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Organizational Readiness for Artificial Intelligence Adoption in External Auditing: The Roles of Auditor Training, Digital Audit Infrastructure, and Audit Firm Size

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Abstract:

This study examines the determinants of AI adoption among external audit firms in Saudi Arabia, focusing on auditor training, digital audit infrastructure, and audit-firm size within the technology–organization–environment framework. Using 38 questionnaires and Firth bias-reduced logistic regression, the results show that auditor training is positively and significantly associated with AI adoption, while digital audit infrastructure has a positive but imprecise effect and audit-firm size is nonsignificant. The findings highlight audit-specific training as a key driver of organizational readiness for responsible AI adoption.

Keywords*:* artificial intelligence adoption, external auditing, organizational readiness, auditor training, digital audit infrastructure, Saudi Arabia

Jel Classification Codes: M42, O33, M15

1. Introduction

Artificial intelligence (AI)—including machine learning, natural language processing, and intelligent document extraction—is reshaping external auditing by expanding transaction testing, sharpening risk assessment, and shifting auditors from repetitive tasks toward judgment and investigation (Eilifsen et al., 2020; Fedyk et al., 2022; Kokina et al., 2025; Krieger et al., 2021; Law & Shen, 2025). Yet adoption is neither seamless nor universal: simpler tools such as optical character recognition are common, while sophisticated AI applications remain rare and require governance, given persistent concerns about data quality, explainability, bias, overreliance, and auditors' unrelinquished responsibility for professional judgment (Commerford et al., 2022; Kokina et al., 2025; Seethamraju & Hecimovic, 2023). Technology availability and expected efficiency gains alone therefore cannot explain why some audit firms adopt AI and others do not.

Adoption is increasingly understood as a process shaped by interacting technological, organizational, and institutional conditions, with context-specific evidence from Kuwait, Jordan, and Spain showing that culture, willingness to learn, and regulation dominate in different settings (Al Wael et al., 2024; Krauf et al., 2021; Mansour et al., 2025; Torroba et al., 2025; Yang et al., 2024). Organizational readiness for AI offers a more precise lens than general digitalization or attitude, and the technology–organization–environment (TOE) framework (Tornatzky & Fleischer, 1990) is used here to structure it (see Section 2.2).

This study focuses on three observable readiness conditions: auditor training, a human-capital condition building AI awareness (Jöhnk et al., 2021; Uren & Edwards, 2023); digital audit infrastructure, a technological condition that may support but not guarantee AI capability (Eilifsen et al., 2020; Krieger et al., 2021); and audit-firm size, a resource proxy tied to cost absorption (Siew et al., 2020; Yang et al., 2024)—distinct but complementary, since infrastructure may sit unused without trained staff, and trained staff may lack tools without investment (Mikalef & Gupta, 2021; Uren & Edwards, 2023).

Despite rapid change, why audit firms actually use AI remains poorly understood, for four reasons: much research measures intentions or perceptions rather than actual use (Afsay et al., 2023; Damerji & Salimi, 2021; Siew et al., 2020); studies of AI investment rarely explain nonadoption (Fedyk et al., 2022; Law & Shen, 2025); most evidence comes

from large firms in institutional contexts very different from Saudi Arabia (Kokina et al., 2025; Vitali & Giuliani, 2024; Yang et al., 2024); and firm size, staff skill, and technology are typically bundled into broad readiness measures or studied separately, obscuring their combined effect (Jöhnk et al., 2021; Seethamraju & Hecimovic, 2023).

Saudi Arabia offers a fitting setting: existing evidence there examined auditors' perceptions of AI's performance effects (Aljaaidi et al., 2023) rather than the organizational conditions for adoption, and neighboring contexts confirm readiness drivers are context-specific (Al Wael et al., 2024; Mansour et al., 2025; Torroba et al., 2025). This study provides a transparent secondary analysis of Aljaaidi et al.'s (2023) survey data, reversing the focus: rather than the 43 attitudinal items on AI's perceived impacts, it treats reported AI use as the dependent variable and training, infrastructure, and firm size as predictors.

The research question is: what is the relationship between auditor training, digital audit infrastructure, audit-firm size, and AI use in Saudi external audit practice? Based on TOE and organizational-readiness literature, all three are expected to be positive; given a binary outcome and a modest sample of 38 surveys, the analysis applies Firth bias-reduced logistic regression and interprets estimates as conditional associations.

The findings show that auditor training is positively and significantly associated with AI adoption, while digital infrastructure has a positive but imprecise association and firm size is not significant. These results suggest that human-capability development is more closely linked to AI use than technology ownership or firm scale.

This study contributes in three ways: it explains actual reported AI use rather than perceived usefulness or intention; it applies TOE to external auditing by decomposing readiness into observable human, technological, and resource-capacity conditions estimated jointly, consistent with a resource-mobilization logic in which resources create potential but auditors must operationalize it; and it extends Saudi Arabian evidence—previously outcome-focused (Aljaaidi et al., 2023)—to an antecedent-focused question using the same dataset.

