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# The Relationship between Agile Internal Auditing and Risk Management: The Role of Artificial Intelligence Technologies – An Empirical Study

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**Abstract:** The research examines whether agile internal auditing is associated with more effective risk management, and whether the adoption of artificial intelligence (AI) strengthens this relationship. Three disclosure indexes, for agile internal auditing (AIADI, 15 items), digital and AI adoption (DAI, 8 items) and enterprise risk management quality (ERMQ, 12 items), are constructed from 635 board of directors' reports of 232 firms listed on the main market of the Saudi Exchange over 2022–2024. The hypotheses are tested with panel regressions that include sector and year fixed effects and firm-clustered standard errors, complemented by simple-slope and Johnson–Neyman analysis, a firm-cluster bootstrap, regression diagnostics and twelve robustness tests. Agile internal auditing ($\beta = 0.515$, $p < 0.01$) and AI adoption ($\beta = 0.390$, $p < 0.01$) are each positively associated with risk management effectiveness. Contrary to complementarity theory, AI adoption does not strengthen the agility effect: the interaction is negative ($\beta = -0.622$, $p = 0.14$) and becomes significant in several robustness tests, suggesting that the two act as partial substitutes. Fewer than 2% of reports describe the internal audit function's own use of analytics or AI. The study provides large-sample evidence on agile internal auditing and replicable archival measures of agility, AI adoption and risk management quality for audit committees, chief audit executives and regulators.

**Keywords:** Agile internal auditing, artificial intelligence, enterprise risk management, disclosure index, moderation analysis, panel regression, Saudi Arabia

## 1 Introduction

In most Saudi listed companies, the internal audit plan is still drawn up once a year and approved by the audit committee before the year begins. Risks do not keep to that calendar. Between 2022 and 2024 alone, listed firms faced higher funding costs, new supervisory rules for finance companies and a rapid push to digitise their operations. Internal audit functions can keep pace in two ways. One is a change of method: agile practices such as rolling, risk-based plans, short work cycles, joint work with the risk and compliance functions and more frequent reporting to the audit committee [1]. The other is a change of tools: analytics, machine learning and automation that let auditors test whole populations and monitor controls continuously [2,3]. The Global Internal Audit Standards encourage both [4]. It is easy to assume that the two belong together. A plan that moves with risk needs current data to know where to move, and analytics add little if their findings wait for the year-end report. The evidence for either claim, however, is thin. Most writing on agile internal auditing is conceptual or rests on single cases [1,5]; studies of AI in auditing rarely follow it through to risk outcomes; and we found no study that looks at the two together.

Saudi Arabia is a good place to study the question because firms have to say a lot about it in public. The Corporate Governance Regulations require each listed company to report every year on the audit committee's work, the internal audit function, the main risks it faces and the effectiveness of internal control, while leaving the choice of audit method to the firm [6]. Banks and finance companies face further internal audit and risk rules from SAMA [7,8], and the national

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strategy for data and AI under Vision 2030 has pushed AI adoption quickly, though not evenly [9]. The result is a large body of comparable text on how internal audit works, how far firms use AI and how they manage risk.

We ask two questions: is agile internal auditing associated with better risk management, and does AI adoption strengthen that link? To answer them, we analysed 635 board reports of 232 main-market firms for 2022–2024 and built three indexes from them: an Agile Internal Audit Disclosure Index (AIADI), a Digital and AI Adoption Index (DAI) and an Enterprise Risk Management Quality Index (ERMQ). Panel regressions with sector and year fixed effects show that firms scoring higher on either agility or AI adoption report more mature risk management. The second answer was not the one we expected. AI adoption does not strengthen the agility effect; if anything, it weakens it, and the negative interaction becomes significant in several robustness tests. The reports suggest why. Mentions of AI rose from 27.5% to 47.8% of reports over the period, but almost all of them describe AI used in the business; fewer than 2% describe internal audit using analytics or AI in its own work.

The paper adds three things to the literature: large-sample evidence on agile internal auditing, which has so far been studied mainly through cases; evidence that whether audit methods and technology reinforce each other depends on where the technology sits; and archival measures of agility, AI adoption and risk management quality that other researchers can replicate, built with an AI-assisted coding procedure that we disclose and verify. Section 2 develops the hypotheses, Section 3 describes the data and measures, Section 4 reports the results, Section 5 discusses them and Section 6 concludes.

## 2 Theoretical framework and hypotheses development

Dynamic capabilities are a firm's ability to sense threats, seize them and reconfigure resources in changing environments [10,11]. A traditional internal audit function runs ordinary routines, an annual plan and engagements that report on completion, whereas agile internal auditing continually revises the plan and redeploys audit resources as the risk profile moves; we therefore treat it as a dynamic capability of the function [12]. Agency theory explains why this matters: internal audit narrows the information gap between managers and the board, so assurance that arrives sooner and covers more of the risk exposure should improve risk oversight [13]. We define risk management effectiveness as the extent to which significant risks are identified, assessed, met with appropriate responses, monitored and reported to the board [14], and measure it from the risk practices firms disclose [15,16].

Agile internal auditing has four dimensions: adaptive planning, iterative execution, stakeholder collaboration and continuous reporting [1,4,17]. Together they shorten the time between the emergence of a risk and its reporting to the audit committee and connect internal audit with the risk and compliance functions [18,19]. We expect:

***H1:*** *Agile internal auditing is positively associated with risk management effectiveness.*

AI adoption covers AI-enabled tools and the digital strategy, analytics, automation and data governance on which they depend [2]. AI promises wider and faster risk coverage, through full-population testing, continuous monitoring and earlier detection of emerging risks, and technology use has been linked to audit quality, internal audit effectiveness and firm performance [3,20,21]. We expect:

***H2:*** *AI adoption is positively associated with risk management effectiveness.*

Complementarity theory holds that two practices are complements when doing more of one raises the return to the other, and substitutes when they deliver the same benefit through different channels [22]. AI can remove the data bottleneck that limits short audit cycles, and agile routines allow the function to act on the continuous flow of AI-generated signals. We therefore hypothesise:

***H3:*** *AI adoption positively moderates the relationship between agile internal auditing and risk management effectiveness, such that the relationship is stronger when AI adoption is high.*

Figure 1 summarises the model.

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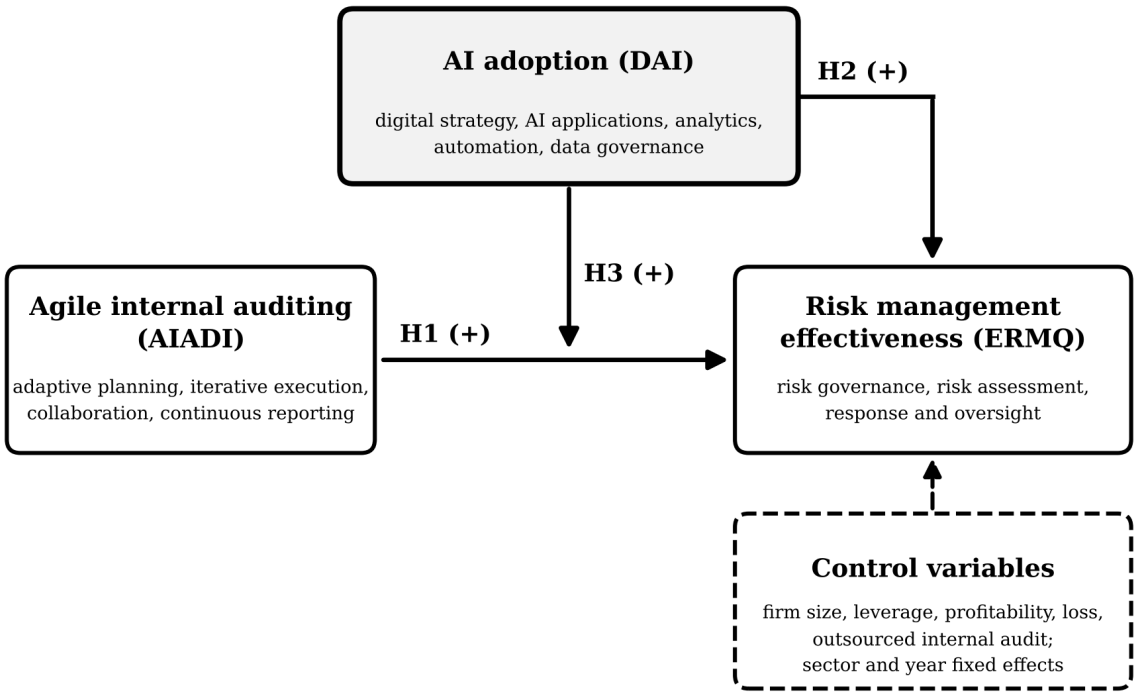



**Fig. 1:** Conceptual model

## 3 Research design

### *3.1 Sample and data*

The population comprises operating companies listed on the main market of the Saudi Exchange (TASI) for fiscal years 2022–2024. The main source is the annual board of directors' report, which contains the audit committee's report on internal audit, the risk disclosures, the annual review of internal control and the firm's strategy. Financial data come from the annual financial summaries on each company's Saudi Exchange profile; 14 firm-years with gaps were completed from the multi-year summary in the board report. Table 1 summarises the sample selection.

