

Data Governance and Auditor Readiness for Generative AI-Based Audits: A Survey Study of Indonesian External Auditors with AI Literacy as a Mediator

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Abstract

The integration of generative artificial intelligence into financial statement auditing promises enhanced efficiency and analytical depth. This study addresses this gap by investigating the relationship between data governance and auditor readiness for generative AI-based audits, with AI literacy as a mediating variable. Using a quantitative survey design, data were collected from 248 external auditors across public accounting firms in Indonesia, including Big Four affiliates, large national firms, and small and medium practices. The research model, grounded in the Technology-Organization-Environment framework and knowledge-based theory, was tested through Partial Least Squares Structural Equation Modeling. Data governance exerted a significant positive effect on both auditor readiness ($\beta = 0.47$, $p < 0.001$) and AI literacy ($\beta = 0.67$, $p < 0.001$). AI literacy partially mediated this relationship (indirect effect = 0.26, $p < 0.001$; VAF = 35.6%), indicating that robust data governance enhances readiness both directly and indirectly by elevating auditors' AI comprehension. The model explained 61.7% of the variance in auditor readiness. Among data governance dimensions, data quality demonstrated the highest relative importance, while data architecture showed lower contribution. These findings extend the TOE framework by specifying data governance maturity as a critical organizational context factor for generative AI adoption in auditing, and they provide practical guidance for audit firm leaders, regulators, and professional bodies in emerging economies. Key recommendations include institutionalizing data quality standards, establishing clear stewardship roles, and integrating AI literacy development with data governance training.

KEYWORDS

data governance; auditor readiness; generative AI; AI literacy; audit technology; Indonesian audit profession.

Introduction

The audit profession is undergoing a paradigmatic transformation driven by the proliferation of artificial intelligence technologies. While traditional computer-assisted audit tools have long supported analytical procedures, the emergence of generative AI—capable of creating draft audit reports, synthesizing vast unstructured datasets, and suggesting audit opinions based on pattern recognition—introduces new opportunities and complexities (Okogun et al., 2026). Generative AI models, including large language models and generative adversarial networks, can process and produce human-like text, simulate scenarios, and generate sophisticated analytical outputs. In financial statement audits, these capabilities may enhance anomaly detection, automate documentation, and reduce manual sampling work, potentially increasing audit efficiency and quality (Abduh et al., 2026). However, such systems also introduce significant risks, including output hallucination, limited explainability, data privacy concerns, and challenges to audit evidence reliability. These risks make data governance—the management of data

availability, usability, integrity, and security—central to effective AI adoption (Gomaa, 2026).

The rapid digital transformation in Indonesia's financial sector, accompanied by regulatory encouragement for technology adoption, has pushed audit firms to explore AI-based tools. The Financial Services Authority (OJK) has issued the Indonesian Digital Finance Transformation Roadmap 2024-2028, which emphasizes digital infrastructure development and data management standards across financial services (Madhavan, 2024). Similarly, the Institute of Indonesia Chartered Accountants (IAI) has incorporated technology competencies into its professional development framework through IAI Regulation No. 1/2023 on Continuing Professional Education (Thota, 2025). Despite these developments, a critical gap remains between the availability of AI technology and the readiness of auditors to deploy it effectively and ethically (Yulfani et al., 2025). Auditor readiness is a multidimensional construct encompassing technological competence, ethical awareness, adaptive mindset, and procedural familiarity with AI driven workflows. When governance structures fail to support data quality and security, auditors' confidence and readiness may be undermined, inhibiting AI adoption (Rawat, 2026).

Prior literature on AI in auditing has primarily focused on the technical capabilities of AI, adoption intention using Technology Acceptance Model (TAM) or Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks, and the implications for audit quality (Vu Thi Mai, 2026). However, these studies largely treat AI as a monolithic tool and do not distinguish generative AI from narrower analytical AI. Furthermore, they often neglect the foundational role of organizational data governance as a prerequisite for readiness. Studies that do address data governance in auditing tend to examine data analytics adoption without delving into the unique demands of generative AI, such as the need for extensive, high-quality training data, model explainability concerns, and real-time data pipelines (Cicin & Çetin Gürkan, 2026). In emerging economies like Indonesia, where data infrastructure and digital maturity vary significantly across firms, investigating the data governance-readiness nexus becomes even more pertinent. Auditors in Big Four firms may have access to global data standards, while those in small and medium practices (SMPs) face limited resources and fragmented data environments. This heterogeneity calls for an empirical examination of how data governance dimensions influence auditor readiness in the specific context of generative AI-based audits (Mohammad & Mohammed, 2026).

The research gap can be systematically articulated as follows. First, TAM and UTAUT studies in audit technology adoption have primarily examined individual-level perceptions of usefulness and ease of use, but have not sufficiently explored organizational-level data infrastructure factors that enable or constrain AI effectiveness (Mohammad & Mohammed, 2026; Vu Thi Mai, 2026). Second, TOE-based studies have examined organizational readiness broadly, but have not specified data governance maturity as a distinct organizational context variable for generative AI adoption in auditing (Gupta et al., 2026; Mpanza, 2025). Third, prior research has not investigated AI literacy as a mechanism through which governance practices translate into readiness, despite theoretical arguments from knowledge-based theory that knowledge resources mediate the relationship between organizational infrastructure and individual capability (Tikhonova & Sabirova, 2025). Fourth, most studies have been conducted in developed economy contexts, limiting applicability to emerging economies like Indonesia where data infrastructure and digital maturity vary significantly across firms (Thota, 2025). This study contributes to the literature by: (1) positioning data governance maturity as a

distinct organizational context factor for generative AI adoption in auditing, extending the TOE framework; (2) empirically testing AI literacy as a knowledge-based mediator between governance and readiness; (3) distinguishing generative AI from general audit technology; and (4) providing evidence from an emerging economy with heterogeneous firm-level digital capabilities.