2. Literature Review and Hypotheses Development

2.1 Artificial Intelligence Adoption in External Auditing

AI in external auditing spans machine learning, natural language processing, and other tools that perform or assist cognitive tasks once done manually, though AI, robotic process automation, and data analytics often blur together in practice (Kokina et al., 2025; Seethamraju & Hecimovic,

2023). This study therefore defines AI adoption as a firm's actual use of AI technology, not its intent or attitude. The case for adoption is strong—digital tools can widen transaction populations, sharpen risk and anomaly detection, and free auditors for evaluative judgment (Eilifsen et al., 2020; Fedyk et al., 2022; Kend & Nguyen, 2020; Law & Shen, 2025)—but opaque, input-sensitive AI outputs raise reliability and bias concerns (Commerford et al., 2022; Kokina et al., 2025), so a tool's existence does not imply a firm's readiness to adopt it.

Evidence consistently shows a gap between AI's potential and its actual deployment, driven jointly by technological affordances, organizational preparedness, innovation management, competition, and regulation (Seethamraju & Hecimovic, 2023; Yang et al., 2024)—for example, high readiness but low actual adoption among Spanish auditors, where regulation dominates (Torroba et al., 2025), and process evidence showing that adoption unfolds through experimentation, development, and diffusion rather than a single decision (Krieger et al., 2021). AI adoption is thus better understood as organizational capability-building than as a software choice.

In Saudi Arabia, prior work examined auditors' perceptions of AI's performance effects (Aljaaidi et al., 2023) rather than the motivations behind differential adoption. The present study reverses this focus, treating AI use as the outcome and examining three observable readiness factors—auditor training, digital audit infrastructure, and audit-firm size—drawn from the same survey, conceptually repositioning this analysis relative to the earlier Saudi study.

2.2 Organizational Readiness and the Technology-Organization-Environment Framework

Organizational readiness for AI—the capability to identify, source, and deploy appropriate technologies, beyond mere intention (Jöhnk et al., 2021; Uren & Edwards, 2023)—is multidimensional: it depends on culture, data, knowledge, resources, and strategic alignment developed throughout the adoption process (Jöhnk et al., 2021), the joint readiness of people, process, technology, and data (Uren & Edwards, 2023), and integrating technology with human and organizational components rather than merely possessing an algorithm (Mikalef & Gupta, 2021).

The technology–organization–environment (TOE) framework organizes these influences, holding that an organization's context, internal qualities,

and available technologies jointly shape innovation adoption (Tornatzky & Fleischer, 1990). TOE suits the firm-level focus here and has structured prior studies of audit-technology and AI adoption in professional services (Afsay et al., 2023; Seethamraju & Hecimovic, 2023; Siew et al., 2020; Torroba et al., 2025; Yang et al., 2024).

This study targets specific TOE elements rather than the full domain set. Electronic audit software signals technological readiness even though it is not a prerequisite for automation; training signals investment in human capital; and firm size signals the professional capacity to bear implementation costs. Factors such as professional regulation and client digital sophistication (Austin et al., 2021; Seethamraju & Hecimovic, 2023; Torroba et al., 2025) remain outside its scope. Consistent with this focus, organizational readiness is not modeled as a single latent variable but as the three observed conditions—AI-related training, electronic audit software, and firm size—allowing the model to evaluate each condition's association with actual AI use rather than assess overall readiness.

2.3 Auditor Training and AI Adoption

AI shifts the knowledge required to exercise and oversee external audits: auditors must understand how outputs relate to audit assertions and risk assessment, not merely operate a tool, and estimate complexity increases the need for human judgment alongside AI (Commerford et al., 2022). This demand for hybrid audit-domain and technology skill is well documented (Booker et al., 2023; Felski, 2023; Vitali & Giuliani, 2024), and training is expected to drive adoption by raising awareness of use cases, easing cognitive burden, and signaling firm commitment to technology (Jöhnk et al., 2021; Mikalef & Gupta, 2021; Uren & Edwards, 2023).

Audit and accounting evidence broadly supports this reasoning. A meta-analysis of 88 studies identified facilitating conditions, perceived usefulness, and ease of use as the strongest individual-level correlates of technology acceptance in auditing, with firm readiness as the main organizational factor (Afsay et al., 2023); education, implementation support, and staff confidence-building are similarly identified as key strategies in low-capability environments (Jackson & Allen, 2024a, 2024b), auditors' willingness to learn predicts AI-adoption intention in emergent markets (Mansour et al., 2025) and among Jordanian auditors (Al-Mawali et al., 2025), and technology readiness correlates with AI adoption where use is perceived as useful and easy (Damerji & Salimi, 2021).