**Table 1:** Sample selection

| Step | Firm-years | Firms |
|---|---|---|
| Board reports located for main-market firms, FY2022–2024 | 685 | 243 |
| Less: reports that could not be opened or converted to text | −18 | |
| Less: other firm-years of firms with a failed report | −12 | −10 |
| Less: reports with garbled Arabic text on extraction | −2 | |
| Firm-years in the panel | 653 | 233 |
| Less: scanned reports without a text layer (not codable) | −18 | −1 |
| Coded firm-years | 635 | 232 |
| Less: firm-years with missing financial data | −10 | −1 |
| Regression sample | 625 | 231 |

### *3.2 Measurement*

The three constructs are measured with dichotomous, unweighted disclosure indexes [23,24]: each item scores 1 when the report discloses the practice as defined in a coding manual, and each index is the share of items scored 1. Duties copied

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from committee charters or regulations score 0 unless the report states that the activity was performed during the year. Appendix A lists all items.

–**AIADI** (15 items) covers adaptive planning, iterative execution, stakeholder collaboration and continuous reporting.
–**DAI** (8 items) covers firm-level digital strategy, concrete AI applications, analytics, automation, data governance and digital investment, plus internal audit's own use of analytics and AI. Mentions of AI as a trend or plan score 0. As text-based alternatives we count core AI terms and data and automation terms in each report [21,25].
–**ERMQ** (12 items) follows COSO [14] and ISO 31000 and covers risk governance, risk identification and assessment, and risk response and oversight [15,16].

*Coding and reliability:* The text of each report was extracted page by page; search patterns retrieved the passages relevant to each item; and a large language model (Claude, Anthropic) applied the coding manual's decision rules to these passages, recording a code and a page reference for every item. Ambiguous cases (286 of 22,225 codes, 1.3%) were coded 0 in the main analysis. Language models can match trained human coders on annotation tasks [26], but their output must be verified: one of the authors independently coded a random 10.4% sample of 66 firm-years, stratified by year and sector group, from the full reports. Agreement between the two sets of codes is measured by percent agreement and Krippendorff's $\alpha$, with $\alpha \geq 0.80$ taken as reliable and 0.667 as the minimum for tentative conclusions [27]. Kuder–Richardson 20 coefficients are 0.61 (AIADI), 0.68 (DAI) and 0.79 (ERMQ).

*Control variables:* SIZE is the log of total assets; LEV is total liabilities over total assets; ROA is profit before zakat and tax over total assets; LOSS equals 1 for a pre-tax loss; and OUTS equals 1 when internal audit is outsourced or co-sourced. LEV and ROA are winsorised at 1% and 99%. Definitions are in Appendix B.

### *3.3 Empirical model*

$$ERMQ_{it} = \beta_0 + \beta_1 AIADI_{it} + \beta_2 DAI_{it} + \beta_3 (AIADI_{it} \times DAI_{it}) + \gamma Controls_{it} + \text{Sector FE} + \text{Year FE} + \varepsilon_{it} \quad (1)$$

H1, H2 and H3 predict $\beta_1$, $\beta_2$ and $\beta_3 > 0$. AIADI and DAI are mean-centred before forming the interaction [28]. We estimate the model by OLS with standard errors clustered by firm [29], probe the interaction with simple slopes and the Johnson–Neyman technique [30,31], test normality, heteroscedasticity and functional form [32,33,34], confirm inference with a pairs cluster bootstrap [35] and, because ERMQ is bounded, also estimate a fractional logit model [36].

## 4 Results

### *4.1 Descriptive statistics*

**Table 2:** Descriptive statistics

| Variable | N | Mean | SD | Min | P25 | Median | P75 | Max |
|---|---|---|---|---|---|---|---|---|
| ERMQ | 625 | 0.412 | 0.230 | 0.000 | 0.250 | 0.333 | 0.583 | 1.000 |
| AIADI | 625 | 0.096 | 0.108 | 0.000 | 0.000 | 0.067 | 0.133 | 0.467 |
| DAI | 625 | 0.127 | 0.170 | 0.000 | 0.000 | 0.125 | 0.250 | 0.750 |
| SIZE | 625 | 21.742 | 1.833 | 17.603 | 20.612 | 21.478 | 22.424 | 28.544 |
| LEV | 625 | 0.502 | 0.233 | 0.037 | 0.332 | 0.511 | 0.679 | 1.087 |
| ROA | 625 | 0.047 | 0.084 | −0.251 | 0.013 | 0.040 | 0.096 | 0.262 |
| LOSS | 625 | 0.190 | 0.393 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 |
| OUTS | 625 | 0.067 | 0.251 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 |
| AI_LN | 625 | 0.625 | 0.986 | 0.000 | 0.000 | 0.000 | 1.099 | 4.317 |

*Notes:* N = 625 firm-years of 231 firms, 2022–2024. LEV and ROA are winsorised at the 1st and 99th percentiles. AI_LN is the log of one plus the number of core AI terms.

The average firm-year discloses 41.2% of the ERMQ items but only 9.6% of the AIADI and 12.7% of the DAI items (Table 2). AIADI and DAI are strongly right-skewed (skewness 1.09 and 1.49) and are zero in 40% and 49% of firm-years, whereas ERMQ is closer to symmetric (Figure 2); Shapiro–Wilk tests [37] reject normality for all three ($p < 0.001$).

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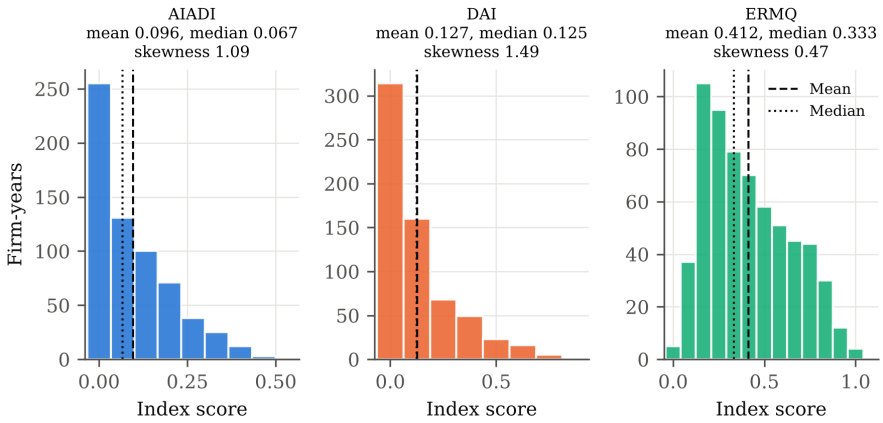



**Fig. 2:** Distributions of the three disclosure indexes (635 coded firm-years)

Dashed lines mark the mean and dotted lines the median.