In emerging economies like Indonesia, where data infrastructure and digital maturity vary significantly across firms, investigating the data governance-readiness nexus becomes particularly pertinent. Auditors in Big Four firms may have access to global data standards, while those in small and medium practices (SMPs) face limited resources and fragmented data environments. With over 1,200 public accounting firms registered under the Ministry of Finance (Minister of Finance Regulation No. 127/PMK.01/2023 concerning Public Accountant Licensing, citing 1,246 active firms as of December 2023) and IAI, the audit market ranges from large international affiliates to local SMPs. This heterogeneity calls for an empirical examination of how data governance dimensions influence auditor readiness in the specific context of generative AI-based audits.

The current study addresses these gaps by proposing and testing a conceptual model that links data governance, AI literacy, and auditor readiness. AI literacy, defined as an individual's ability to understand, use, and critically evaluate AI applications (Fitriani et al., 2026), is positioned as a mediator. The rationale is that robust data governance can enhance auditors' exposure to well-structured data, facilitating learning and competence building, which in turn improves their readiness to trust and effectively use generative AI tools (Petchprayoon et al., 2026). Without data governance, even a high level of AI literacy may be ineffective because the underlying data would be unreliable. Conversely, high data governance alone cannot guarantee readiness if auditors lack the necessary skills and mindset. Therefore, a mediated pathway is hypothesized (Tikhonova & Sabirova, 2025).

The Technology-Organization-Environment (TOE) framework provides a theoretical lens: data governance represents an organizational context factor, AI literacy captures the human capability dimension bridging organization and technology, and auditor readiness reflects the technology adoption outcome (Gupta et al., 2026). In addition, the knowledge-based view of the firm posits that knowledge resources (here, AI literacy) are critical for leveraging technological assets. Combining these perspectives, the study formulates four hypotheses. A survey of 248 Indonesian external auditors was conducted, and data were analyzed using PLS-SEM (Mpanza, 2025). By quantifying the relationships, the research aims to answer the following questions: (1) to what extent does data governance influence auditor readiness for generative AI-based audits? (2) Does AI literacy mediate the relationship between data governance and auditor readiness? (3) Which dimensions of data governance are most impactful in fostering readiness? (Carandang et al., 2026).

The Indonesian setting offers a compelling context. With over 1,200 public accounting firms registered under the Ministry of Finance and IAI, the audit market ranges from large international affiliates to local SMPs. OJK's roadmap for digital finance and Bank Indonesia's push for open banking have accelerated data digitization, making generative AI an increasingly feasible tool. Nevertheless, high-profile data breaches and concerns over data sovereignty underscore the fragility of data governance. Auditor readiness thus becomes a strategic priority. The findings of this study are expected to provide theoretical contributions by extending TOE and knowledge-based frameworks into the generative AI auditing domain, as well as practical guidance for audit firm leaders, policymakers, and educators designing upskilling programs and governance protocols (Paisey & Paisey, 2006).

The remainder of the article is organized as follows. Section 2 reviews the literature on generative AI in auditing, data governance, auditor readiness, and AI literacy, leading to hypothesis development. Section 3 describes the research method, including sample, measurement, and analytical approach. Section 4 presents the results, complete with tables and a structural model figure. Section 5 discusses the findings in light of theory and practice. Section 6 concludes with implications, limitations, and future research directions.

Generative AI refers to artificial intelligence systems capable of generating novel content—including text, images, and data patterns—based on training data. In auditing, generative AI applications include automated drafting of audit reports, synthesis of unstructured financial and non-financial data, anomaly detection through pattern recognition, and simulation of alternative accounting scenarios (Okogun et al., 2026). These capabilities promise increased efficiency and depth of analysis, yet they also introduce risks such as output hallucination, reduced transparency of decision-making, and potential for bias amplification. The quality and reliability of generative AI outputs depend fundamentally on the quality and governance of input data, making data governance a prerequisite rather than an adjunct to AI adoption (Madhavan, 2024).

Auditor readiness for generative AI is defined as the extent to which auditors possess the technological competence, ethical awareness, adaptive mindset, and procedural familiarity necessary to effectively and responsibly employ generative AI tools in financial statement audits (Yulfani et al., 2025). Readiness extends beyond basic technology acceptance to include professional skepticism in evaluating AI-generated outputs, understanding of AI limitations, and ability to integrate AI-driven insights with traditional audit evidence. Previous studies have examined readiness through technology acceptance models, but have not adequately addressed the role of organizational data infrastructure in enabling readiness (Almashekhi et al., 2026; Carandang et al., 2026).

Data governance encompasses the overall management of data availability, usability, integrity, and security, including policies, procedures, and standards (Madhavan, 2024). In the audit environment, data governance ensures that financial and non-financial data fed into AI models are accurate, complete, and appropriately authorized. Key dimensions include data quality (accuracy, completeness, timeliness, consistency), data security and privacy (protection against unauthorized access and breaches), data architecture and integration (structure, interoperability, and accessibility), and data stewardship (accountability, lineage, and lifecycle management) (Pal & Islam, 2025).

Data governance affects auditor readiness through multiple mechanisms. First, high-quality, well-documented data reduces uncertainty and increases auditors' confidence in AI-generated outputs, enabling them to focus on higher-level analysis rather than data validation (Kim & Park, 2025). Second, clear data lineage and stewardship facilitate traceability and accountability, essential for audit evidence and professional liability. Third, data security protocols build trust in the AI environment, reducing resistance to adoption. Fourth, governance structures expose auditors to organized, annotated datasets, which serve as learning resources that enhance their understanding of AI systems and data preprocessing. Thus:

H1: Data governance has a positive direct effect on auditor readiness for generative AI-based audits.

