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AI Adoption, Audit Outcomes, and Professional Reputation

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ABSTRACT

This study examines the adoption of AI-powered audit tools in Indonesia, analyzing organizational antecedents, cognitive-perceptual mediators, and the moderating role of corporate governance in shaping audit efficiency, audit decision quality, and auditor professional reputation. Using data from 320 external auditors and partial least squares structural equation modeling, results show that top management support and innovation climate significantly promote AI adoption, while technology readiness and vendor ecosystem support do not. Auditor confidence mediates the link between AI adoption and audit efficiency, and perceived usefulness mediates the link with audit decision quality. Corporate governance strengthens the effect of AI adoption on auditor confidence, and both efficiency and decision quality enhance professional reputation. Findings underscore the need for strong leadership, innovation-friendly cultures, and robust governance to maximize the benefits of AI in emerging market auditing.

KEYWORDS

AI auditing; auditor confidence; corporate governance; audit quality; Indonesia

Introduction

Artificial intelligence (AI) has emerged as a transformative force across multiple industries, reshaping operational processes, decision-making frameworks, and innovation strategies. In sectors such as healthcare, finance, manufacturing, retail, legal services, and energy, AI has been leveraged to improve predictive accuracy, operational efficiency, and product innovation, while also raising new challenges related to trust, integration, and governance. Recent studies, for instance, have shown how AI and knowledge management jointly drive proactive green innovation in the oil and gas sector, with trust and sustainability acting as important moderators that strengthen these effects.[1] Such findings illustrate that the success of AI initiatives often depends not only on technological capability but also on contextual factors that shape user acceptance and organizational outcomes.

Within the accounting and auditing profession, AI is part of a broader digital transformation ecosystem that includes disruptive technologies such as blockchain, cloud-based accounting information systems, big data analytics, and robotic process automation. Research on blockchain adoption in auditing demonstrates how performance expectancy, transparency, and efficiency influence behavioral intentions and, ultimately, professional outcomes such as knowledge acquisition and user satisfaction.[2] Similarly, studies on advanced accounting information systems (AIS) and cloud-based AIS have found that organizational factors like top management support, IT competency, and trust play a pivotal role in translating technology adoption into higher data quality and decision quality.[3,4] These insights highlight that AI adoption in auditing should be understood as part of a wider technological evolution in the profession, where both behavioral and organizational enablers determine whether technology delivers its promised value.

In Indonesia, the government's "Making Indonesia 4.0" roadmap and related digitalization initiatives have accelerated the adoption of emerging technologies, including in the accounting and auditing professions.[5] AI-powered audit tools offer capabilities such as automated data extraction, anomaly detection, and risk pattern identification, which can enhance audit accuracy, efficiency, and scope.[6] However, despite growing interest, empirical research on AI adoption in Indonesian auditing remains limited. Existing studies have tended to focus on narrow determinants such as technological readiness or perceived ease of use without fully exploring how AI adoption translates into broader performance outcomes or the psychological mechanisms that enable such translation.[7]

This study advances the discussion by adopting a fully mediated perspective, positing that the benefits of AI adoption for audit performance are realized primarily through two perceptual and behavioral

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mechanisms: auditor confidence and perceived usefulness. Rather than assuming that AI tools inherently improve efficiency or decision quality, the model argues that these improvements occur when auditors trust the technology's outputs and perceive them as adding meaningful value to the audit process. These mediators capture the human acceptance and engagement factors that determine whether AI capabilities are integrated into professional judgment. Corporate governance is introduced as a moderator to account for institutional differences that may strengthen or weaken the link between AI adoption and these mediators.

The Indonesian auditing context presents unique cultural and institutional dynamics, including hierarchical decision-making structures, variability in governance maturity, and evolving trust in digital tools.[8] International findings on AI adoption, often drawn from developed economies,[9,10] may have limited applicability in this setting. By integrating the Technology Acceptance Model, the Technology—Organization—Environment framework, and governance theory, this study examines technological readiness, top management support, innovation climate, and vendor ecosystem support as antecedents of AI adoption, with auditor confidence and perceived usefulness as the exclusive pathways through which adoption influences audit efficiency and audit decision quality, ultimately affecting professional reputation.