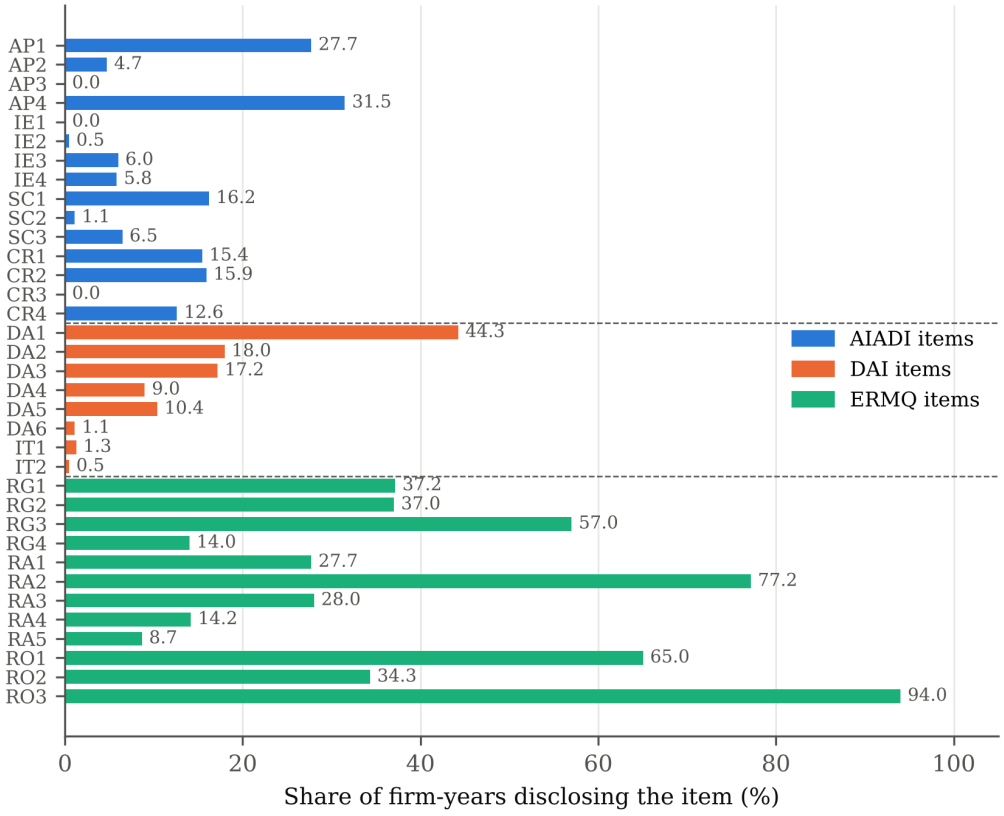



**Fig. 3:** Share of firm-years disclosing each index item

Dashed lines separate the AIADI, DAI and ERMQ items.

Figure 3 shows that traditional practices dominate audit disclosure: audit committee approval of the plan (31.5%) and a risk-based plan (27.7%). Plan revisions (4.7%) and continuous auditing (0.5%) are rare, and no report mentions an agile methodology, risk-triggered plan changes or interim escalation. A digital strategy (44.3%) and a concrete AI application (18.0%) are common, but internal audit's own use of analytics (1.3%) or AI (0.5%) is almost never reported.

Between 2022 and 2024, mean DAI rose from 0.081 to 0.185 and the share of reports mentioning AI from 27.5% to 47.8%, ERMQ rose from 0.365 to 0.460, and AIADI barely changed (Figure 4). Financial firms score higher on ERMQ

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(0.590 vs 0.368; Welch $t = 10.39$. $p < 0.001$) and DAI (0.176 vs 0.115: $p = 0.002$) but not on AIADI ($p = 0.118$) (Figure 5), and EF

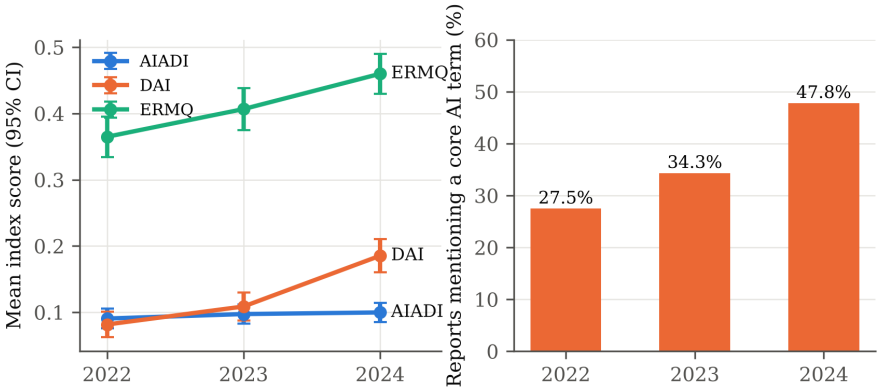



**Fig. 4:** Mean index scores by year with 95% confidence intervals (left) and the share of board reports mentioning at least one core AI term (right)

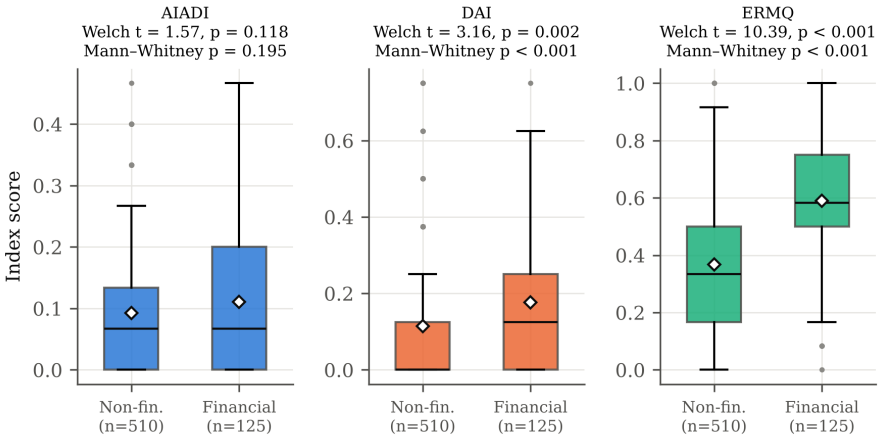



**Fig. 5:** Distribution of the indexes in non-financial and financial firms

Boxes show the interquartile range, lines the median and diamonds the mean.

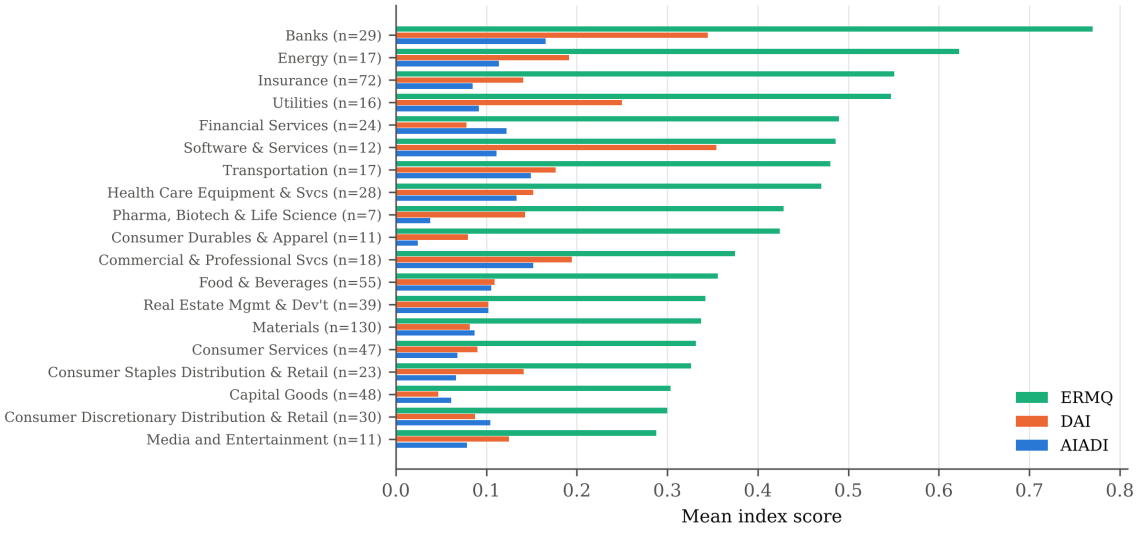



**Fig. 6:** Mean index scores by Saudi Exchange sector (sectors with at least seven firm-years), ordered by ERMQ

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### *4.2 Correlation analysis*

ERMQ correlates positively with AIADI ($r = 0.42$), DAI ($r = 0.53$) and SIZE ($r = 0.52$); AIADI and DAI are only moderately correlated ($r = 0.32$), and DAI correlates strongly with the text-based AI measure ($r = 0.76$), supporting its validity (Table 3, Figure 7). The decile means in Figure 8 show that ERMQ rises steadily with both indexes without thresholds or reversals.