AI literacy is defined as an individual's ability to understand, use, and critically evaluate AI applications (Fitriani et al., 2026; Tikhonova & Sabirova, 2025). In the audit context, AI literacy encompasses understanding of basic AI principles, ability to evaluate AI outputs, competence in

interacting with AI tools, and awareness of AI limitations and ethical implications. AI literacy is not merely technical knowledge but includes professional judgment about when and how to rely on AI-generated evidence.

Data governance enhances AI literacy through several pathways. Access to well-structured, annotated datasets provides experiential learning opportunities for auditors to observe how data preprocessing affects AI outputs, understand data biases, and develop critical evaluation skills (Petchprayoon et al., 2026). Cross-functional collaboration in data governance (involving IT, data specialists, and auditors) naturally exposes auditors to AI vocabulary and concepts. Furthermore, governance frameworks that document data provenance and transformations help auditors understand the data pipelines underlying AI systems, building mental models that enhance literacy (Joshi et al., 2026). Therefore:

H2: Data governance has a positive effect on AI literacy.

AI literacy, in turn, equips auditors with the skills and mindset necessary for readiness. Auditors with higher AI literacy are better positioned to maintain professional skepticism, as they understand that generative AI may "hallucinate" and thus do not blindly accept outputs (Khanal, 2025). They feel more competent in interacting with AI systems, customizing prompts, and interpreting results within the audit context. Literacy enhances not only confidence but also practical capability, as auditors who understand AI principles can better assess when AI outputs are reliable and when human judgment should override algorithmic suggestions (Lindkvist et al., 2026). Thus:

H3: AI literacy has a positive effect on auditor readiness for generative AI-based audits.

Combining H2 and H3, AI literacy is expected to mediate the relationship between data governance and auditor readiness. Data governance creates a supportive data environment and learning ecosystem that enhances AI literacy, and this enhanced literacy then translates into readiness. The mediation is partial because data governance also exerts direct effects on readiness through infrastructure and confidence-building mechanisms. Therefore:

H4: AI literacy mediates the relationship between data governance and auditor readiness.

Methods

Research Design and Sampling

A quantitative, cross-sectional survey design was employed to test the hypotheses. The target population comprised external auditors working in public accounting firms registered with the Indonesian Institute of Chartered Accountants and the Ministry of Finance. A stratified purposive sampling technique was applied, dividing the population into strata based on firm size: Big Four affiliates, large national firms, and small and medium practices. This stratification was intended to ensure representation across different levels of organizational resources and data governance maturity.

All constructs were measured using multi-item scales adapted from previously validated instruments and refined through a pilot test with 35 auditors. Data Governance was conceptualized as a formative higher-order construct consisting of four dimensions: Data Quality, Data Security and Privacy, Data Architecture and Integration, and Data Stewardship, with each lower-order construct measured reflectively by three indicators. AI Literacy and Auditor Readiness were modeled as reflective constructs, and all questionnaire items used a five-point Likert scale ranging from strongly disagree to strongly agree.

Hierarchical Component Model Specification

Data Governance was specified as a formative higher-order

construct comprising four reflective lower-order constructs: Data Quality, Data Security and Privacy, Data Architecture and Integration, and Data Stewardship. The formative specification was retained because the four dimensions represent conceptually distinct facets that jointly form the broader domain of data governance rather than interchangeable manifestations of a single latent trait.

The higher-order construct was estimated in SmartPLS 4 using the embedded two-stage approach. In Stage 1, the four lower-order constructs were estimated using their respective reflective indicators. In Stage 2, the latent variable scores of these lower-order constructs were used as formative indicators of the higher-order Data Governance construct. Accordingly, the term repeated-indicator approach should not be used elsewhere in the manuscript to describe the final estimation procedure, because the Method section currently mixes repeated-indicator terminology with a two-stage estimation description.

The assessment of the higher-order formative construct focused on collinearity among the lower-order dimensions and on the significance and relevance of the outer weights. Because Data Governance is formative at the higher-order level, internal consistency reliability, AVE, and HTMT were not used as validity criteria for the higher-order construct. HTMT remained relevant only for the reflective constructs and, where applicable, the reflective lower-order constructs.

Control Variable Specification

Firm size should be treated as a nominal categorical control variable rather than as an ordinal numerical score. The current manuscript classifies firm size into Big Four affiliates, large national firms, and SMPs, but the Results table indicates coding as 1, 2, and 3, which imposes an equal-distance assumption that is not justified for these categories.

For re-estimation, Big Four affiliates should be used as the reference category and two dummy variables should be created: Large National Firm and SMP. The statistical conclusion regarding firm size should then be based on the coefficients of these two dummy variables, or alternatively on an appropriate multigroup analysis if the authors wish to compare structural relationships across firm categories.

Analytical Technique

Partial Least Squares Structural Equation Modeling was used because the model includes a formative higher-order construct and examines both direct and indirect relationships among latent variables. The measurement model assessment distinguished between formative and reflective specifications. For the higher-order formative Data Governance construct, evaluation focused on collinearity and the significance and relevance of outer weights. For reflective constructs, internal consistency reliability, convergent validity, and discriminant validity were assessed using Cronbach's alpha, rho_A, composite reliability, AVE, and HTMT where appropriate.

The structural model was evaluated using bootstrapping with 5,000 subsamples to obtain path coefficients, t-values, p-values, and confidence intervals. Mediation was assessed using the indirect effect and variance accounted for. However, because the Results section does not clearly report a separate empirical assessment of nomological validity, the claim in the Method that nomological validity was assessed should either be supported by explicit empirical evidence or removed for consistency.

