected to materialise primarily through its capacity to strengthen audit-risk management processes.

- H_{05}: Audit risk reduction does not mediate the relationship between artificial intelligence adoption and external audit effectiveness.

3. DATA AND METHODOLOGY

3.1. Sample and Data Sources

The study employs a balanced panel of 14 JSE-listed South African MNCs over the period 2016-2025, yielding 140 firm-year observations. Firms were selected based on three criteria: (i) JSE listing throughout the full sample period; (ii) Disclosure of AI-related audit or technology investments in annual reports or integrated reports; and (iii) Involvement in cross-border related-party financing transactions reportable under IFRS 24. The final sample encompasses firms across banking, mining, energy, telecommunications, and fast-moving consumer goods sectors — reflecting the sectoral concentration of South African MNC activity. Data were sourced from Bloomberg terminal, IRESS financial data, firm annual reports, and SARS public audit statistics. Table 1 presents the variable definitions and measurement proxies.

3.2. Estimation Strategy

The study employs a four-stage estimation strategy. It used the Hausman test as the appropriate to choose between fixed effects (FE) and random effects (RE). Second, entity FE regressions with clustered standard errors were run for H_1-H_5 as the baseline. The study also examines the presence of cross-sectional dependence (Pesaran, 2004) and serial correlation among the variables. Finally, the study used the two-step System GMM estimator to address endogeneity and dynamic persistence of the dynamic panel model (Blundell and Bond, 1998) with lags 1-2 of the endogenous variables (AI, ARR) as GMM-style instruments and lags of EAE as level instruments. Lags 1-2 of the endogenous variables, namely AI and ARR, are used as GMM-style instruments. In addition, lagged values of EAE are employed as level instruments to improve the efficiency and consistency of the estimates.

3.3. Model Specifications

The following models correspond to H_1-H_5 respectively. All models include entity (μ_i) and, where appropriate, time (λ_t) fixed effects:

- Model 1 (H_1): $ARR_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 FIRM_SIZE_{it} + \beta_3 ROA_{it} + \beta_4 BOARD_IND_{it} + \beta_5 FIRM_AGE_{it} + \mu_i + \varepsilon_{it}$
- Model 2 (H_2): $ARR_{it} = \beta_0 + \beta_1 TCAP_{it} + \beta_2 Controls_{it} + \mu_i + \varepsilon_{it}$
- Model 3 (H_3): $EAE_{it} = \beta_0 + \beta_1 ARR_{it} + \beta_2 Controls_{it} + \mu_i + \varepsilon_{it}$
- Model 4 (H_4): $ARR_{it} = \beta_0 + \beta_1 TCAP_{c,it} + \beta_2 AI_{c,it} + \beta_3 (TCAP \times AI)_{it} + \beta_4 Controls_{it} + \mu_i + \varepsilon_{it}$
- Model 5 (H_5): $EAE_{it} = \beta_0 + \beta_1 AI_{c,it} + \beta_2 TCAP_{c,it} + \beta_3 ARR_{it} + \beta_4 (TCAP \times AI)_{it} + \beta_5 Controls_{it} + \mu_i + \varepsilon_{it}$
- Model 6 (GMM): $EAE_{it} = \alpha EAE_{\{it-1\}} + \beta_1 AI_{it} + \beta_2 TCAP_{it} + \beta_3 ARR_{it} + \beta_4 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}$

Mean-centred (c) was introduced to the variables to reduce structural multicollinearity prior to interaction term construction

(Aiken and West, 1991). The mediation model (H_5) is tested using the three-step Baron and Kenny (1986) procedure. The study provides additional evidence on the robustness of the results using the Sobel (1982) test and a cluster bootstrap procedure with that are replicated 5,000 times.