**Table 3:** Pearson correlation matrix

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| (1) ERMQ | 1 | | | | | | | | |
| (2) AIADI | 0.42*** | 1 | | | | | | | |
| (3) DAI | 0.53*** | 0.32*** | 1 | | | | | | |
| (4) SIZE | 0.52*** | 0.38*** | 0.47*** | 1 | | | | | |
| (5) LEV | 0.31*** | 0.18*** | 0.21*** | 0.30*** | 1 | | | | |
| (6) ROA | 0.02 | 0.07* | 0.18*** | 0.11*** | −0.22*** | 1 | | | |
| (7) LOSS | −0.15*** | −0.08* | −0.23*** | −0.24*** | 0.09** | −0.68*** | 1 | | |
| (8) OUTS | −0.11*** | 0.00 | −0.08** | −0.13*** | −0.14*** | −0.10** | 0.10** | 1 | |
| (9) AI_LN | 0.45*** | 0.31*** | 0.76*** | 0.45*** | 0.16*** | 0.18*** | −0.21*** | −0.06 | 1 |

*Notes:* N = 625. ***, ** and * denote significance at the 1%, 5% and 10% levels (two-tailed).

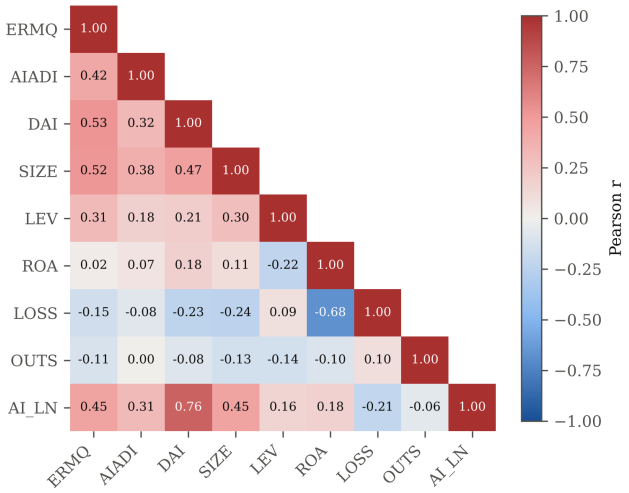



**Fig. 7:** Heat map of Pearson correlations between the study variables (N = 625)

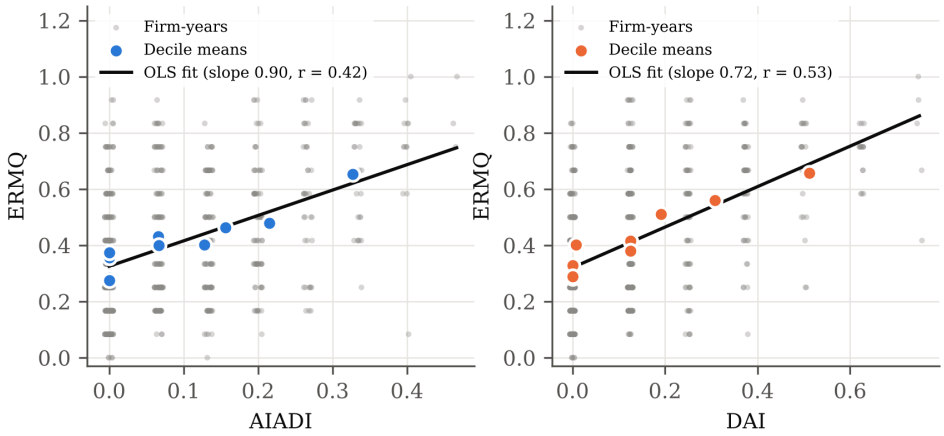



**Fig. 8:** Risk management quality against agile internal audit disclosure (left) and AI adoption (right): firm-years (grey), decile means and the ordinary least squares fit

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### *4.3 Hypothesis tests*

**Table 4:** Agile internal auditing, AI adoption and risk management effectiveness

| Variable | Model 1 | Model 2 (H1) | Model 3 (H2) | Model 4 (H3) |
|---|---|---|---|---|
| AIADI | | 0.567*** | 0.487*** | 0.515*** |
| | | (0.111) | (0.107) | (0.107) |
| DAI | | | 0.361*** | 0.390*** |
| | | | (0.065) | (0.069) |
| AIADI × DAI | | | | −0.622 |
| | | | | (0.421) |
| SIZE | 0.055*** | 0.039*** | 0.026*** | 0.027*** |
| | (0.011) | (0.010) | (0.009) | (0.009) |
| LEV | 0.105* | 0.073 | 0.074 | 0.068 |
| | (0.063) | (0.063) | (0.059) | (0.060) |
| ROA | −0.087 | −0.123 | −0.155 | −0.175 |
| | (0.152) | (0.145) | (0.136) | (0.136) |
| LOSS | −0.026 | −0.033 | −0.021 | −0.023 |
| | (0.027) | (0.026) | (0.025) | (0.026) |
| OUTS | −0.011 | −0.031 | −0.027 | −0.028 |
| | (0.043) | (0.037) | (0.031) | (0.031) |
| Constant | −0.821*** | −0.400 | −0.122 | −0.126 |
| | (0.266) | (0.261) | (0.240) | (0.238) |
| Sector and year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 625 | 625 | 625 | 625 |
| Firms (clusters) | 231 | 231 | 231 | 231 |
| $R^2$ | 0.431 | 0.486 | 0.528 | 0.531 |
| Adjusted $R^2$ | 0.406 | 0.463 | 0.506 | 0.508 |

*Notes:* The dependent variable is ERMQ. AIADI and DAI are mean-centred. OLS with sector and year fixed effects; firm-clustered standard errors in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

AIADI is positive and significant when added (Model 2: $\beta = 0.567$, $p < 0.01$), as is DAI (Model 3: $\beta = 0.361$, $p < 0.01$), and both remain so in the full model (Model 4: $\beta = 0.515$ and 0.390, $p < 0.01$). A one-standard-deviation increase in AIADI corresponds to 0.24 standard deviations of ERMQ, and in DAI to 0.29 (Figure 9). H1 and H2 are supported. The interaction is negative and insignificant ($\beta = -0.622$, $p = 0.14$), so H3 is not supported. Wald tests confirm that adding AIADI ($F(1,230) = 26.00$) and DAI ($F(1,230) = 31.06$) improves the model, whereas adding the interaction does not ($F(1,230) = 2.18$, $p = 0.141$) (Table 5).

**Table 5:** Hierarchical model comparison and joint tests

| Test | Restriction | F | df | p-value | $\Delta R^2$ |
|---|---|---|---|---|---|
| Step 1 → 2 | AIADI = 0 | 26.00 | (1, 230) | < 0.001 | 0.055 |
| Step 2 → 3 | DAI = 0 | 31.06 | (1, 230) | < 0.001 | 0.042 |
| Step 3 → 4 | AIADI × DAI = 0 | 2.18 | (1, 230) | 0.141 | 0.003 |
| Main terms (Model 4) | AIADI = DAI = AIADI × DAI = 0 | 20.41 | (3, 230) | < 0.001 | — |
| Sector fixed effects (Model 4) | All sector effects = 0 | 3.46 | (19, 230) | < 0.001 | — |
| Year fixed effects (Model 4) | Both year effects = 0 | 6.86 | (2, 230) | 0.001 | — |

*Notes:* Wald tests based on the firm-clustered covariance matrix (231 clusters).