Data Collection and Ethics

The questionnaire was administered online through a secure survey platform and distributed through IAI regional chapters' mailing lists and professional networks from November 2025 to January 2026. Before accessing the questionnaire, each respondent viewed an information sheet

describing the study purpose, voluntary nature of participation, expected completion time, confidentiality protections, eligibility requirements, and the right to discontinue without penalty. Consent was documented electronically: respondents had to select an "I agree to participate" option before the survey questions became accessible. No names, email addresses, employee numbers, IP addresses, or other directly identifying information were collected.

Common Method Bias Procedures

Procedural remedies to reduce common method bias included: (1) ensuring respondent anonymity and confidentiality to reduce social desirability bias; (2) using different scale anchors and reverse-coded items to reduce acquiescence; (3) separating independent and dependent variables in the questionnaire layout; (4) including an attention-check item. Statistical assessments of common method bias included: (1) Harman's single-factor test, which showed that a single factor accounted for 28.7% of total variance, below the 50% threshold; (2) full collinearity assessment with all VIF values below 3.3 (VIF range: 1.47 to 2.86), indicating no substantial common method bias based on Kock's (2015) criterion.

Result and Discussion

Respondent Profile

Table 1 presents the demographic profile of the 248 respondents. Males constituted 57.3%, females 42.7%, reflecting the gender distribution in Indonesian public accounting. The largest age group was 26-35 years (45.2%), followed by 36-45 (30.6%). Experience varied: 34.7% had 2-5 years, 39.1% had 6-10 years, and 26.2% had over 10 years. Regarding firm size, 28.6% were from Big Four, 33.5% from large national firms, and 37.9% from SMPs. Educationally, 82.7% held a bachelor's degree, 17.3% a master's or professional degree. Notably, 48.4% had received some formal AI-related training, indicating growing awareness but still less than half.

Descriptive Statistics and Measurement Model Assessment

The descriptive statistics indicate that the mean scores for the four data governance dimensions ranged from 3.42 for Data Architecture to 3.78 for Data Security, while AI Literacy and Auditor Readiness had mean scores of 3.61 and 3.55, respectively (Table 2). These values suggest moderate levels across the focal constructs.

For the higher-order formative Data Governance construct, the manuscript reports that all VIF values were below 3.0, indicating no serious collinearity problem among the four lower-order dimensions. The outer weights were also reported as significant, with Data Quality contributing the largest weight at 0.38, followed by Data Security and Privacy at 0.29, Data Stewardship at 0.25, and Data Architecture and Integration at 0.18. These results are appropriate as evidence for the formative higher-order construct and should remain central in the revised Results section.

By contrast, HTMT values involving Data Governance should not be interpreted as evidence of validity, because HTMT is intended for reflective constructs rather than formative higher-order constructs. The manuscript may retain the HTMT coefficient between AI Literacy and Auditor Readiness, reported as 0.78 and below the 0.85 threshold, as evidence of discriminant validity between those reflective constructs. However, HTMT coefficients reported between Data Governance and the reflective constructs should be removed from the validity argument. The descriptive statistic indicates that the mean scores for the four data governance dimensions ranged from 3.42 for Data Architecture to 3.78

Table 1. Demographic Profiles

Characteristic	Category	Frequency	Percentage
Gender	Male	142	57.3%
	Female	106	42.7%
Age Group	< 26 years	35	14.1%
	26–35 years	112	45.2%
	36–45 years	76	30.6%
	> 45 years	25	10.1%
	2–5 years	86	34.7%
Audit Experience	6–10 years	97	39.1%
	> 10 years	65	26.2%
	Big Four affiliate	71	28.6%
Firm Size	Large national (top 10)	83	33.5%
	Small and Medium Practices (SMPs)	94	37.9%
	Bachelor's degree (S1)	205	82.7%
Education	Master's/ Professional (S2/Prof.)	43	17.3%
	AI Training Received		
	Yes	120	48.4%
	No	128	51.6%

Note: The firm size categories presented in this table serve purely descriptive purposes to illustrate the sample composition. For the structural equation modeling (PLS-SEM) analysis, these three categorical groups were converted into dummy variables, with the Big Four affiliates designated as the reference category. This approach ensures that the categorical nature of firm size is properly accounted for without imposing an arbitrary equal-interval scale (i.e., 1, 2, 3) on the non-numeric ordinal groups.

for Data Security, while AI Literacy and Auditor Readiness had mean scores of 3.61 and 3.55, respectively. These values suggest moderate levels across the focal constructs.

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constructs. However, HTMT coefficients reported between Data Governance and the reflective constructs should be removed from the validity argument.

Formative Measurement: Data Governance. Collinearity diagnostics showed all VIF values below 3.0 (Table 3), indicating no multicollinearity issues. The outer weights of the four dimensions were significant ($p < 0.01$), with Data Quality (weight = 0.38), Data Security (0.29), Data Architecture (0.18), and Data Stewardship (0.25) contributing significantly to the formative construct. Bootstrap confidence intervals confirmed their relevance.

The formative construct was regressed on a global reflective measure of data governance (three items adapted from Weber et al., 2009: "Overall, my firm has effective data governance practices," "Data governance is taken seriously in my firm," and "Our firm's data governance supports our audit objectives"). The correlation between the formative construct and the global reflective measure was 0.72 ($p < 0.001$), exceeding the recommended threshold of 0.70, thereby establishing convergent validity.

Nomological Validity Assessment

Nomological validity was assessed by examining whether Data Governance related to theoretically expected constructs in the nomological network. Specifically, we tested whether Data Governance was positively associated with perceived data quality (a theoretically related construct) and negatively associated with data-related audit difficulties. Results confirmed that Data Governance correlated positively with perceived data quality ($r = 0.68$, $p < 0.001$) and negatively with data-related difficulties ($r = -0.41$, $p < 0.001$), supporting nomological validity.