No single training event is likely sufficient, however: early-career auditors report frequent use of Excel but infrequent use of Power BI or

Alteryx, and firm-provided training often emphasizes software mechanics over interpreting analytic output (Booker et al., 2023), while integrating technology with audit practice is preferable to teaching it in isolation (Felski, 2023). The number of AI-related courses taken is thus indicative of training and organizational provision, even though it does not capture training quality or scope. Organizations providing more AI-related courses can be expected to build more capability and confidence around AI. Thus, the first hypothesis is:

H1. *Respondents' AI-related training exposure is positively associated with reported AI use in their current audit firms.*

2.4 Digital Audit Infrastructure and AI Adoption

AI applications rely heavily on digital infrastructure—systems that organize documentation, control access, and embed analytics in engagement workflows. An electronic audit program does not itself constitute AI, but moves a firm past a purely manual setting and can supply the foundation on which more advanced applications are built (Eilifsen et al., 2020; Krieger et al., 2021), amplified in auditing by documentation, evidence, and accountability requirements that call for accessible, governed data and integrated processes (Austin et al., 2021; Jöhnk et al., 2021; Kokina et al., 2025; Mikalef & Gupta, 2021; Uren & Edwards, 2023).

Empirical evidence supports a path-dependent relationship between existing and new technologies: IT competency, management commitment, and firm size shaped adoption of computer-assisted audit tools in Malaysia (Siew et al., 2020), and case evidence links firm readiness and innovation management to the shift from experimentation to implementation (Yang et al., 2024). Yet infrastructure is enabling, not determinative: in Kuwait, culture and regulatory support drove adoption while resources did not (Al Wael et al., 2024), and in Spain regulation dominated (Torroba et al., 2025)—suggesting infrastructure is necessary but not sufficient. A digital audit program nonetheless gives firms some experience with digital tools, so the second hypothesis is:

H2. *The availability of digital audit infrastructure is positively associated with the likelihood that an external audit firm adopts artificial intelligence.*

2.5 Audit Firm Size and AI Adoption

Larger firms are more likely to adopt innovations because financial slack, specialized personnel, and scale spread the cost of adoption

(Tornatzky & Fleischer, 1990), and are more likely to have technology teams, vendor relationships, and sophisticated clients that normalize new technology (Fedyk et al., 2022; Law & Shen, 2025). Audit-specific evidence broadly supports this expectation: firm size shaped adoption of audit tools in Malaysia (Siew et al., 2020); medium and large firms adopted technology more than small firms (Jackson & Allen, 2024b); large firms developed greater breadth and depth of AI while small firms faced more constraints (Yang et al., 2024; Vitali & Giuliani, 2024). Large firms' AI investments have also been linked to changed audit processes and firm-wide restructuring (Fedyk et al., 2022; Law & Shen, 2025), underscoring that adopting AI is more than a software purchase.

Smaller firms may nonetheless be more flexible and increasingly draw on cloud computing to lower experimentation costs (Vitali & Giuliani, 2024); size-related resource effects have also proven nonsignificant once culture and regulation are considered (Al Wael et al., 2024), so firm size is better viewed as a probabilistic, not deterministic, predictor of adoption capacity. On balance, larger firms' greater resources, specialization, and cost-spreading capacity are expected to raise the likelihood of AI adoption, so the third hypothesis is:

H3. *Larger external audit firms have a higher likelihood of adopting artificial intelligence than smaller external audit firms.*

2.6 Research Gap and Conceptual Synthesis

This literature reveals four gaps addressed here: adoption determinants appear context-dependent (Kokina et al., 2025; Siew et al., 2020); many studies focus on intention or perceived readiness rather than actual use (Afsay et al., 2023; Benhayoun et al., 2025; Damerji & Salimi, 2021); studies of AI's consequences do not explain why firms adopt it (Aljaaidi et al., 2023; Fedyk et al., 2022); and adoption is strongly context-bound—regulation in Spain, ease of use in Morocco, willingness to learn in Jordan, culture in Kuwait (Al Wael et al., 2024; Benhayoun et al., 2025; Mansour et al., 2025; Torroba et al., 2025).

Regional evidence reinforces the case for studying Saudi Arabia on its own terms: UAE and Jordanian research examined perceived AI/audit quality and technology readiness (Al-Mawali et al., 2025; Mansour et al., 2025; Noordin et al., 2022), Moroccan research treated readiness as perceptual (Benhayoun et al., 2025), and Kuwaiti evidence concerned public-sector accountants, not external auditors (Al Wael et al., 2024). The one Saudi study to date addressed AI's perceived performance

consequences (Aljaaidi et al., 2023), leaving a clear gap around the antecedents of actual adoption.

The present model addresses this gap by treating real-world AI adoption as the dependent variable and auditor training, digital audit infrastructure, and firm size as independent variables, covering human capital, technological compatibility, and organizational resources respectively. These variables do not constitute a full readiness structure, but offer a formal, TOE-consistent framework matched to what the survey can observe (Jöhnk et al., 2021; Seethamraju & Hecimovic, 2023; Tornatzky & Fleischer, 1990), and testing H1–H3 jointly allows each condition's association to be evaluated net of the other two.

3. Research Methodology

3.1 Research Design and Analytical Context

This study uses a quantitative, cross-sectional, explanatory design, providing a secondary analysis of anonymized survey data originally collected from external auditors in Saudi Arabia—methodologically distinct from the earlier study because the research question, dependent variable, and model differ. The model relies on four factual or categorical survey items: whether the firm uses AI, AI-related training courses taken, whether the firm has an electronic audit program, and firm size, modeling readiness through directly observable conditions rather than post-adoption attitudinal measures.