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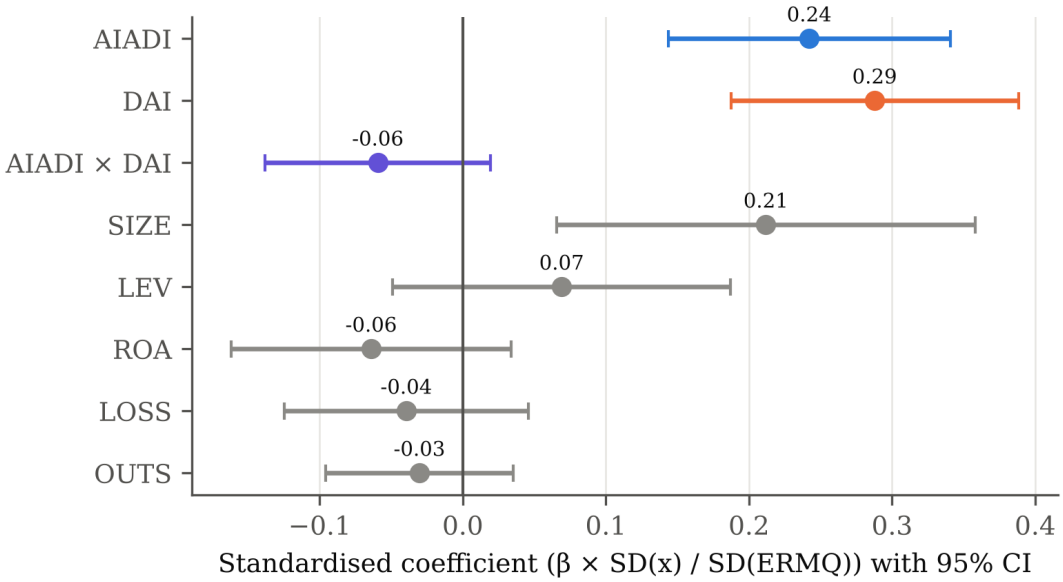



**Fig. 9:** Standardised coefficients from Model 4 with 95% confidence intervals based on firm-clustered standard errors

The agility slope is 0.621 at low DAI (−1 SD), 0.515 at the mean and 0.409 at high DAI (+1 SD), all $p < 0.01$ (Figure 10). The Johnson–Neyman analysis shows that the effect remains significant for DAI below 0.45, which covers 93% of firm-years (Figure 11), and the predicted-response surface bends toward the origin, the signature of a substitutive interaction (Figure 12). Among the dimensions, stakeholder collaboration is the strongest predictor when all four are entered together ($\beta = 0.197$, $p < 0.01$), followed by adaptive planning ($\beta = 0.092$, $p = 0.05$) and continuous reporting ($\beta = 0.110$, $p = 0.09$) (Figure 13).

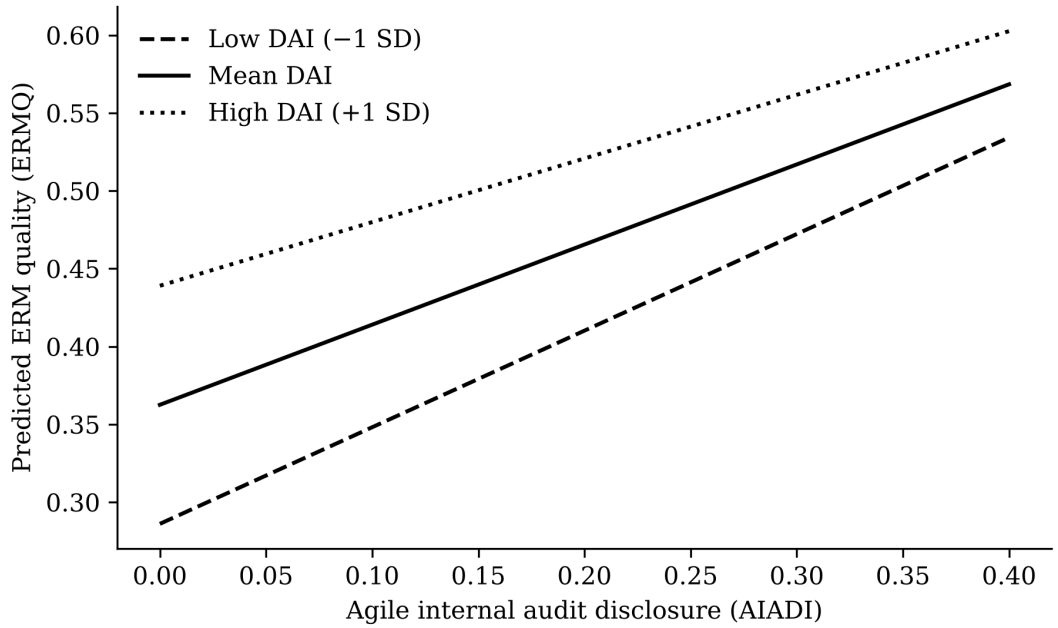



**Fig. 10:** Simple slopes of agile internal auditing at low (−1 SD), mean and high (+1 SD) AI adoption, from Model 4

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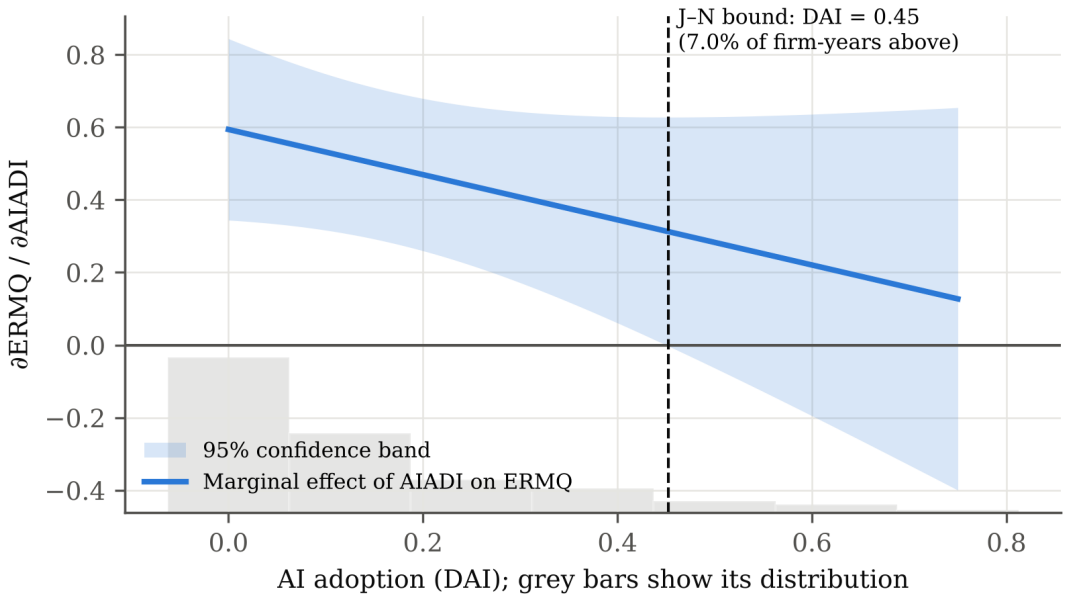



**Fig. 11:** Johnson–Neyman plot: marginal effect of AIADI on ERMQ across the observed range of DAI with a 95% confidence band; grey bars show the distribution of DAI

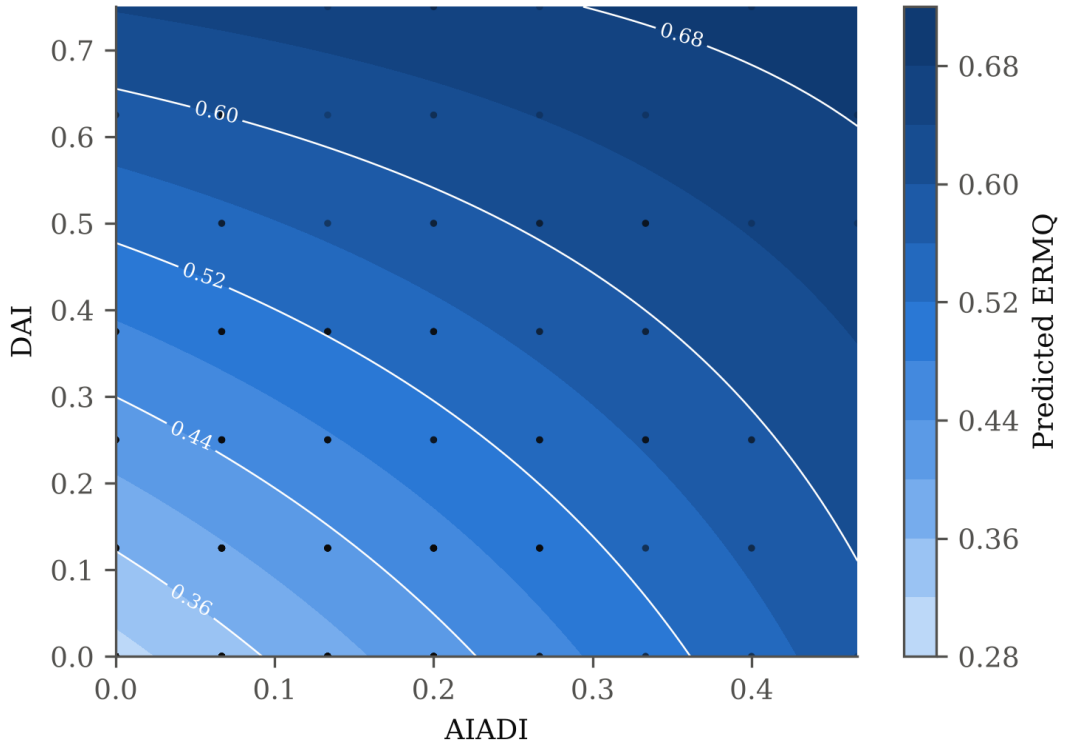



**Fig. 12:** Predicted ERMQ over the joint range of AIADI and DAI from Model 4 (other variables at their means); dots are observed firm-years