The research contributes theoretically by situating AI adoption within the broader technological transformation of the auditing profession and by demonstrating that performance gains are contingent on human perceptions and institutional enablers. Practically, it offers actionable insights for Indonesian audit firms, regulators, and technology vendors on aligning AI investments with leadership support, innovation culture, and governance structures to build trust, enhance performance, and strengthen professional reputation in a rapidly evolving regulatory environment.

Literature review

The adoption and effective use of artificial intelligence (AI) in auditing can be explained through a multi-theoretical lens that combines the Technology Acceptance Model (TAM), the Technology-Organization-Environment (TOE) framework, and governance theory. TAM emphasizes that technology usage is shaped by user perceptions,[11] particularly perceived usefulness, the belief that a tool enhances job performance and perceived ease of use, which is closely related to trust and confidence in its outputs.[12] In the auditing context, perceived usefulness has been shown to strongly influence the integration of advanced tools into audit procedures, especially when these tools improve efficiency, decision accuracy, and fraud detection capabilities.[13,14] Building on this, the present study incorporates perceived usefulness as a mediator between AI adoption and audit decision quality, while auditor confidence functions as another mediator capturing the psychological assurance that AI-generated outputs are accurate, reliable, and ethically sound.[9]

The TOE framework extends this perspective by considering the organizational and environmental factors that influence adoption decisions.[15] Within its technological dimension, variables such as readiness, compatibility, and maturity determine whether AI can be implemented effectively.[16] The organizational dimension highlights the importance of top management support, leadership commitment, and a culture of innovation,[17] while the environmental dimension reflects the role of vendor ecosystems and external pressures.[18] Prior research on advanced accounting information systems and cloud-based AIS has shown that these factors significantly shape adoption outcomes, yet their influence may vary depending on market maturity.[4,19] In emerging markets such as Indonesia, internal enablers like leadership commitment and innovation climate may be more decisive than technical readiness or vendor support, given the uneven state of infrastructure and external ecosystems.[20]

Governance theory complements these perspectives by emphasizing the role of oversight structures, ethical standards, and regulatory compliance in shaping both the decision to adopt AI and the extent to which it is trusted in practice.[21] Strong governance mechanisms, including active audit committees, transparent reporting, and clear accountability, can reduce the perceived risks of AI adoption by ensuring data integrity, mitigating algorithmic bias, and aligning usage with professional standards. Such mechanisms parallel the trust-enhancing role identified in other AI adoption studies, where the presence of robust governance has amplified the positive effects of technology on organizational outcomes.[22]

Integrating these three perspectives provides a more comprehensive explanation of AI adoption than any single theory could offer. While TAM accounts for the individual-level beliefs that drive effective use, TOE captures the organizational capabilities and environmental conditions that enable adoption, and governance theory addresses the institutional safeguards that build trust and accountability. The overlaps between these perspectives, such as the similarity between TAM's perceived usefulness and TOE's relative advantage, reinforce the need

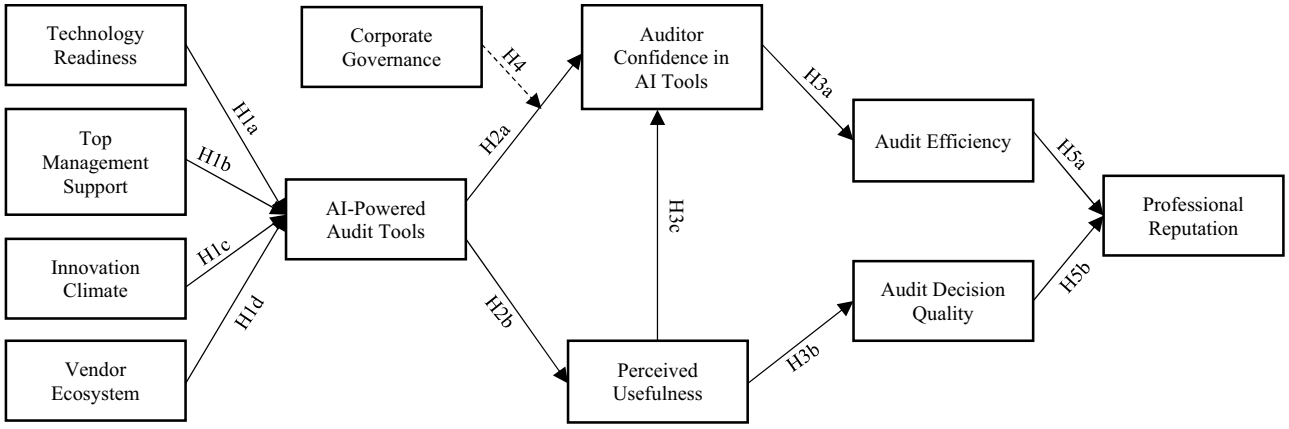


Figure 1. Research model.