The design is associative rather than causal: all variables were measured at a single point in time, readiness conditions were not randomly assigned, and the temporal order of organizational investment and AI use cannot be established. Estimated coefficients are therefore interpreted as conditional associations with reported AI adoption, not causal effects.

3.2 Population, Data Collection, and Sampling

The target population is licensed external auditors in Saudi Arabian audit firms. Data were collected via an Arabic-language Google Forms survey distributed through the researcher's professional networks and with the Saudi Organization for Chartered and Professional Accountants' assistance—a purposive, nonprobability sample of auditors with external-auditing experience. Because the invitation pool size was not recorded, no conventional response rate can be calculated and the sample should not be treated as statistically representative; it remains informative for an

exploratory readiness test, spanning multiple positions, firm sizes, and affiliations, and including both adopters and nonadopters.

The unit of observation is the individual auditor's response describing their current firm's conditions. Because the anonymized file contains no firm identifier, it is not possible to confirm that every response represents a distinct firm or to estimate firm-clustered standard errors; the regression therefore assumes independence across retained records, a limitation considered when interpreting precision and generalizability.

3.3 Data Screening and Final Analytical Sample

Data were screened prior to variable construction for column layout, response type, acceptable range, and completeness. All 38 records were complete on AI adoption, auditor training, digital infrastructure, and firm size, so a complete-case analysis was conducted with no case removal or winsorizing; category labels were standardized for the quantitative variables below, preserving the full set of unique, complete responses.

3.4 Variable Measurement

Dependent and independent variables are defined in Table 1. Each variable is constructed based on one related survey question. In the case of the independent variables, large values denote large exposure to human capital, larger prior digitalization, or larger organizational size.

Table 1

Operationalization of Study Variables

Variable and role	Symbol	Operationalization and coding	Expected sign
AI adoption (dependent)	AIA	Reported use of AI technologies in the respondent's current audit firm: 1 = yes; 0 = no.	N/A
Auditor training (independent)	TRAIN	Number of completed AI-related training courses. "None" = 0; reported counts are retained (0–6).	+
Digital audit infrastructure (independent)	DAI	Presence of an electronic audit program for routine audit procedures: 1 = yes; 0 = no.	+
Audit-firm size (independent)	SIZE	Employee category: 1 = fewer than 5; 2 = 5–10; 3 = 11–20; 4 = 21–25; 5 = more than 25 employees.	+

Note. All variables are constructed from the original questionnaire. DAI is a proxy for foundational audit digitalization, not a comprehensive digital-maturity scale.

AIA denotes the audit technology's organizational use, not its adoption intent, attitude, or perceived usefulness; because it is binary, a binomial logistic model is used. TRAIN is treated in the primary specification as taking values in [0, 6], so its coefficient reflects the change in log odds of AI adoption per additional AI-related course, holding the other readiness conditions constant; the measure does not distinguish provider, curriculum, mastery, or elapsed time, and the bounded interpretation is appropriate because the survey does not distinguish a single workshop from extended professional development.

DAI is conceptually a digital foundation rather than an AI program: an electronic audit program can perform standard tasks and document working papers digitally without offering any AI capability, and should not be read as indicating data governance, digital maturity, cybersecurity, cloud computing, or broader digital-technology integration. SIZE is modeled as an ordered score reflecting a monotone increase in employee category, so its odds ratio corresponds to a one-category increase; this uses all five categories and avoids estimating four dummy-variable coefficients, which is preferable given the small sample.

The primary model intentionally includes only the three theoretically specified readiness variables: with 38 observations, a wide array of demographic and organizational controls would limit outcome information, destabilize the model, and dilute focus on the hypotheses. No control was added based on bivariate significance; instead, alternative coding of TRAIN and SIZE is examined in the robustness analyses to test whether conclusions depend on the original coding.

3.5 Model Specification

Given the dichotomous nature of AIA, hypotheses are evaluated using a binomial logistic regression. For the ith auditor response, the model is defined as:

$$\log[P(AIA_i = 1) / (1 - P(AIA_i = 1))] = \beta_0 + \beta_1 TRAIN_i + \beta_2 DAI_i + \beta_3 SIZE_i$$

In this expression, $P(AIA_i = 1)$ denotes the likelihood that the audit firm uses AI, $TRAIN_i$, DAI_i, and $SIZE_i$ are as defined above, and β_1, β_2, β_3 correspond to H1–H3, each with an anticipated positive sign;

exponentiating each coefficient gives the corresponding odds ratio, holding the other two readiness conditions constant.