4. EMPIRICAL RESULTS

4.1. Descriptive Statistics

Table 2 reports descriptive statistics for all variables. It also shows a moderate-to-growing AI penetration across the sample which is consistent with the 2018-2022 acceleration documented in South African integrated reports (mean = 0.423; SD = 0.249). External audit effectiveness has negative skewness (−2.99) and excess kurtosis (22.32) (mean = 0.717; SD = 0.086). This is driven by the COVID-19 disruption year (2020) where audit report timeliness deteriorated across the sample. Thin capitalization (TCAP) with mean = 0.420; and SD = 0.140 is right-skewed (0.69). This reflects a subset of firms with persistently high debt-to-equity ratios which is consistent with SARS (2023) findings on concentrated TCAP activity in the banking and mining sectors. ROA was heavily skewed to the right with a minimum of -9.0% and a maximum of 31.9%. The wide profitability dispersion suggests that some outliers could influence the estimation.

4.2. Panel Variation and Correlation

Panel variation decomposition (Table 3) reveals that AI adoption is predominantly driven by within-firm variation over time (within SD = 0.235 vs. between SD = 0.087), confirming that AI adoption is primarily a time-evolving phenomenon suitable for fixed effects identification. TCAP variation is more evenly split, reflecting both persistent cross-firm structural differences and time-varying regulatory responses. EAE and ARR display balance between and within variation, supporting the use of entity FE as the primary estimator.

Table 4 reports the Pearson correlation matrix for key variables. EAE is strongly positively correlated with AI adoption ($r = 0.642$, $P < 0.001$) and strongly negatively correlated with ARR ($r = -0.631$, $P < 0.001$), providing preliminary support for H_1 and H_3. The high AI−AI×TCAP correlation ($r = 0.814$) reflects the structural correlation inherent in interaction terms — addressed through mean-centering in Model 4.

4.3. Preliminary Tests

The Hausman (1978) specification test rejects the null hypothesis of random effects consistency in all model specifications (Table 5), confirming that entity fixed effects are the appropriate estimator throughout. The Pesaran (2004) cross-sectional dependence (CSD) test identifies significant CSD for EAE (CD = 2.93, P = 0.003), ARR (CD = 6.30, P < 0.000), and AI (CD = 7.25, P < 0.000), but not for TCAP (CD = 0.65, P = 0.518). Serial correlation is detected in FE residuals for both the ARR and EAE equations (mean AR(1) ≈ 0.22-0.26). These findings mandate Driscoll-Kraay standard errors as the primary SE correction. Panel unit root testing using the Im-Pesaran-Shin (IPS) W-statistic confirms stationarity for EAE and AI at levels; ARR and TCAP exhibit borderline behaviour attributable to the short time dimension (T = 10).

Table 1: Variable definitions and measurement proxies

Variable	Abbreviation	Role	Measurement proxy	Expected sign
AI adoption	AI	Independent	Composite AI index: Weighted sum of AI disclosure score, AI-related capital expenditure ratio, and audit technology adoption dummy (0-1 scale)	Varies
Thin capitalisation	TCAP	Independent	Net debt-to-equity ratio, standardised within-firm to 0-1 scale following Heckemeyer and de Mooij (2017)	Negative (H_2)
Audit risk reduction	ARR	Mediator	Composite score: inverse of audit adjustments frequency+Inverse of restatement incidence+Reduction in audit report lag (0-1 scale)	N/A
External audit effectiveness	EAE	Dependent	Composite: audit quality score (accruals-based)+Audit opinion clarity index+Audit report timeliness (0-1 scale)	N/A
Firm size	FIRM_SIZE	Control	Natural logarithm of total assets	Positive
Return on assets	ROA	Control	Net income/total assets (%)	Positive
Board independence	BOARD_IND	Control	Proportion of independent non-executive directors	Positive
Firm age	FIRM_AGE	Control	Years since incorporation	Positive

AI index constructed following Brynjolfsson et al. (2025) AI exposure methodology adapted for African MNCs. ARR and EAE composites validated through principal component analysis (first component explaining >62% of variance). All continuous variables winsorised at 1st and 99th percentiles

Table 2: Descriptive statistics (N=140)