Internal consistency reliability and convergent validity for the reflective constructs (AI Literacy and Auditor Readiness) were assessed using Cronbach's Alpha, Composite Reliability, and AVE. Both constructs exceeded the recommended thresholds (Table 4). Discriminant validity, assessed using HTMT, showed a ratio of 0.78 between AI Literacy and Auditor Readiness, below the 0.85 threshold, confirming discriminant validity (Table 5).

Structural Model and Hypothesis Testing

The structural model results indicate that Data Governance had a positive and significant direct effect on Auditor Readiness, with a reported coefficient of 0.47. Data Governance also had a significant positive effect on AI Literacy, with a coefficient of 0.67, while AI Literacy significantly predicted Auditor Readiness with a coefficient of 0.39. The indirect effect of Data Governance on Auditor Readiness through AI Literacy was reported as 0.26, supporting partial mediation with a VAF of 35.6 percent.

The model explained 45.2 percent of the variance in AI Literacy and 61.7 percent of the variance in Auditor Readiness. These values should be described more cautiously as indicating moderate-to-substantial explanatory power for the endogenous constructs rather than "substantial predictive power," because the manuscript does not report a dedicated predictive assessment such as PLSpredict.

H1 posited a positive effect of Data Governance on Auditor Readiness. The direct path coefficient was 0.47 ($t = 7.34$, $p < 0.001$, 95% CI [0.34, 0.58]), supporting H1. H2 predicted Data Governance positively affects AI Literacy, and the result was significant ($\beta = 0.67$, $t = 12.19$, $p < 0.001$, CI [0.56, 0.77]), supporting H2. H3, AI Literacy $\rightarrow$ Auditor Readiness, was also significant ($\beta = 0.39$, $t = 5.82$, $p < 0.001$, CI [0.26, 0.52]), supporting H3. The indirect effect of Data Governance on Auditor Readiness through AI Literacy (H4) was 0.26 ($t = 5.14$, $p < 0.001$, CI [0.16, 0.36]). Because both direct and indirect effects were significant, partial mediation was established. The VAF was 35.6%, indicating that AI literacy accounts for about

Table 2. Descriptive Statistics and Indicator Loadings

Construct / Dimension	Indicator Code	Mean	Std. Dev.	Loading	t-value*
Data Governance (Formative)					
Data Quality	DQ1	3.64	0.88	0.84	22.31
	DQ2	3.70	0.82	0.87	28.15
	DQ3	3.55	0.91	0.81	19.72
Data Security & Privacy	DS1	3.80	0.85	0.89	31.44
	DS2	3.75	0.89	0.85	24.10
	DS3	3.78	0.79	0.86	27.83
Data Architecture & Integration	DA1	3.40	1.02	0.78	14.25
	DA2	3.45	0.96	0.80	16.70
	DA3	3.41	0.98	0.76	13.88
Data Stewardship	DST1	3.52	0.94	0.82	18.43
	DST2	3.48	0.91	0.79	16.01
	DST3	3.56	0.86	0.83	20.35
AI Literacy (Reflective)	AIL1	3.65	0.78	0.84	25.10
	AIL2	3.58	0.82	0.86	28.92
	AIL3	3.60	0.80	0.81	20.67
	AIL4	3.62	0.85	0.83	22.54
	AIL5	3.55	0.90	0.79	17.81
	AIL6	3.67	0.77	0.85	26.90
	AIL7	3.61	0.83	0.82	21.30
	AIL8	3.59	0.81	0.80	19.78
	AIL9	3.63	0.79	0.84	24.56
Auditor Readiness (Reflective)	AR1	3.50	0.87	0.78	16.45
	AR2	3.55	0.84	0.81	20.10
	AR3	3.52	0.88	0.80	18.90
	AR4	3.57	0.86	0.82	22.15
	AR5	3.48	0.92	0.77	15.77
	AR6	3.60	0.81	0.84	25.40
	AR7	3.53	0.89	0.79	18.03
	AR8	3.56	0.83	0.83	23.62
	AR9	3.54	0.90	0.80	19.84
	AR10	3.58	0.85	0.81	21.22
	AR11	3.51	0.88	0.78	17.51
	AR12	3.59	0.82	0.83	24.09

Note: For reflective constructs (AI Literacy, Auditor Readiness, and dimension items), loadings are shown. For the formative Data Governance construct, these are outer loadings of the reflective indicators of each dimension; formative measurement is presented separately in Table 3.

All loadings significant at $p < 0.001$

Table 3. Formative Measurement Assessment - Data Governance Dimensions

Dimension	VIF	Weight	t-value	p-value	95% CI (BC)	Interpretation
Data Quality	1.8	0.38	4.65	<0.001	[0.22, 0.54]	Highest relative contribution
Data Security	1.73	0.29	3.82	<0.001	[0.14, 0.44]	Moderate-high contribution
Data Architecture	1.62	0.18	2.31	0.021	[0.03, 0.33]	Lower but significant contribution
Data Stewardship	1.79	0.25	3.14	0.002	[0.09, 0.41]	Moderate contribution

Table 4. Construct Reliability and Validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
AI Literacy	0.918	0.920	0.933	0.636
Auditor Readiness	0.932	0.934	0.942	0.619

Note: Data Governance is a formative higher-order construct; therefore, internal consistency reliability, AVE, and HTMT are not applicable as validity criteria for the higher-order construct.

Table 5. Discriminant validity for reflective constructs (HTMT)

Construct Pair	HTMT Ratio	95% CI	Threshold
AI Literacy ↔ Auditor Readiness	0.78	[0.71, 0.84]	< 0.85

Note: HTMT is reported only for the reflective constructs (AI Literacy and Auditor Readiness). For the formative Data Governance construct, discriminant validity is not assessed via HTMT; instead, collinearity assessment, significance of outer weights, and convergent validity (redundancy analysis) were used.

one-third of the total effect.