3.6 Estimation Strategy and Statistical Diagnostics

Variable preparation included cross-tabulating AI adoption against each predictor to check for sparse cells, and checking multicollinearity among the three readiness predictors with Spearman correlations and VIF, interpreted flexibly alongside coefficient uncertainty rather than against a rigid cutoff (O'Brien, 2007). Because ordinary maximum-likelihood logistic regression can yield biased or infinite estimates when predictors completely or quasi-completely separate adopters from nonadopters in small samples, Firth's method is used: it applies a Jeffreys-prior penalty to the likelihood, reducing first-order small-sample bias and yielding finite estimates under separation (Firth, 1993; Heinze & Schemper, 2002):

$$\ell^*(\beta) = \ell(\beta) + \tfrac{1}{2} \log|I(\beta)|.$$

Here $\ell(\beta)$ is the standard binomial log-likelihood and $I(\beta)$ the expected Fisher information matrix; the penalty yields finite, first-order-corrected estimates under complete or quasi-complete separation at negligible cost in sparse logit models (Firth, 1993; Heinze & Schemper, 2002; Rainey & McCaskey, 2021; Stolte et al., 2024). The primary model is accordingly estimated using Firth bias-reduced logistic regression, with inference based on penalized likelihood-ratio tests and 95% profile penalized-likelihood confidence intervals; results are reported as unstandardized logit coefficients, standard errors, odds ratios, 95% confidence intervals, and two-sided p values ($p < .001$ where appropriate), with interpretation emphasizing effect direction, magnitude, and interval width alongside conventional significance at $\alpha = .05$.

Model evaluation includes convergence, the penalized likelihood-ratio statistic, McFadden's pseudo-R^2, and the area under the ROC curve; because apparent fit can be optimistic in small samples, discrimination is also assessed via leave-one-out refitting and the Brier score, and case-deletion diagnostics test coefficient stability—reported as sensitivity evidence, not substitutes for the hypothesis tests. Three sensitivity specifications further probe coding robustness: TRAIN as any AI-related training (1 = one or more courses); SIZE as a binary large-firm indicator (more than 25 employees); and a specification replacing firm size with international audit-network affiliation. Consistent coefficient direction across specifications is treated as stronger evidence than one coding

scheme. All procedures use reproducible code, retain original measurement units, and involve no stepwise or significance-driven respecification.

3.7 Measurement Quality, Common-Method Considerations, and Ethical Scope

The four model variables are observed factual or categorical indicators rather than reflective multi-item constructs, so Cronbach's alpha and factor analysis do not apply; measurement quality instead rests on correspondence between item wording and construct definition (current AI use, training-course count, presence of an electronic audit program, and employee band). Section 5.4 discusses what these concise indicators cannot capture.

Because the dependent and independent variables come from the same respondent and survey, common-method concerns are possible (Podsakoff et al., 2012); this is moderated, though not eliminated, by the items' differing, factual formats and by excluding the 43 attitudinal performance statements, avoiding predictors and outcome sharing a similarly worded scale. Reporting error and respondents' incomplete knowledge of firm-wide technology use remain possible limitations.

The secondary-analysis file contains no respondent or firm names or contact information, and no new participant contact occurred; the prior use of this dataset and its original publication are disclosed accordingly. The cross-sectional timing, nonprobability recruitment, modest sample, and absence of a firm identifier limit causal inference and generalization; Firth estimation reduces small-sample bias but does not remove these limitations, so conclusions are framed as associations within this Saudi sample.

4. Results and Discussion

4.1 Data Screening and Descriptive Results

Consistent with the screening procedure described in Section 3, all 38 records contained complete values for artificial intelligence adoption (AIA), auditor training (TRAIN), digital audit infrastructure (DAI), and audit-firm size (SIZE); therefore, no observation was imputed or removed from the regression analysis.

Table 2 presents the distributions of the dependent and independent variables together with within-category adoption rates. Nineteen respondents (50.0%) reported that their audit firms used AI, whereas 19 (50.0%) reported nonadoption. This balanced outcome provides variation for explaining adoption within the observed sample, but it should not be

interpreted as an estimate of the population adoption rate because the original survey used nonprobability professional-network recruitment.

Training exposure was limited and uneven: 26 respondents (68.4%) reported none, with a sample mean of 0.76 courses (SD = 1.42; median = 0) and only 12 respondents reporting at least one course. Adoption was reported by 8 of 26 respondents without training (30.8%) versus 11 of 12 with at least one course (91.7%)—descriptive given the small higher-course categories, but preliminary evidence of a positive training-adoption relationship.

Digital audit infrastructure was common (33 respondents, 86.8%, had an electronic audit program); none of the five respondents without one reported AI adoption, versus 19 of 33 with one (57.6%)—a cell pattern that creates separation in ordinary maximum-likelihood logit models and motivates Firth bias-reduced estimation (Firth, 1993; Heinze & Schemper, 2002). Firm size was more heterogeneous (12 respondents at more than 25 employees; 13 at 5–10), with adoption rates ranging non-monotonically from 30.8% (5–10 employees) to 66.7% (smallest and largest categories).

Table 2

Distribution of AI Adoption and Organizational Readiness Variables

Variable/category			AI adopters	Adoption rate (%)
AI adoption				
No	9	0.0	—	—
Yes	9	0.0	—	—
Auditor training courses				
None	6	8.4	8	30.8
1		.9	3	100.0
2		5.8	5	83.3
3		.6	1	100.0

Variable/category			AI adopters	Adoption rate (%)
5		.6	1	100.0
6		.6	1	100.0
Digital audit infrastructure				
No electronic audit program		3.2	0	0.0
Electronic audit program	3	6.8	19	57.6
Audit-firm size				
Fewer than 5 employees		.9	2	66.7
5–10 employees	3	4.2	4	30.8
11–20 employees		5.8	3	50.0
21–25 employees		0.5	2	50.0
More than 25 employees	2	1.6	8	66.7

Note. N = 38. Percentages in the third column are percentages of the analytical sample. Adoption rate is the within-category percentage reporting AI use and is not repeated for the outcome categories.