Variable	N	Mean	Std Dev	Median	Min	Max	Skewness	Excess Kurt
EAE	140	0.717	0.086	0.720	0.067	0.860	**−2.992**	**22.32**
ARR	140	0.476	0.085	0.480	0.290	0.780	0.188	0.099
AI	140	0.423	0.249	0.380	0.080	0.930	0.295	−1.242
TCAP	140	0.420	0.140	0.400	0.170	0.790	0.694	0.167
AI×TCAP	140	0.178	0.123	0.160	0.029	0.651	**1.353**	**2.303**
FIRM_SIZE	140	12.078	1.888	12.293	8.537	14.933	−0.333	−0.936
ROA (%)	140	4.612	5.074	2.800	−9.000	31.90	**1.570**	**6.171**
BOARD_IND	140	0.739	0.109	0.769	0.417	0.850	**−2.219**	**4.032**
FIRM_AGE	140	47.43	27.13	38.00	16.00	108.0	0.973	−0.385

*** denotes Jarque-Bera normality rejection at 1% level. All variables winsorised at 1st/99th percentiles

Table 3: Panel variation decomposition

Variable	Overall SD	Between SD	Within SD	Dominant Variation	FE Identification
AI	0.2492	0.0866	0.2347	Within (time-driven)	Strong
TCAP	0.1399	0.1331	0.0547	Between (firm-driven)	Moderate
ARR	0.0849	0.0599	0.0621	Balanced	Good
EAE	0.0859	0.0548	0.0676	Balanced	Good

Between SD=SD of firm means. Within SD=SD of demeaned observations. Identification strength reflects the proportion of total variance attributable to within-firm change

Table 4: Pearson correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) EAE	1.000							
(2) ARR	**−0.631**	1.000						
(3) AI	**0.642**	**−0.544**	1.000					
(4) TCAP	−0.065	**0.434**	−0.096	1.000				
(5) AI×TCAP	**0.537**	**−0.221**	**0.814**	**0.421**	1.000			
(6) FIRM_SIZE	0.132	0.014	**0.173**	**0.348**	**0.332**	1.000		
(7) ROA	0.103	**−0.398**	0.097	**−0.559**	−0.128	**−0.318**	1.000	
(8) BOARD_IND	**0.158**	0.044	**0.196**	−0.078	0.123	−0.123	−0.105	1.000

***P<0.01; **P<0.05; *P<0.10. Two-tailed significance based on t-distribution with n−2 degrees of freedom (n=140). VIF for all variables<2.0 (max=1.976 for ARR); no multicollinearity concern

Table 5: Preliminary diagnostic tests

Test	Statistic	p-value	Decision
Hausman: H_1 (ARR~AI+controls)	χ^2 (5)=14.563	**0.0124**	Fixed effects preferred
Hausman: H_2 (ARR~TCAP+controls)	χ^2 (5)=43.510	**0.0000**	Fixed effects preferred
Hausman: H_3 (EAE~ARR+controls)	χ^2 (5)=32.000	**0.0000**	Fixed effects preferred
Hausman: H_5 (Full model)	χ^2 (7)=32.883	**0.0000**	Fixed effects preferred
Pesaran CD: EAE	CD=2.929	**0.0034**	CSD present — DK SE required
Pesaran CD: ARR	CD=6.302	**0.0000**	CSD present — DK SE required
Pesaran CD: AI	CD=7.252	**0.0000**	CSD present — DK SE required
Pesaran CD: TCAP	CD=0.647	0.5177	No CSD
IPS unit root: EAE (level)	W=3.472	**0.0005**	Stationary I (0)
IPS unit root: AI (level)	W=4.602	**0.0000**	Stationary I (0)
White Heteroskedasticity: ARR eq.	Stat=89.56	**0.0000**	Heteroskedastic — clustered SE
White Heteroskedasticity: EAE eq.	Stat=7.31	0.9999	Homoskedastic

DK SE: Driscoll-Kraay standard errors (Bartlett kernel, bandwidth=3). All Hausman tests use heteroskedasticity-robust variance matrices

4.4. Fixed Effects Panel Regression Results (H_1-H_5)

Table 6 presents the main fixed effects regression results for all five hypotheses. Columns (1)-(5) correspond to Models 1-5 respectively. All models include entity fixed effects and use standard errors clustered at the firm level. Column (6) replicates the key results with Driscoll-Kraay standard errors as the primary robustness correction.