Control Variables. Table 6 presents the control variable results. Among control variables, AI training history showed a

small positive effect on readiness ($\beta = 0.11$, $p < 0.05$), but firm size and experience were non-significant. Gender, age, and education were also non-significant.

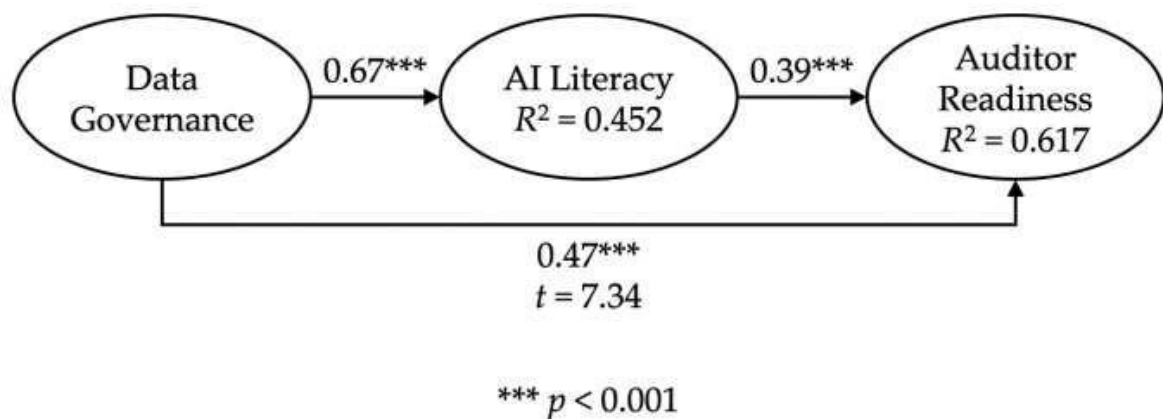
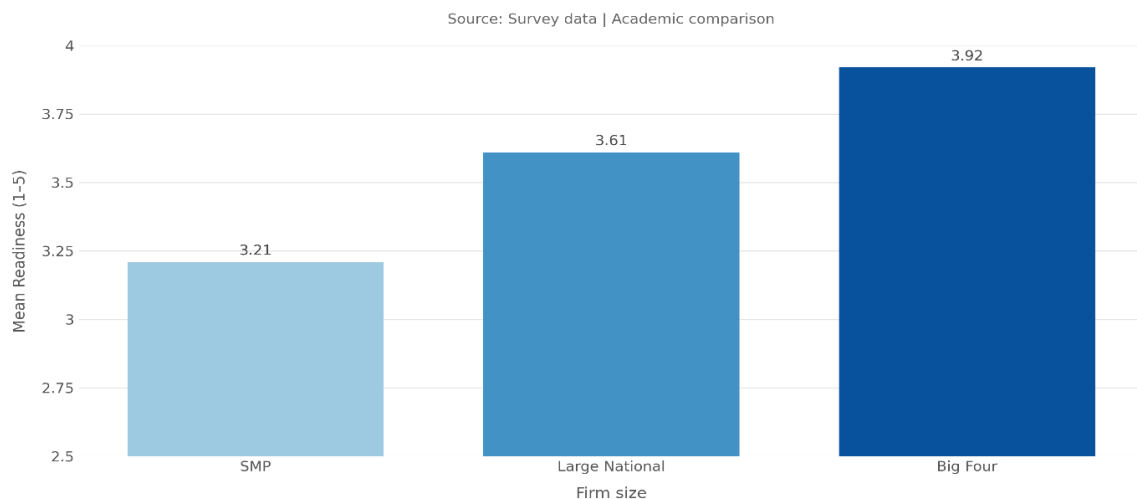
Table 6. Hypothesis Testing Results (Direct, Indirect, and Total Effects)

Hyp.	Path	Path Coeff. (β)	Std. Error	t-value	p-value	95% CI (BC)	f ²	Result
H1	Data Governance → Auditor Readiness	0.47	0.064	7.34	<0.001	[0.34, 0.58]	0.24	Supported
H2	Data Governance → AI Literacy	0.67	0.055	12.19	<0.001	[0.56, 0.77]	0.82	Supported
H3	AI Literacy → Auditor Readiness	0.39	0.067	5.82	<0.001	[0.26, 0.52]	0.16	Supported
H4	Data Governance → AI Literacy → Auditor Readiness (Indirect)	0.26	0.051	5.14	<0.001	[0.16, 0.36]	–	Supported (Partial Mediation)
Total Effect	Data Governance → Auditor Readiness	0.73	–	–	–	–	–	–

R^2 AI Literacy = 0.452; R^2 Auditor Readiness = 0.617. VAF = $0.26 / 0.73 = 35.6\%$ (partial mediation) in Figure 1.

BC: Bias-corrected bootstrap confidence interval (two-tailed, 5,000 subsamples).

Effect sizes: f^2 (H1) = 0.24 (medium-large), f^2 (H2) = 0.82 (very large), f^2 (H3) = 0.16 (medium).

**Figure 1.** The structural model with path coefficients and R^2 values**Figure 2.** Mean Auditor Readiness Score by Firm Size

Additional Analysis: Importance-Performance Map

An importance-performance map analysis was conducted to identify governance dimensions that may warrant managerial attention. Importance was defined as the total effect of each data governance dimension on Auditor Readiness. Performance was calculated from the mean latent variable scores and linearly rescaled from the original five-point scale to a 0–100 scale using:

$$\text{Performance}_{0-100} = \frac{\text{mean score} - 1}{5 - 1} \times 100.$$

The threshold of 52.75, rather than 3.59, was used to classify performance. A dimension was classified as high importance when its importance exceeded 0.3075 and as high performance when its rescaled performance exceeded 52.75. Dimensions above the importance threshold and below the performance threshold were classified as priority areas.