for a combined approach that reflects both personal acceptance and structural readiness. This study therefore adopts a multi-theoretical framework to capture the complex interplay of cognitive, organizational, and institutional forces shaping AI adoption in auditing. In line with this approach, AI adoption is conceptualized not as an intention but as the actual organizational use and integration of AI-powered audit tools into core audit processes, encompassing their application in evidence gathering, risk assessment, and decision-making.[23] This operationalization ensures that the model examines realized impacts rather than hypothetical intentions, aligning the theoretical grounding with the study's empirical focus.

Although the Technology Acceptance Model (TAM) remains a foundational framework for understanding user perceptions toward technology, scholars have increasingly questioned its adequacy for explaining behavioral responses to artificial intelligence. Gursoy argued that TAM's focus on perceived usefulness and ease of use overlooks emotional, ethical, and trust-based dimensions that are critical when users engage with autonomous systems.[24] Similar critiques emphasize that AI adoption often involves cognitive dissonance, perceived loss of control, and algorithmic opacity that extend beyond classical TAM variables. Therefore, while this study employs TAM as a baseline to capture user cognition, it recognizes its conceptual limitations within AI auditing contexts and complements it with the Technology—Organization—Environment (TOE) framework and governance theory to address organizational and institutional influences (See Figure 1). Future research may incorporate additional constructs such as trust, perceived autonomy, and ethical comfort to enrich TAM-based models in AI studies.

Hypothesis development

Antecedents of AI-Powered audit tool adoption

The adoption of AI-powered audit tools is shaped by a combination of technological, organizational, and environmental factors, as articulated in the Technology-Organization-Environment (TOE) framework.[25] This framework posits that adoption likelihood increases when technological capability is sufficient, organizational support is strong, and the external environment provides adequate resources and infrastructure. In this study, four antecedents are modeled: technological readiness, top management support, innovation climate, and vendor ecosystem support. These variables reflect the interaction of internal and external enablers in determining whether AI can be effectively implemented in audit practice.

Technological readiness, within the TOE technological context, refers to the extent to which an organization possesses the infrastructure, digital capability, and data maturity necessary for AI deployment.[25] It includes elements such as secure IT systems, big data handling, cloud integration, and real-time analytics.[25] From a TOE perspective, readiness reduces adoption barriers by ensuring compatibility and mitigating integration costs, while also aligning with TAM's "perceived ease of use" by reducing the effort required to implement new systems. Evidence from advanced AIS implementation and cloud AIS usage confirms that technologically mature firms integrate advanced tools more effectively.[3,4] However, in emerging markets like Indonesia, infrastructure disparity can result in inconsistent adoption even when AI tools are available. Drawing from this logic, technologically prepared audit

firms should be more capable of leveraging AI to enhance performance.

H1a: Technological readiness positively influences the adoption of AI-powered audit tools.

Top management support is central to the TOE organizational context and is also consistent with governance theory's emphasis on leadership accountability in shaping strategic initiatives. Support from senior leaders influences technology adoption by aligning projects with strategic goals, securing resources, and fostering an innovation-supportive culture.[26] In hierarchical and risk-averse professional service environments, such as auditing, leadership endorsement legitimizes technology usage and can influence auditors' perceived usefulness of AI tools (TAM perspective). Prior studies in accounting information systems and blockchain adoption have demonstrated that leadership commitment significantly increases adoption by overcoming cultural resistance.[27] In Indonesia's auditing sector, where decision-making is centralized, the role of top management support is likely to be even more pronounced.

H1b: Top management support positively influences the adoption of AI-powered audit tools.

Innovation climate reflects the organizational culture's receptiveness to experimentation and change. Within TOE's organizational dimension, an innovation-supportive culture encourages exploration of new methods and technologies, while in TAM terms, it can enhance both perceived usefulness and ease of use by normalizing technological experimentation.[25] In audit environments dominated by professional skepticism and regulatory compliance, an innovation climate fosters conditions where auditors can engage in pilot testing and adopt AI without fear of reputational repercussions. Research on public sector digital transformation and AIS confirms that innovation-oriented environments increase assimilation of advanced technologies.[3,28] In Indonesia, where auditing practices are adapting to regulatory digitalization, cultivating such a climate may be critical to sustained AI integration.