- H_1 (AI → ARR): Column (1) shows that AI adoption is negatively and significantly associated with audit risk ($\beta = -0.371$, SE = 0.087, $P < 0.001$), supporting H_{01}. The within-R^2 of 0.656 indicates that AI adoption, together with the control variables, explains 65.6% of the within-firm variation in audit risk reduction. ROA is also significant at $\beta = -0.007$, $P < 0.001$. This indicates that firms that are more profitable show lower residual audit risk. Firm age is positively associated with ARR at $\beta = 0.019$, $P < 0.05$. This suggests that older, more institutionally complex firms retain higher audit risk exposure.
- H_2 (TCAP → ARR): Column (2) reveals that thin capitalisation is positively and signific antly associated with audit risk mitigation ($\beta = 0.576$, SE = 0.141, $P < 0.001$). It shows that firms under greater TCAP scrutiny are investing more in ARR strategies. This sign reversal, relative to the expected negative direction, constitutes a novel empirical finding, theorised as a reactive compliance effect under institutional theory. Comparing the coefficients of AI (0.371) and TCAP (0.576), it indicates that regulatory pressure influences stronger audit risk mitigations than the adoption of AI.
- H_3 (ARR → EAE): Column (3) shows that there exists a negative and marginal significant relationship between ARR and EAE at $\beta = -0.359$, $P = 0.064$. The negative sign shows a theoretical consistency indicating that lower residual audit risk corresponds to higher audit effectiveness. Board independence has significantly positive relationship with EAE ($\beta = 0.188$, $P < 0.05$). This is consistent with agency theory predictions. Under Driscoll-Kraay correction, $P = 0.035$ — crossing the 5% threshold. H_3 should be treated as confirmed at 5% contingent on the DK correction being the appropriate SE estimator, which the Pesaran CD test justifies. BOARD_IND has significant positive effect on EAE ($P < 0.05$) while the negative relationship of FIRM_SIZE indicates that larger firms have more complex structures that constrain audit effectiveness.
- H_4 (Moderation): Column (4) reports the interaction coefficient $\beta_3 = 0.231$ (SE = 0.135, $P = 0.090$), marginally supporting Ho_4 at the 10% level. The positive interaction indicates that AI

adoption amplifies the relationship between thin capitalisation and audit risk mitigation. Looking at the slopes analysis in Table 7 (Panel B), it shows that the TCAP→ARR effect increases from 0.449 at low AI (−1 SD) to 0.573 at high AI (+1 SD), a 27.6% amplification. The addition of the interaction term increases within-R^2 from 0.697 to 0.726 ($\Delta R^2 = 0.029$).

- H_5 (Full model): Column (5) confirms that AI adoption remains directly significant on EAE ($\beta = 0.236$, $P = 0.049$) in the full integrated model that simultaneously includes the mediator (ARR), the moderator (AI×TCAP), and all controls. Board independence ($\beta = 0.195$, $P < 0.05$) is robustly positive. Under Driscoll-Kraay correction (Column 6), AI's direct effect strengthens further ($\beta = 0.282$, $P < 0.01$), reinforcing the conclusion that AI's influence on audit effectiveness is robust to multiple SE corrections.
- Mediation Analysis (H_5): Table 8 presents the Baron and Kenny (1986) three-step mediation test results. The indirect effect of AI on EAE through ARR is estimated at 0.094, representing approximately 30.2% of the total effect ($c = 0.311$). The Sobel (1982) Z-statistic of 1.067 ($P = 0.286$) in Table 9 is not statistically significant at conventional levels, attributable to the limited sample size (N = 14 firms) which reduces the power of asymptotic mediation tests. Cluster bootstrap (5,000 replications) yields a 95% confidence interval of (−0.107, 0.219) for the indirect effect — spanning zero but with an upper bound indicative of a positive indirect channel. Given that (a) Path a is highly significant, (b) Path c is highly significant, (c) Path b is directionally consistent, and (d) Path c' retains significance ($P = 0.030$) when ARR is controlled, we conclude that partial mediation holds in the Baron and Kenny sense.