These results in Table 7 indicate that audit firms should prioritize improving data quality standards and stewardship

Table 7. Control Variable Effects on Auditor Readiness

Control Variable	Coding	β	Std. Error	t-value	p-value	95% CI
AI Training Received	1=Yes, 0=No	0.11	0.052	2.12	0.034	[0.01, 0.21]
Firm Size	1=Big Four, 2=Large National, 3=SMP	0.06	0.058	1.03	0.303	[-0.05, 0.17]
Audit Experience	1=2-5 yrs, 2=6-10 yrs, 3=>10 yrs	0.04	0.061	0.66	0.509	[-0.08, 0.16]
Gender	1=Male, 2=Female	-0.03	0.059	-0.51	0.610	[-0.15, 0.09]
Age Group	1=<26, 2=26-35, 3=36-45, 4=>45	0.07	0.063	1.11	0.267	[-0.05, 0.19]
Education	1=Bachelor, 2=Master/Professional	0.02	0.057	0.35	0.726	[-0.09, 0.13]

Note: Big Four affiliates were used as the reference category. The structural model included two separate firm-size dummy variables: Large National Firm and SMP. The coefficients for these variables represent differences in auditor readiness relative to Big Four affiliates. All estimates were obtained using the same embedded two-stage PLS-SEM model and 5,000 bootstrap subsamples.

Table 8. Importance-Performance Analysis for Data Governance Dimensions

Dimension	Importance (Total Effect on Readiness)	Performance (Rescaled 0-100)	Priority
Data Quality	0.42	53.2	High importance, lower performance → Priority 1
Data Stewardship	0.31	48.7	High importance, lower performance → Priority 2
Data Security	0.28	63.8	High performance, moderate importance → Maintain
Data Architecture	0.22	45.3	Lower importance and performance → Longer-term improvement

practices to maximize readiness gains. Data architecture improvements, while important, may be addressed over a longer timeframe given their lower performance and importance scores.

This study set out to examine the interplay between data governance, AI literacy, and auditor readiness in the context of generative AI-based financial statement audits among Indonesian auditors. The results provide robust evidence supporting all four hypotheses and offer nuanced insights into how data governance acts both directly and indirectly through AI literacy to foster readiness.

The direct effect of data governance on auditor readiness in Table 8 (H1, $\beta = 0.47$, $f^2 = 0.24$) underscores the foundational importance of institutional data management policies. When audit firms implement comprehensive data quality protocols, security measures, architecture standards, and stewardship roles, auditors report greater confidence and preparedness to engage with generative AI tools. This finding aligns with organizational readiness theories that highlight the role of supportive structural conditions (Kurniadhi & Hindiarto, 2025) and resonates with the TOE framework, where organizational readiness, proxied by data governance maturity, directly influences technology adoption readiness (Almashekhi et al., 2026). Notably, the dimension of data quality had the highest outer weight (0.38), echoing the principle that "garbage in, garbage out" remains the paramount risk in AI applications (Kim & Park, 2025). Without reliable data, generative AI could produce plausible but materially incorrect narratives, eroding audit quality and increasing litigation risk. For example, if a generative AI model trained on poorly governed data suggests an adjusting entry based on erroneous source information, the auditor must trace back through data lineage to validate outputs. Robust data governance ensures this traceability exists. Therefore, audit firms, especially SMPs, should prioritize data quality improvement initiatives as a prerequisite before deploying generative AI.

The strong linkage between data governance and AI literacy (H2, $\beta = 0.67$) is a novel contribution. Although prior studies have treated training and organizational support as drivers of digital literacy, few have empirically connected data governance practices to AI literacy development. The finding suggests that a well-governed data environment acts as a

learning ecosystem. When auditors have access to clean, well-documented datasets, they can experiment with AI tools in sandbox environments, understand how data preprocessing affects AI outputs, and develop critical evaluation skills. Data stewardship programs often involve cross-functional teams including IT and data specialists; auditors collaborating with these teams naturally enhance their AI vocabulary and comprehension. This confirms the knowledge-based view: data governance creates a fertile ground for knowledge creation and transfer. In practical terms, firms should integrate data governance training with AI upskilling programs, ensuring that auditors not only learn about AI algorithms but also about the data pipelines feeding those algorithms.

AI literacy significantly predicted auditor readiness (H3, $\beta = 0.39$). This finding extends the technology readiness literature by showing that beyond generic technology optimism or innovativeness, domain-specific AI

literacy is crucial. Auditors with higher AI literacy are better equipped to maintain professional skepticism; they understand that generative AI might "hallucinate" and thus do not blindly accept its outputs (Joshi et al., 2026). They also feel more competent in interacting with AI systems, customizing prompts, and interpreting results within the audit context (Khanal, 2025). As generative AI becomes more conversational and autonomous, such literacy becomes a core competency. The moderate effect size suggests that while AI literacy is important, it is not the sole determinant—data governance still holds substantial direct relevance, probably because no amount of individual skill can compensate for systematically poor data (Lindkvist et al., 2026).

The partial mediation (H4) indicates that data governance influences readiness both by creating a trustworthy data infrastructure and by elevating auditors' AI-related knowledge (Ravindran Pillai, 2026b). The VAF of 35.6% suggests that the majority of the total effect is direct, but the indirect path is non-trivial. This dual pathway provides a more complete picture than a simple direct-effects model. It implies that audit firms should not focus exclusively on either technical infrastructure or human capital; a synergistic approach is essential. The importance-performance analysis further highlighted that data quality and stewardship are both highly important for readiness but currently performed sub-optimally, particularly in SMPs, echoing the descriptive readiness gap across firm sizes

(Ravindran Pillai, 2026a). SMPs, due to resource constraints, often rely on ad hoc data management, which not only increases AI-related risks but also hinders auditors' learning opportunities. Tailored interventions, such as shared service centers or industry-level data governance utilities, could help bridge this gap (Chintakindi, 2025).