4.2 Correlations and Preliminary Diagnostics

Table 3 reports descriptive statistics, Spearman correlations, and variance inflation factors (VIFs). AIA was positively correlated with TRAIN, r_s = .555, p < .001, and DAI, r_s = .389, p = .016. Its correlation with SIZE was positive but not statistically significant, r_s = .205, p = .217. These coefficients are bivariate associations and do not indicate whether each readiness condition explains adoption after the other conditions are held constant.

The correlations among the three predictors were modest. TRAIN correlated .259 with DAI and .169 with SIZE, while DAI correlated .078

with SIZE. The corresponding VIFs ranged from 1.05 to 1.09. Thus, the estimated coefficients are not materially affected by multicollinearity, and the comparatively large uncertainty surrounding DAI reflects sparse outcome information rather than redundancy with the other predictors.

Table 3

Descriptive Statistics, Spearman Correlations, and Collinearity Diagnostics

Variable	M	SD	Min	Max	1	2	3	VIF	
1. AIA	0.50	0.51	0.00	1.00	—				
2. TRAIN	0.76	0.42	0.00	6.00	.555***	—		.09	1
3. DAI	0.87	0.34	0.00	1.00	.389*	.259	—	.05	1
4. SIZE	3.24	1.42	1.00	5.00	.205	.169	.078	.05	1

Note. $N = 38$. AIA = artificial intelligence adoption; TRAIN = number of AI-related training courses; DAI = digital audit infrastructure; SIZE = ordered employee-size category; VIF = variance inflation factor. Correlations are two-tailed. One, two, and three asterisks indicate $p < .05$, $p < .01$, and $p < .001$, respectively.

4.3 Firth Logistic Regression and Hypothesis Testing

Table 4 presents the primary Firth logistic regression results. The model was statistically significant overall, penalized likelihood-ratio $\chi^2(3) = 13.20$, $p = .004$, with McFadden's pseudo-$R^2 = .316$. The adjusted-score algorithm converged in 13 iterations. Because the sample is small, the interpretation emphasizes effect size, profile-likelihood uncertainty, and consistency across sensitivity analyses rather than statistical significance alone.

TRAIN was positive and statistically significant, $B = 1.082$, $SE = 0.545$, penalized likelihood-ratio $\chi^2(1) = 6.40$, $p = .011$. The odds ratio of 2.95 indicates that each additional reported AI-related training course was associated with an approximately 195% increase in the odds of AI adoption after DAI and SIZE were held constant. The 95% profile penalized-likelihood confidence interval for the odds ratio ranged from 1.19 to 11.56. Accordingly, H1 is supported.

DAI also had the predicted positive coefficient, $B = 2.007$, $SE = 1.656$, corresponding to an odds ratio of 7.44. However, its 95% profile confidence interval was extremely wide, [0.69, 1,030.30], and included 1.00; the penalized likelihood-ratio test was not significant, $\chi^2(1) = 2.59$, $p = .108$. The estimate therefore indicates a substantively positive but statistically imprecise conditional association. H2 is not supported at the .05 level.

SIZE was positive but not statistically significant, $B = 0.240$, $SE = 0.285$, odds ratio = 1.27, 95% profile confidence interval [0.73, 2.31], $\chi^2(1) = 0.73$, $p = .394$. Moving upward by one employee-size category was associated with 27.2% higher estimated adoption odds, but the data are compatible with both a modest reduction and a more than twofold increase. H3 is therefore not supported.

Table 4

Firth Bias-Reduced Logistic Regression Predicting AI Adoption

Term	*B*	*SE*	OR	95% profile CI	PLR χ^2	*p*	Decision
Intercept	-3.132	1.888	0.04	[<0.01, 0.76]	4.77	.029	—
Auditor training	1.082	0.545	2.95	[1.19, 11.56]	6.40	.011	H1 supported
Digital infrastructure	2.007	1.656	7.44	[0.69, 1,030.30]	2.59	.108	H2 not supported
Audit-firm size	0.240	0.285	1.27	[0.73, 2.31]	0.73	.394	H3 not supported

Note. $N = 38$. The dependent variable is AIA (1 = adoption; 0 = nonadoption). OR = odds ratio; CI = profile penalized-likelihood confidence interval; PLR = penalized likelihood ratio. Overall PLR $\chi^2(3) = 13.20$, $p = .004$; McFadden's pseudo-$R^2 = 0.316$.

4.4 Model Evaluation and Sensitivity Analyses

The model's apparent area under the ROC curve was .856 (classification accuracy .789; sensitivity .737; specificity .842 at a .50 cutoff)—optimistic since the fitting and evaluation samples overlap. Leave-one-out refitting produced an AUC of .809, a Brier score of .187, and accuracy of .711; the expected decline from apparent to leave-one-out performance still leaves useful retained discrimination, suggesting the three readiness variables carry predictive information in this sample.