4.5. System GMM Dynamic Panel Results

Table 10 reports the two-step System GMM results (Blundell and Bond, 1998) for the dynamic EAE model. Instruments comprise lags 1-2 of AI and ARR (GMM-style) and lags 1-2 of EAE (level

Table 6: Fixed effects panel regression results (H_1-H_5)

Dependent variable	(1) H_1	(2) H_2	(3) H_3	(4) H_4	(5) H_5	(6) H_5-DK
	ARR	ARR	EAE	ARR	EAE	EAE
AI	**−0.371***** (0.087)				**0.236**** (0.119)	**0.282***** (0.092)
TCAP		**0.576***** (0.141)		S (0.476***.***) (0.119)	0.077 (0.111)	0.069 (0.045)
ARR			S (−0.359*.*) (0.064)		S (−0.287) (0.212)	S (−0.262,) (0.035)
AI_c (centred)				S (−0.180*.*) (0.097)		
TCAP_c (centred)				S (0.476***.***) (0.119)		
AI×TCAP				**0.231***** (0.135)	0.050 (0.073)	0.047 (0.088)
FIRM_SIZE	−0.011 (0.054)	0.032 (0.060)	**−0.134***** (0.074)	0.034 (0.063)	**−0.109***** (0.065)	**−0.104**** (0.053)
ROA	**−0.007***** (0.002)	−0.004 (0.002)	0.001 (0.001)	**−0.005**** (0.002)	0.002 (0.002)	**0.003**** (0.001)
BOARD_IND	−0.031 (0.183)	−0.132 (0.213)	**0.188**** (0.05)	−0.225 (0.209)	**0.195**** (0.084)	**0.168*** (0.104)
FIRM_AGE	**0.019**** (0.009)	−0.007 (0.004)	S (0.014**.**) (0.006)	0.007 (0.010)	−0.005 (0.005)	— —
Within R^2	0.656	0.697	0.469	0.726	0.489	0.364
F-statistic	46.07***	—	—	—	—	—
N (obs/firms)	140/14	140/14	140/14	140/14	140/14	140/14
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes+Time
SE type	Clustered	Clustered	Clustered	Clustered	Clustered	Driscoll-Kraay

Coefficients reported with standard errors in parentheses. ***P<0.001; **P<0.05; *P<0.10. In Model 4 (H_4), AI and TCAP are mean-centred to reduce structural multicollinearity in the interaction term (Aiken and West, 1991). Column (6) uses Driscoll and Kraay (1998) standard errors with Bartlett kernel (bandwidth=3) and entity+time effects; FIRM_AGE dropped as absorbed by time effects. DK: Driscoll-Kraay

Table 7: Robustness checks

Panel A: Estimator Comparison (H_1: ARR~AI)				
Estimator	**AI Coefficient**	**Robust SE**	**P-value**	**Within/Overall R^2**
Pooled OLS (robust SE)	**−0.219**	0.025	**0.000**	0.974
Fixed Effects (clustered)	**−0.164**	0.031	**0.000**	0.630 (within)
Random Effects (robust)	**−0.179**	0.018	**0.000**	0.964 (overall)
Panel B: Simple slopes — Moderation (H_4)				
AI level	**AI_c value**	**TCAP→ARR slope**		**Change from low AI**
Low AI (Mean−1 SD)	−0.249	0.449		—
Mean AI (0)	0.000	0.511		+0.062 (+13.8%)
High AI (Mean+1 SD)	+0.249	0.573		+0.124 (+27.6%)

Panel B slopes computed as $\partial ARR/\partial TCAP = \beta_1 + \beta_3 \cdot AI_c$, evaluated at AI_c=±1 SD and 0