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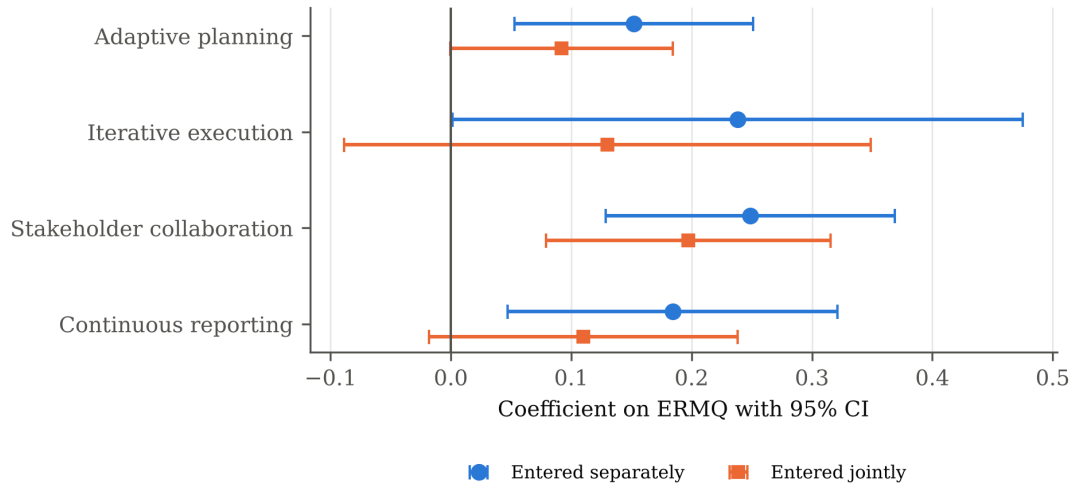



**Fig. 13:** Coefficients of the four AIADI dimensions with 95% confidence intervals, entered separately and jointly (with DAI, controls and fixed effects)

### *4.4 Diagnostics and bootstrap inference*

Residuals are approximately normal (Jarque–Bera = 3.80, $p = 0.150$), but heteroscedastic (Breusch–Pagan $p < 0.001$), which the clustered errors address; the significant RESET test reflects the bounded dependent variable, as squared terms are insignificant (Table 6, Figure 14). A cluster bootstrap with 2,000 resamples of firms gives 95% intervals that exclude zero for AIADI and DAI and include zero for the interaction (Figure 15).

**Table 6:** Regression diagnostics and bootstrap confidence intervals (Model 4)

| Test or statistic | Value | p-value | Interpretation |
|---|---|---|---|
| Jarque–Bera normality test | 3.80 | 0.150 | Normality not rejected |
| Breusch–Pagan (Koenker) heteroscedasticity test | 111.34 (df = 29) | $< 0.001$ | Robust errors used |
| Ramsey RESET (fitted$^2$ and fitted$^3$) | $F(2, 230) = 8.83$ | $< 0.001$ | Bounded DV; see fractional logit |
| Variance inflation factor: mean / maximum | 1.48 / 1.99 | — | No multicollinearity |
| Cluster bootstrap 95% CI: AIADI | [0.301, 0.718] | $< 0.001$ | Excludes zero |
| Cluster bootstrap 95% CI: DAI | [0.225, 0.514] | $< 0.001$ | Excludes zero |
| Cluster bootstrap 95% CI: AIADI × DAI | [−1.451, 0.220] | 0.141 | Includes zero |

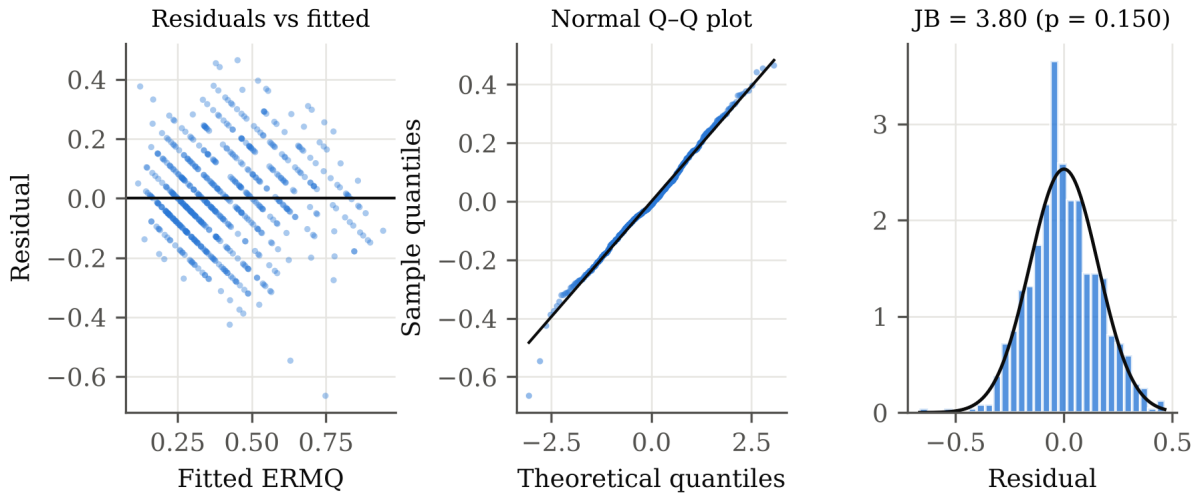



**Fig. 14:** Residual diagnostics for Model 4: residuals against fitted values, normal Q–Q plot, and residual histogram with a fitted normal density

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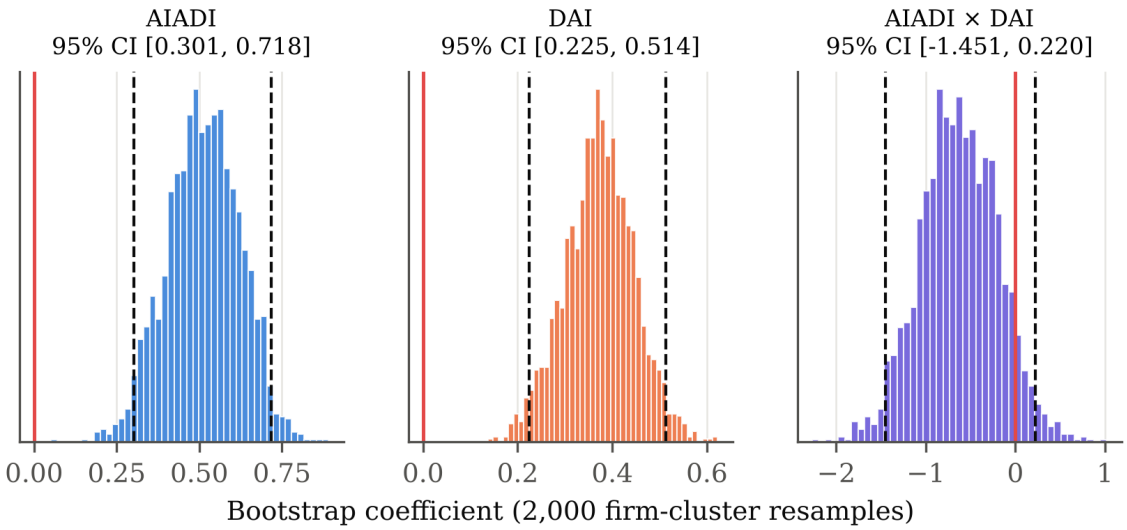