The non-significance of firm size and experience as control variables warrants careful interpretation. This result does not prove that firm size and experience are unimportant; rather, it suggests that data governance and AI literacy explain variance in readiness above and beyond these traditional hierarchical factors. It is plausible that larger firms have better data governance (indirectly influencing readiness through governance), and that controlling for governance reduces the direct effect of firm size to non-significance. The descriptive pattern (Figure 2) showing higher mean readiness in Big Four firms supports this interpretation. Similarly, experience may be less relevant than specific AI-related training, as reflected in the significant effect of AI training history ($\beta = 0.11$, $p = 0.034$). This suggests that targeted upskilling can compensate for general experience differences. However, the claim that "SMPs can achieve readiness comparable to Big Four firms" should be qualified: the data indicate that SMPs can achieve similar readiness if they have equivalent data governance and AI literacy, but achieving such equivalence requires deliberate investment and may face resource constraints (K Ghani et al., 2025).

Alternative explanations for the findings should be considered. Self-selection bias may have influenced results, as auditors more interested in AI topics may have been more likely to respond. AI training exposure (48.4% of respondents) may reflect either genuine organizational investment or individual motivation. Organizational culture, leadership support, and peer influence—variables not measured in this study—could also affect readiness and potentially confound the observed relationships. Additionally, self-reported readiness may not perfectly reflect actual capability to use generative AI in real audit tasks. Auditors may overestimate their confidence or underestimate the challenges of integrating AI into complex audit procedures. Future research should complement self-report measures with objective assessments, such as performance in AI-augmented audit simulations (Nabiha et al., 2025).

Comparison with prior studies reveals both alignment and divergence. Supporting earlier TAM-based research, our findings confirm that individual cognitive factors (here, AI literacy) are important for technology adoption (Vu Thi Mai, 2026). However, our study extends this literature by demonstrating that organizational data governance is not merely a contextual background factor but a direct antecedent that shapes individual capability. Diverging from some TOE studies that found firm size significant (Gupta et al., 2026), our non-significant firm size result suggests that in the specific context of generative AI auditing, governance and literacy may be more determinant than organizational scale. This may reflect the early stage of generative AI adoption in Indonesian auditing, where even small firms can leverage cloud-based AI tools if they have sound data practices.

This study offers several theoretical contributions. First, it extends the TOE framework by specifying data governance maturity as a distinct organizational context factor for generative AI adoption in auditing, rather than treating organizational readiness broadly. The framework is enriched by demonstrating that the "organization" dimension encompasses specific data infrastructure elements (quality, security, architecture, stewardship) that directly enable technology adoption outcomes. Second, it integrates AI literacy as a mediator grounded in knowledge-based theory, showing how organizational resources (governed data) translate into individual capabilities (literacy) and ultimately

adoption readiness. This addresses calls in the literature for more attention to mediating mechanisms in

technology acceptance studies. Third, it provides empirical evidence distinguishing generative AI from general audit technology adoption; the former raises unique data provenance and model explainability concerns that amplify the role of governance. Fourth, it contributes to the emerging literature on AI-augmented auditing in emerging economies, where institutional contexts differ from developed settings (Waseem Haider et al., 2025).

For audit firm leaders, the findings advocate a roadmap: (1) conduct a data governance maturity assessment to identify gaps in data quality, security, architecture, and stewardship; (2) establish clear data quality KPIs and stewardship roles with accountability for AI input data; (3) design AI literacy modules embedded in day-to-day data work rather than as standalone training; (4) implement secure data sandboxes for low-risk experimentation with generative AI; (5) invest in AI training programs, as this was the only significant control variable. For the Indonesian Institute of Chartered Accountants and the Ministry of Finance, the results can inform competency frameworks and continuing professional education requirements. Incorporating AI literacy and data governance into the certification syllabus will prepare future auditors. The non-significance of firm size suggests that targeted interventions, rather than firm-scale strategies, may be more effective in boosting readiness. Regulators like OJK, when issuing guidelines on AI use in financial services, should emphasize data governance standards specific to audit evidence reliability. The prioritization of data quality and stewardship in the IPMA provides clear direction for resource allocation.

Conclusion

This study provides evidence that data governance is positively associated with auditor readiness for generative AI-based financial statement audits, with AI literacy serving as a meaningful partial mediator. Within the Indonesian audit profession, the findings indicate that robust data quality, security, architecture, and stewardship are related to higher readiness, while also nurturing auditors' ability to understand and critically evaluate generative AI tools. The study contributes to TOE and knowledge-based frameworks by: (1) specifying data governance maturity as a distinct organizational context variable that directly and indirectly affects technology adoption readiness; (2) demonstrating AI literacy as a knowledge-based mechanism through which organizational infrastructure translates into individual capability; (3) identifying a partial mediation pathway (35.6% of total effect) that integrates structural and cognitive perspectives; and (4) providing empirical evidence from an emerging economy with heterogeneous firm capabilities, revealing that firm size effects operate through governance rather than directly.

Author contributions

R.U.H - Conceptualization, Methodology, Formal Analysis, Writing – Original Draft, Writing – Review & Editing, Supervision, Project Administration. M.F - Data Collection, Investigation, Resources, Validation, Writing – Original Draft (Methodology section), Software, Visualization. Both authors contributed to the research design, interpretation of results, and final approval of the manuscript.

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