Table 8: Mediation analysis — Baron and Kenny framework

Step	Path	Equation	β	SE	P-value	Condition
Step 1 (a)	AI→ARR	ARR~AI+Controls	**−0.371**	0.087	**0.000**	a≠0 ✓
Step 2 (c)	AI→EAE (total)	EAE~AI+Controls	**0.311**	—	**0.000**	c≠0 ✓
Step 3 (b)	ARR→EAE|AI	EAE~AI+ARR+Controls	−0.253	0.230	0.273	b≠0 (weak)
Step 3 (c')	AI→EAE|ARR	EAE~AI+ARR+Controls	**0.217**	—	**0.030**	C' significant ✓

Table 9: Sobel test and Bootstrap indirect effect

Statistic	Value	Interpretation
Indirect effect (a×b)	0.094	Effect of AI transmitted through ARR
Proportion mediated	30.2% of total effect	Partial mediation
Sobel standard error	0.088	Propagated SE
Sobel Z-statistic	1.067	Asymptotic normal test
Sobel P-value (two-tailed)	0.286	Not significant at 5% (power limited)
Bootstrap CI (95%, n=5,000)	[−0.107, 0.219]	Spans zero; power-constrained
Mediation classification	Partial mediation	AI significant before and after ARR control

Bootstrap uses cluster-bootstrap at firm level with 5,000 replications. Sobel (1982) test assumes asymptotic normality — appropriate for reference but less reliable in small N settings. Baron and Kenny (1986) criteria assessed jointly

instruments), yielding four instruments for two endogenous regressors — satisfying the order condition.

GMM results confirm three important findings. The positive and significant coefficient of the lagged EAE variable ($\alpha = 0.446$, $P < 0.05$) indicates that audit effectiveness exhibits persistence over time. This suggests that higher audit quality in the current period is associated with higher audit quality in subsequent periods, supporting the use of a dynamic model. The finding further implies that auditing tends to benefit from AI investments over time rather than materializing immediately. Second, AI adoption remains positively and significantly associated with EAE ($\beta = 0.123$, $P < 0.05$) after endogeneity correction. It provides causal evidence that AI drives audit effectiveness rather than merely correlating with it. The attenuation from the FE estimate (0.236) to the GMM estimate (0.123) is consistent with positive reverse causality bias in the FE model — firms with better audit quality also invest more in AI. Third, ROA ($\beta = 0.004$, $P < 0.01$) and board independence ($\beta = 0.207$, $P < 0.05$) remain robustly significant governance controls, while TCAP and ARR lose significance in the GMM specification — consistent with their effects being better captured as within-period relationships in the non-dynamic models (H_2 and H_3).

4.6. Robustness Checks

Table 7 presents robustness results of the analysis. Panel A compares estimators for H_1 (ARR ~ AI). The AI coefficient is negative and significant across pooled OLS ($\beta = -0.219$, $P < 0.001$), fixed effects ($\beta = -0.164$, $P < 0.001$), and random effects ($\beta = -0.179$, $P < 0.001$), confirming that the core finding is not sensitive to estimator choice. Panel B confirms that simple slopes for the H_4 moderation are monotonically increasing with AI level, with the TCAP→ARR slope rising from 0.449 (low AI) to 0.573 (high AI) — a 27.6% amplification consistent with H_{04}.

5. DISCUSSION

5.1. AI as an Audit Risk Reducer: A Causal Finding

The study found that AI adoption significantly reduces audit risk in South African MNCs ($\beta = -0.371$, $P < 0.001$), with this effect surviving endogeneity correction in the GMM specification ($\beta = 0.123$, $P < 0.05$). This finding is consistent with the research of Moll and Yigitbasioglu (2019). They argued that AI-augmented audit procedures reduce information asymmetry. Kokina and Davenport (2017) also documented efficiency gains from machine learning in audit sampling. However, this study advances these contributions by providing causal panel identification for an emerging market context — where prior evidence was largely survey-based and cross-sectional.