**Fig. 15:** Cluster bootstrap distributions (2,000 resamples of firms) of the coefficients of AIADI, DAI and their interaction; dashed lines mark the 95% percentile interval and the red line zero

## *4.5 Robustness tests*

**Table 7:** Robustness tests

| Test | AIADI | DAI / moderator | AIADI × moderator | N | Adj. $R^2$ |
|---|---|---|---|---|---|
| (1) Dependent variable measured at $t+1$ | 0.496*** (0.128) | 0.332*** (0.100) | −0.672 (0.689) | 390 | 0.469 |
| (2) Moderator = ln(1 + core AI terms) | 0.511*** (0.110) | 0.051*** (0.013) | −0.026 (0.080) | 625 | 0.490 |
| (3) Moderator = AI and data terms per 10,000 words | 0.551*** (0.112) | 0.016** (0.007) | 0.005 (0.047) | 625 | 0.471 |
| (4) Uncertain items coded 1 | 0.517*** (0.102) | 0.375*** (0.065) | −0.500 (0.362) | 625 | 0.526 |
| (5) Equal-weighted dimension indexes | 0.519*** (0.106) | 0.564*** (0.099) | −1.179** (0.531) | 625 | 0.500 |
| (6) Non-financial firms | 0.421*** (0.128) | 0.440*** (0.085) | −0.372 (0.533) | 504 | 0.420 |
| (7) Financial firms (banks, insurers, finance) | 0.590*** (0.134) | 0.278** (0.120) | −1.145** (0.517) | 121 | 0.470 |
| (8) Fractional logit (coefficients) | 2.254*** (0.465) | 1.717*** (0.312) | −2.857 (2.070) | 625 | — |
| (9) Control for report length | 0.392*** (0.104) | 0.236*** (0.068) | −0.524 (0.398) | 625 | 0.552 |
| (10) Excluding hand-filled financial data | 0.519*** (0.107) | 0.385*** (0.070) | −0.631 (0.420) | 618 | 0.508 |
| (11) Firm and year fixed effects | 0.155 (0.187) | 0.252*** (0.074) | −0.705** (0.344) | 625 | 0.839 |
| (12) ERMQ without RG1 and RO3 | 0.570*** (0.118) | 0.458*** (0.073) | −0.814* (0.455) | 625 | 0.480 |

*Notes:* Each row re-estimates Model 4 with the change described; firm-clustered standard errors in parentheses. Model (11) replaces sector with firm fixed effects; model (1) uses 2022–2023 only. ***, ** and * denote significance at the 1%, 5% and 10% levels.

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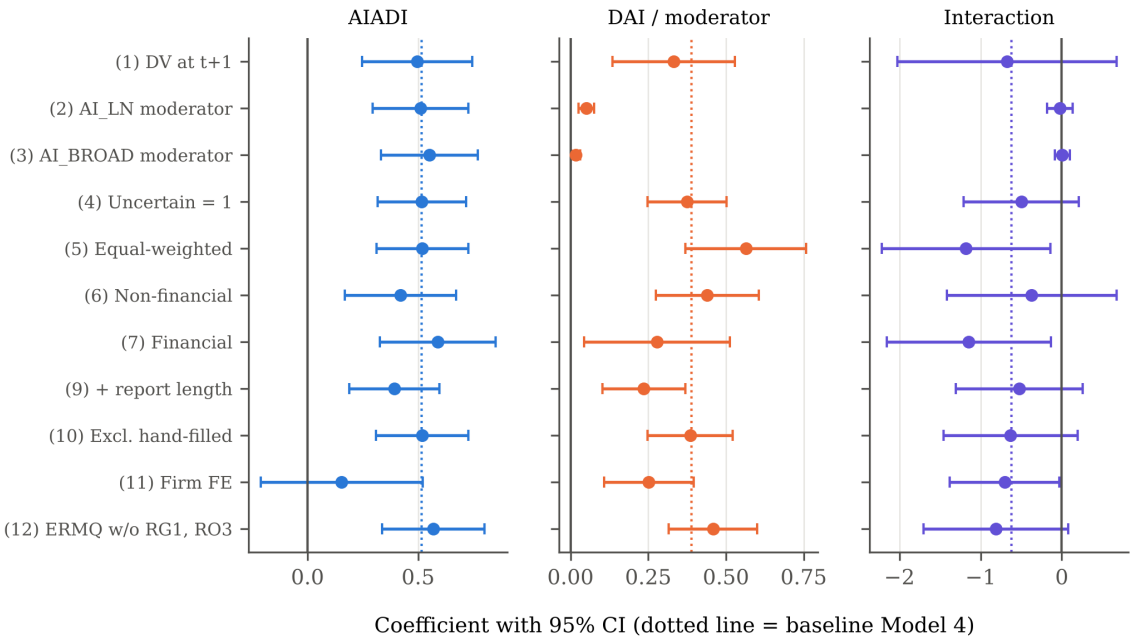



**Fig. 16:** Forest plot of the robustness tests (fractional logit omitted because of its different scale); dotted lines show the baseline Model 4 estimates

AIADI remains positive and significant in eleven of twelve tests, including with ERMQ measured one year ahead, alternative coding, equal weights, both sector groups, a fractional logit and a control for report length (Table 7, Figure 16). The exception is the firm fixed-effects model, because AIADI varies little within firms over three years; the association is mainly between firms. DAI is significant in all tests. The interaction is negative in eleven tests and significant in three, and never positive and significant. Table 8 summarises the results.

**Table 8:** Summary of hypothesis tests

| Hypothesis | Expected sign | Result | Decision |
|---|---|---|---|
| H1. Agile internal auditing is positively associated with risk management effectiveness. | + | $\beta = 0.515$, $p < 0.01$; bootstrap CI [0.301, 0.718] | Supported |
| H2. AI adoption is positively associated with risk management effectiveness. | + | $\beta = 0.390$, $p < 0.01$; bootstrap CI [0.225, 0.514] | Supported |
| H3. AI adoption strengthens the agility–risk management relationship. | + | $\beta = -0.622$, $p = 0.14$; bootstrap CI [−1.451, 0.220] | Not supported |

## 5 Discussion

Firms whose board reports describe more agile internal audit practices also report more developed risk management. That fits the idea behind H1: an audit function that revises its plan as risks change, works alongside the other assurance providers and reports to the audit committee during the year, not only at its end, helps the organisation notice risks earlier and act on them [11,13]. What drives the result is worth noting. It is not sprint-style execution, which almost no report mentions, but collaboration with the risk and compliance functions and risk-based planning. In Saudi firms, agility so far looks less like a new audit method and more like closer ties between internal audit and the rest of the risk system [19]. The complete absence of the words “agile” or “sprint” in 635 reports means either that the method is still rare [1,5] or that firms using it do not say so.

AI adoption shows its own positive association with risk management, both across firms and, unlike agility, within firms over time, in line with earlier work on technology and audit or firm outcomes [3,20,21]. We are careful about what

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this means. The DAI is dominated by AI used in operations, customer service and planning, so the result supports H2 for AI in the organisation; it says little about AI in the hands of auditors, because so few reports describe that.

The rejection of H3 is the most interesting result. We expected the two practices to be complements [22]; in the data they behave more like partial substitutes. The most likely reason, in our view, is where the AI sits. Complementarity assumes that the audit team can use the technology. In our sample it is the business that uses it. A firm whose operations already flag risks through dashboards and automated controls gets less extra benefit from an agile audit function, while a firm without such tools depends more on internal audit to carry new risks to the board. Two other explanations cannot be ruled out: boards have limited attention for governance initiatives, and bounded indexes compress differences at the top of the scale. The second is less likely, since the negative interaction survives the fractional logit model.

The practical message for chief audit executives and audit committees is encouraging, because the practices most closely linked to risk management cost little: a risk-based plan that is reviewed during the year, regular coordination with risk and compliance, and frequent reporting of findings and follow-up. Building analytics inside the internal audit function itself may be what turns agility and AI into complements. For the Capital Market Authority and SAMA, guidance asking firms to describe how internal audit worked during the year, rather than repeating the duties in its charter, would give investors much more useful information.