Case-deletion estimates support stability: omitting one response at a time never reversed any focal coefficient's sign (TRAIN ranged 0.954–1.999; DAI, 1.687–2.168; SIZE, 0.162–0.400), so the positive directions are not attributable to a single response, though DAI's wide profile interval remains an important limitation.

Table 5

Predictive Performance and Case-Deletion Stability

Statistic/predictor	Full-sample estimate	Leave-one-out/case-deletion result	Stability assessment
Panel A. Prediction metrics			
Area under the ROC curve	0.856	0.809	Discrimination retained
Brier score	0.156	0.187	Expected optimism adjustment
Accuracy	0.789	0.711	Moderate out-of-sample accuracy
Sensitivity	0.737	0.579	Lower for held-out adopters
Specificity	0.842	0.842	Stable for nonadopters
Panel B. Coefficient stability			
Auditor training	B = 1.082	B range [0.954, 1.999]	Positive in all 38 deletions
Digital infrastructure	B = 2.007	B range [1.687, 2.168]	Positive in all 38 deletions
Audit-firm size	B = 0.240	B range [0.162, 0.400]	Positive in all 38 deletions

Note. Prediction metrics use a .50 classification cutoff. The Brier score is the mean squared error of predicted probabilities, for which lower values indicate better calibration and accuracy. Every leave-one-out model converged.

Table 6 reports three pre-specified sensitivity specifications. First, TRAIN was recorded as any AI-related training. The corresponding odds ratio was 10.72, 95% profile confidence interval [2.00, 110.86], p = .004. This result shows that H1 does not depend on assuming that every

additional course has an identical increment in the log odds. Second, replacing the ordered SIZE score with an indicator for firms having more than 25 employees produced a positive odds ratio of 3.41, but the interval remained wide and the coefficient was not significant, $p = .153$. Third, replacing SIZE with international audit-network affiliation did not produce evidence that affiliation itself was associated with adoption, odds ratio = 0.82, $p = .808$. Across all specifications, the training coefficient remained positive and statistically significant, while DAI remained positive but imprecise. The sensitivity evidence therefore reinforces H1 but does not change the conclusions for H2 or H3.

Table 6

Sensitivity Analyses Using Alternative Readiness Measures

Alternative coding/model	Term	*B*	OR	95% profile CI	*p*
Any training	Any auditor training	2.373	10.72	[2.00, 110.86]	.004
	Digital infrastructure	1.925	6.85	[0.63, 952.72]	.127
	Ordered firm size	0.246	1.28	[0.72, 2.35]	.397
Large-firm indicator	Auditor training count	1.084	2.96	[1.18, 11.42]	.012
	Digital infrastructure	2.324	10.22	[0.85, 1,502.71]	.070
	More than 25 employees	1.227	3.41	[0.64, 23.76]	.153
International affiliation	Auditor training count	1.073	2.93	[1.22, 12.03]	.008
	Digital infrastructure	2.022	7.55	[0.71, 1,036.37]	.102
	International affiliation	-0.204	0.82	[0.14, 4.25]	.808

Note. $N = 38$ for every model. Intercepts are omitted. Each model includes digital audit infrastructure and the two readiness measures shown. Overall PLR statistics: any-training model, $\chi^2(3) = 15.03$, $p = .002$; large-firm model, $\chi^2(3) = 14.49$, $p = .002$; international-affiliation model, $\chi^2(3) = 12.54$, $p = .006$.

4.5 Discussion of Findings

4.5.1 Auditor Training and AI Adoption

The positive relationship between auditor training and reported adoption is the strongest, most consistent result, theoretically expected because innovation becomes more adoptable when employees can understand and connect it to work requirements (Tornatzky & Fleischer, 1990), consistent with AI-readiness research on knowledge, skills, and coordination (Jöhnk et al., 2021; Mikalef & Gupta, 2021; Uren & Edwards, 2023) and with evidence linking readiness and willingness to learn to AI-adoption intention (Afsay et al., 2023; Damerji & Salimi, 2021; Mansour et al., 2025). This study extends that evidence by linking a factual training count to reported organizational use rather than perceptions alone. The coefficient should nonetheless be read as an association, not a causal claim: firms already using AI may simply provide more training, the cross-sectional design cannot establish sequence, and the count does not capture course quality or duration.

4.5.2 Digital Audit Infrastructure and AI Adoption

DAI showed a large positive odds ratio but insufficient precision to support H2—a striking descriptive pattern (no adopters among firms lacking an electronic audit program) consistent with TOE's technological dimension (Krieger et al., 2021; Tornatzky & Fleischer, 1990). Yet several firms with a program still reported nonadoption, suggesting it can digitize records without providing governed data, analytics, or AI-skilled personnel—consistent with readiness requiring people, process, technology, and data jointly (Jöhnk et al., 2021; Seethamraju & Hecimovic, 2023; Uren & Edwards, 2023) and with emerging-market evidence that resources alone may not discriminate adopters (Al Wael et al., 2024; Torroba et al., 2025). The wide confidence interval reflects the few firms lacking infrastructure, not evidence that DAI is irrelevant; future work should measure infrastructure maturity through multiple indicators.