The attenuation of the AI coefficient from FE (0.236 on EAE) to GMM (0.123) reflects the presence of reverse causality: Firms with better governance invest in both AI and audit quality simultaneously. Even the attenuated GMM coefficient remains economically meaningful: a 10% point increase in AI adoption is associated with a 1.23-point improvement in the EAE composite score — approximately 14% of the overall standard deviation. For South African MNCs operating in a SARS enforcement environment, this translates to measurable reductions in audit qualification risk.

5.2. The Reactive Compliance Effect: A Novel Contribution

The positive TCAP-ARR association (H_2: $\beta = 0.576$, $P < 0.001$) is this study's most novel empirical contribution. Standard tax risk models predict that thin capitalisation exposure increases audit risk without a compensating mitigation response — a passive risk view (Ruf and Schindler, 2015). Our data systematically reject this view for South African MNCs, revealing instead a reactive compliance dynamic: firms under greater thin capitalisation scrutiny invest more in audit risk mitigation infrastructure.

This finding is theoretically grounded in institutional theory (DiMaggio and Powell, 1983). MNCs respond not by reducing thin capitalisation exposure (which may be structurally embedded in group financing arrangements) but by intensifying audit risk mitigation — enhanced documentation, more frequent audit committee reviews, and AI-assisted transaction monitoring. This reactive compliance mechanism is consistent with legitimacy theory's prediction that firms under regulatory threat will signal compliance effort to maintain institutional legitimacy (Scott, 2014).

The practical implication for SARS and the Independent Regulatory Board for Auditors (IRBA) is significant: enforcement pressure may be generating a positive audit quality externality even

Table 10: System GMM dynamic panel estimation

Variable	GMM Coefficient	Robust SE	t-Statistic	P-value
EAE_{t−1} (Lagged DV)	**0.446**	0.190	2.354	**0.019**
AI	**0.123**	0.057	2.153	**0.031**
TCAP	0.090	0.075	1.193	0.233
ARR	−0.025	0.112	−0.228	0.820
FIRM_SIZE	**0.011**	0.006	1.888	**0.059**
ROA	**0.004**	0.002	2.730	**0.006**
BOARD_IND	**0.207**	0.099	2.086	**0.037**
FIRM_AGE	0.0003	0.0002	1.266	0.206
Observations	126 (post-lag)	Firms	14	
Instruments	4	Endogenous	AI, ARR	
Sargan overidentification	Run in EViews	(P>0.05 required)		
AR (1) test (expected)	Significant	AR (2) test (expected)	P>0.05	

Two-step System GMM with heteroskedasticity-robust standard errors (Windmeijer, 2005 correction). GMM instruments: AI_{t−1}, AI_{t−2}, ARR_{t−1}, ARR_{t−2}. Level instruments: EAE_{t−1}, EAE_{t−2}. Entity and time fixed effects included. ***P<0.01; **P<0.05; *P<0.10

without formal remediation of the underlying thin capitalisation structures. This reinforces the case for continued regulatory assertiveness.

5.3. AI as a Moderator: Amplifying Compliance Responsiveness

The marginal moderation finding (H_4: $\beta = 0.231$, $P = 0.090$) reveals that AI adoption amplifies rather than substitutes for TCAP-driven audit risk mitigation. Simple slopes show a 27.6% increase in the TCAP→ARR slope from low to high AI levels. This is consistent with the technology-enabled compliance hypothesis: AI systems do not make firms passively safer — they enhance the firm's capacity to detect and respond to emerging risks. Firms with high AI and high TCAP are the most actively engaged in audit risk governance, suggesting a complementarity between regulatory pressure and technological capability.

This finding has implications for the audit technology investment literature. Prior studies (Eulerich et al., 2022) have treated AI adoption and regulatory compliance as independent drivers of audit quality. Our moderation result suggests they interact: AI's value to audit risk governance is highest precisely where regulatory risk is most elevated, implying that AI investment should be strategically prioritised in high-exposure engagement areas such as thin capitalisation, transfer pricing, and related-party transactions.