## 6 Conclusion

We set out to test whether agile internal auditing improves risk management in Saudi listed firms and whether AI adoption makes it work better. Using indexes built from 635 board reports for 2022–2024, we find that agility and AI adoption are each linked to stronger risk management, but that AI, as Saudi firms currently use it, does not make agile auditing more effective. The two appear to cover some of the same ground.

Four results stand out. First, agile internal auditing is positively and significantly associated with risk management quality ($\beta = 0.515$, $p < 0.01$): a one-standard-deviation increase in the agility index corresponds to about a quarter of a standard deviation in the risk management index. The effect rests mainly on stakeholder collaboration and risk-based, adaptive planning rather than on sprint-style execution. Second, AI adoption has its own positive association with risk management quality ($\beta = 0.390$, $p < 0.01$), which holds both across firms and within firms over time. Third, the two do not reinforce each other: the interaction is negative ($\beta = -0.622$, $p = 0.14$), the agility slope falls from 0.621 at low AI adoption to 0.409 at high adoption, and the agility effect is no longer significant once the AI index exceeds 0.45, a level reached by 7% of firm-years. Fourth, disclosure of agile audit practice is thin: no report mentions an agile or sprint-based audit methodology, fewer than 5% report revising the audit plan during the year, and fewer than 2% describe internal audit's own use of analytics or AI.

These results carry two lessons for theory. For the dynamic capabilities view [10,11], they suggest that the capability of an internal audit function lies less in the speed of its work cycle than in its connections: the dimensions that matter are those that tie internal audit to the risk owners and to the board. For complementarity theory [22], they show that two practices that look complementary in principle can act as substitutes when they sit in different parts of the organisation. Whether AI strengthens internal audit depends on whether auditors themselves use it, not on how much AI the firm has adopted.

For practice, the findings suggest an order of priorities. Chief audit executives can strengthen the function's contribution to risk management with steps that need little investment: reviewing the audit plan against the risk register during the year, holding regular joint sessions with the risk and compliance functions, and reporting findings and follow-up to the audit committee between annual reports. Audit committees can ask for these practices explicitly when they approve the plan. As AI spreads through Saudi firms, the next step is to give internal audit access to the same data and tools that the business already uses, so that auditors can test whole populations and monitor risk indicators continuously instead of duplicating what management systems already flag. For the Capital Market Authority and SAMA [6,7,8], the thin disclosures point to a simple reform: asking firms to report how the audit plan changed during the year, how often internal audit reported to the audit committee and whether it uses analytics would let investors distinguish an active audit function from a formal one.

Several limitations qualify these findings. The indexes record what firms disclose, not what they do. The results are associations, and the agility effect comes mainly from differences between firms rather than changes within them. The AI-assisted coding may have missed relevant passages that the search patterns did not retrieve, which would bias the estimates toward zero. The AI measure cannot isolate AI used by auditors, and the panel covers only three years of one market.

Future research can build on this study in several directions. Surveys or interviews with chief audit executives would show whether the practices firms disclose match those they use and would allow internal audit's own use of AI to be measured directly. Longer panels would make it possible to study how changes in audit practice within firms affect risk outcomes, and outcome measures such as restatements, regulatory penalties or credit-rating changes would complement

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the disclosure-based risk management index. Comparisons with other Gulf markets that share Saudi Arabia's governance model would show whether the substitution between agility and AI is specific to the Saudi setting. Finally, as more firms bring AI into internal audit itself, researchers will be able to test directly whether auditor-side AI turns agility and AI into complements.

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**Data Availability Statement:** The data were collected from board of directors' reports and company profiles that are publicly available on the Saudi Exchange website (www.saudiexchange.sa). The coded dataset, the coding manual and the coding log with page references are available from the corresponding author on reasonable request.

**Conflict of Interest:** The authors declare no conflicts of interest.

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## Appendix A. Index items and disclosure frequencies

Each item scores 1 when the board report discloses the practice as defined in the coding manual and 0 otherwise. The last column reports the share of the 635 coded firm-years in which the item was scored 1.

**Table A1:** Index items and disclosure frequencies

| Code | Item (scored 1 when disclosed) | % of firm-years |
|---|---|---|
| **AIADI — Adaptive planning** | | |
| AP1 | Audit plan based on risk assessment | 27.7 |
| AP2 | Plan revised during the year | 4.7 |
| AP3 | Plan changes linked to emerging risks | 0.0 |
| AP4 | Audit committee reviewed/approved the plan | 31.5 |
| **AIADI — Iterative execution** | | |
| IE1 | Agile or sprint-based methodology | 0.0 |
| IE2 | Continuous auditing by internal audit | 0.5 |
| IE3 | Special or ad hoc reviews performed | 6.0 |
| IE4 | Charter/methodology updated or quality assessment | 5.8 |
| **AIADI — Stakeholder collaboration** | | |
| SC1 | Coordination with risk/compliance (three lines) | 16.2 |
| SC2 | Coordination with external auditor | 1.1 |
| SC3 | Advisory/consulting services provided | 6.5 |
| **AIADI — Continuous reporting** | | |
| CR1 | At least quarterly reporting to the audit committee | 15.4 |
| CR2 | Follow-up of recommendations reported | 15.9 |
| CR3 | Interim escalation of significant issues | 0.0 |
| CR4 | Functional reporting of the head of IA to the audit committee | 12.6 |
| **DAI — Firm-level digital and AI adoption** | | |
| DA1 | Digital transformation strategy or programme | 44.3 |
| DA2 | Specific AI or machine-learning application | 18.0 |
| DA3 | Data analytics used in decision-making | 17.2 |
| DA4 | Robotic process or intelligent automation | 9.0 |
| DA5 | Data governance or data protection programme | 10.4 |
| DA6 | Amount of IT/digital investment disclosed | 1.1 |
| **DAI — Internal audit technology** | | |
| IT1 | Internal audit uses data analytics/CAATs | 1.3 |
| IT2 | Internal audit uses AI or continuous controls monitoring | 0.5 |
| **ERMQ — Risk governance** | | |
| RG1 | Board risk committee or formally assigned risk mandate | 37.2 |
| RG2 | Chief risk officer or risk management function | 37.0 |
| RG3 | Board-approved risk policy/framework | 57.0 |
| RG4 | Reference to COSO ERM, ISO 31000 or regulatory framework | 14.0 |
| **ERMQ — Risk identification and assessment** | | |
| RA1 | Risk appetite or tolerance disclosed | 27.7 |
| RA2 | Principal risks described | 77.2 |
| RA3 | Likelihood–impact assessment or risk register | 28.0 |
| RA4 | Emerging risks discussed | 14.2 |
| RA5 | Scenario analysis or stress testing | 8.7 |
| **ERMQ — Risk response and oversight** | | |
| RO1 | Mitigation actions for key risks | 65.0 |
| RO2 | Risk management integrated with strategy | 34.3 |
| RO3 | Board/AC opinion on internal control effectiveness | 94.0 |

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## Appendix B. Variable definitions

**Table B1:** Variable definitions

| Variable | Definition | Source |
|---|---|---|
| ERMQ | Enterprise Risk Management Quality Index: items scored 1 divided by 12 (Appendix A) | Board report |
| AIADI | Agile Internal Audit Disclosure Index: items scored 1 divided by 15 (Appendix A) | Board report |
| DAI | Digital and AI Adoption Index: items scored 1 divided by 8 (Appendix A) | Board report |
| AI_LN | Natural logarithm of one plus the number of core AI terms in the report | Board report text |
| AI_BROAD | Core AI terms plus data and automation terms per 10,000 words (winsorised at 1% and 99%) | Board report text |
| SIZE | Natural logarithm of total assets (SAR) | Company profile |
| LEV | Total liabilities divided by total assets (winsorised at 1% and 99%) | Company profile |
| ROA | Profit before zakat and income tax divided by total assets (winsorised at 1% and 99%) | Company profile |
| LOSS | 1 if profit before zakat and income tax is negative, 0 otherwise | Company profile |
| OUTS | 1 if internal audit is outsourced or co-sourced to an external firm, 0 otherwise | Board report |
| Sector FE | Indicators for the Saudi Exchange sectors | Saudi Exchange |
| Year FE | Indicators for fiscal years 2022, 2023 and 2024 | — |

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