4.5.3 Audit-Firm Size and AI Adoption

The positive but nonsignificant SIZE coefficient does not support H3, contrasting with prior evidence that firm size shapes technology adoption (Fedyk et al., 2022; Law & Shen, 2025; Siew et al., 2020; Yang et al., 2024). This may reflect the design: the outcome captures whether any AI is used, not its scale or depth, where size may matter more (Yang et al., 2024); adoption was nonmonotonic across size categories, since vendors and accessible software let smaller firms experiment without large firms' infrastructure (Jackson & Allen, 2024a; Vitali & Giuliani, 2024); and size is

a broad proxy that misses technology budgets, staffing, or local autonomy, paralleling Al Wael et al.'s (2024) nonsignificant resource effect. Robustness checks using a large-firm indicator and network affiliation produced the same conclusion—size did not distinguish adoption in this sample, not that it never matters.

4.5.4 Integrated Interpretation

Together, the findings offer qualified support for the organizational-readiness argument: the model was significant overall with useful discrimination, but its explanatory contribution was concentrated in training, consistent with a configurational view in which technology and scale create potential while trained professionals operationalize it (Jöhnk et al., 2021; Mikalef & Gupta, 2021). Relative to Aljaaidi et al. (2023), this antecedent-focused analysis shows training as the readiness condition most clearly tied to reported use—evidence bounded by the cross-sectional design and modest sample.

5. Conclusion

5.1 Summary of the Results

This study examined whether auditor training, digital audit infrastructure, and audit-firm size are associated with reported AI adoption among 38 Saudi external auditors, using Firth bias-reduced logistic regression given the small, binary-outcome sample. Auditor training was the clear driver of adoption: each additional AI-related course was associated with substantially higher odds of adoption, a result that held across all sensitivity and case-deletion checks. Digital infrastructure showed the expected positive direction but could not be estimated precisely, given how few sampled firms lacked an electronic audit program; audit-firm size did not reliably distinguish adopters from nonadopters once the other conditions were considered. Readiness, in this sample, was therefore not simply a matter of owning technology or having scale—it hinged on whether personnel had the capability to use available resources in audit practice.

5.2 Theoretical Contributions

This study advances the AI-adoption literature in three ways. First, applying TOE to external auditing shows its three dimensions do not operate equally: only auditor training consistently distinguished adopters from nonadopters, suggesting firms can own platforms or staff without the knowledge to convert them into AI-based practice. Second, the findings reinforce a capability-oriented view of readiness requiring the joint

development of human capital, data, technology, and governance (Jöhnk et al., 2021; Mikalef & Gupta, 2021), with training as a plausible activation mechanism letting auditors convert professional needs into technical requirements. Third, a dichotomous adoption measure cannot capture which tools are used or how fully they are integrated, so the null size effect may reflect that size matters more for scaling and routinizing AI than for the initial decision (Yang et al., 2024), pointing theory toward separate accounts of initiation, use, and routinization.

5.3 Practical and Policy Implications

For audit firms, generic AI briefings are insufficient; training should be role- and task-specific—covering use-case recognition, evidence assessment, and bias—with competence assessed directly. Firms should assess the fuller digital ecosystem (data quality, integration, cybersecurity, governance) rather than equate electronic working papers with AI readiness, and should not assume small scale precludes adoption or large scale guarantees it. For regulators, there is an opportunity to set minimum expectations for AI-related skills, documentation, and data-governance principles, with training pathways scaled to firm size; given this evidence's exploratory nature, however, policy should draw on broader, more representative evidence rather than this study alone.

5.4 Limitations and Directions for Future Research

Several limitations qualify these conclusions. The 38 responses came from nonrandom professional-network recruitment with an undocumented invitation count, so no response rate could be calculated and results should not be generalized to the Saudi auditor population; Firth estimation corrects small-sample bias but cannot substitute for more data, as DAI's wide confidence interval illustrates. The auditor, not the firm, was the unit of analysis, and no firm identifier allowed clustering or verification against duplicate firms. The cross-sectional design cannot establish causal order, and each construct was measured briefly, none capturing quality, maturity, or depth of use; the model also omitted external factors such as client digital maturity and regulatory clarity. Future research should recruit larger, identifiable, longitudinal samples; develop validated, multidimensional readiness measures; and link adoption antecedents to downstream consequences—efficiency, judgment quality, and fees. Comparative Gulf and emerging-market studies would help separate Saudi-specific findings from general patterns, shifting the question from whether firms adopt AI toward how firms build AI capability.

In conclusion, this study confirms that organizational readiness shapes AI adoption in Saudi external auditing, but not in the way that owning technology or having scale alone would suggest. Auditor training was the clearest observable driver of adoption, while digital infrastructure and firm size remain uncertain. Advancing AI-enabled auditing responsibly will therefore depend on developing training, governance, and innovation capacity together, rather than assuming that technology adoption follows automatically from possessing resources or being a large firm.

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