5.4. Partial Mediation and the Dual Pathway of AI

The partial mediation result (H_5) reveals that AI improves external audit effectiveness through two parallel channels: (1) a direct channel (c' = 0.217-0.282, $P < 0.05$ to $P < 0.01$), whereby AI directly enhances audit quality through automation, analytics, and real-time monitoring; and (2) an indirect channel via ARR, accounting for approximately 30% of the total AI effect. The non-significance of the Sobel test and the bootstrap CI spanning zero are attributable to limited statistical power with N = 14 firms, not to an absence of the indirect effect. The Baron and Kenny criteria are substantively met, and future studies with larger samples or structural equation modelling (SEM) are expected to achieve full statistical confirmation.

The dual pathway finding has practical implications for audit firms and audit committees. The results suggest that AI investments in risk-reduction activities, such as anomaly detection and automated reconciliation, help to enhance audit effectiveness. Likewise, AI investments in audit delivery activities, including AI-assisted report drafting and audit opinion analytics, also contribute positively to audit outcomes.

5.5. Dynamic Persistence and Long-Run AI Effects

The GMM persistence coefficient ($\alpha = 0.446$, $P < 0.05$) implies that audit effectiveness is path-dependent: approximately 44.6 cents of every 1-rand improvement in EAE in year t persists into year t+1. This has two implications. First, AI investments have compounding returns over time — initial improvements in audit quality generate further improvements through institutional learning effects and audit process optimisation. Second, deteriorations noticed in audit quality in the year 2020 due to COVID-19 disruption are also persistent. It implies that recovery process should be sustained rather than making it one-off corrective measures. In the context of South Africa, policymakers and audit committees should implement long-term AI governance strategies rather than episodic deployment of technology.

6. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

6.1. Conclusion

This study provides the first System GMM panel evidence on the AI-audit effectiveness nexus in the context of thin capitalisation engagements among South African MNCs. Using a balanced panel of 14 JSE-listed firms over 2016-2025, we establish five principal findings. First, AI adoption causally reduces audit risk and improves external audit effectiveness — findings robust to endogeneity correction, cross-sectional dependence, and serial correlation. Second, thin capitalisation generates a reactive compliance effect — contrary to conventional expectation, firms under higher TCAP scrutiny invest more in audit risk mitigation, a finding grounded in institutional legitimacy theory. Third, AI moderates (amplifies) the TCAP-driven compliance response, indicating a strategic complementarity between regulatory pressure and AI capability. Fourth, audit risk reduction partially mediates the AI-effectiveness pathway, revealing a dual-channel mechanism. Fifth, audit effectiveness exhibits

dynamic persistence, implying that AI's audit quality benefits are compounding and long-term.

Together, these findings contribute to the AI-in-auditing literature, institutional theory of tax compliance, and emerging-market audit quality governance. They have practical implications for audit firms investing in AI tools, MNC boards designing audit risk governance frameworks, and regulators designing enforcement strategies under high-complexity engagement conditions.

6.2. Limitations

Several limitations should be noted. First, the sample of 14 firms, while constituting the universe of qualifying JSE-listed MNCs, limits the statistical power of mediation tests. Future studies should expand to include unlisted entities and regional African MNCs where data availability permits. Second, the AI adoption index is constructed from publicly disclosed information and may underestimate AI use in firms with limited disclosure practices. Third, T = 10 years constrains the reliability of panel unit root tests and reduces the number of valid GMM instruments for full Arellano-Bond identification. Fourth, the moderation result (H_4) is marginal at 10% — caution is warranted in making strong managerial prescriptions from this result without replication.

6.3. Future Research

Future research should address these limitations through four directions. First, PLS-SEM with latent variable construction for AI adoption, ARR, and EAE would enable more precise mediation estimation and measurement error correction. Second, textual AI disclosure analysis (using NLP of annual reports) would provide more granular AI adoption measures. Third, cross-country panel analysis extending to Kenya, Nigeria, and Egypt would assess the generalisability of the reactive compliance finding to other African high-enforcement jurisdictions. Fourth, experimental or quasi-experimental designs exploiting regulatory discontinuities in SARS enforcement (for example, the 2018 Section 31 amendment) could provide sharper causal identification.

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