H1c: Innovation climate positively influences the adoption of AI-powered audit tools.

Vendor ecosystem support represents the environmental dimension of TOE, encompassing the availability and quality of external providers that deliver technical assistance, system updates, training, and scalable platforms. In emerging markets, where internal development capabilities may be limited, vendor partnerships are vital for bridging knowledge gaps and ensuring operational continuity.[29] Vendor support also reinforces TAM's perceived ease of use by reducing implementation complexity and providing ongoing technical assurance. Evidence from blockchain and cloud AIS adoption indicates that external ecosystem strength can accelerate adoption by improving trust and reducing uncertainty.[30] In Indonesia's relatively young audit technology market, the presence of a robust vendor network may play a decisive role in motivating adoption.

H1d: Vendor ecosystem support positively influences the adoption of AI-powered audit tools.

Taken together, these four antecedents align with TOE's proposition that technology adoption is not solely a function of technical capability but is contingent on organizational commitment and environmental support. By integrating TAM's focus on user perceptions with TOE's multilevel structure, this framework captures both the human and systemic enablers of AI adoption in auditing, offering a comprehensive basis for examining how these factors operate in Indonesia's evolving audit landscape.

AI-Powered audit tool adoption and its effects

The adoption of AI-powered audit tools represents a profound shift in how auditors collect, analyze, and evaluate evidence, integrating capabilities such as machine learning, natural language processing, and predictive analytics to automate procedures, detect anomalies, and augment professional judgment.[31] From the perspective of the Technology—Organization—Environment (TOE) framework, AI adoption constitutes a technological innovation that alters internal workflows, while the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) explain how user perceptions influence subsequent behaviors. Although AI is often associated with efficiency gains, its real value in auditing lies in shaping auditor confidence, perceived usefulness, operational efficiency, and decision quality.

Auditor confidence refers to the belief that AI tools are accurate, reliable, and professionally appropriate for audit contexts. TPB posits that behavioral beliefs about

a system's reliability shape intentions to use it.[32] In auditing, confidence functions as a prerequisite for meaningful integration; even highly capable tools remain underutilized if auditors lack trust in their outputs. Prior research in AI and blockchain assurance confirms that trust perceptions strongly determine technology assimilation.[33] In emerging markets like Indonesia, where regulatory oversight and public accountability are increasing, confidence in AI tools also depends on their alignment with audit standards and ethical obligations.

H2a: The adoption of AI-powered audit tools positively influences auditor confidence in AI tools.

Perceived usefulness, a core construct in TAM,[34] captures the degree to which auditors believe that AI enhances their audit task performance. Usefulness perceptions emerge when technology demonstrably improves efficiency, accuracy, and decision support. In professional service settings, including auditing, empirical studies have shown that perceived usefulness outweighs perceived ease of use in predicting adoption intentions, particularly among senior practitioners with heightened professional liability concerns.[35] Evidence from accounting information systems and cloud AIS studies also suggests that when technological integration aligns with task requirements, perceived usefulness drives sustained utilization.[36] In the Indonesian auditing environment, where firms are adapting to digital reporting and evolving client demands, AI adoption is expected to enhance perceived usefulness by improving data analysis speed and accuracy.

H2b: The adoption of AI-powered audit tools positively influences perceived usefulness of AI tools.

Auditor confidence and perceived usefulness

While AI-powered audit tools can significantly improve audit quality and efficiency, these benefits are contingent upon perceptual and behavioral mechanisms that influence how auditors integrate the technology into their professional workflows.[6] Drawing on the Technology Acceptance Model (TAM) and behavioral auditing literature, this study identifies auditor confidence and perceived usefulness as critical mediators linking AI adoption to audit performance. TAM emphasizes that beliefs about a system's trustworthiness and utility shape behavioral intentions and actual use,[37] while the behavioral auditing perspective stresses that professional attitudes influence how technological outputs are interpreted and applied in judgment-intensive contexts.[38,39]

Auditor confidence refers to the belief that AI tools produce credible, reliable, and ethically aligned outputs, extending beyond technical performance to encompass trust in the system's decision-support role.[40] Confidence is particularly important in tasks requiring professional judgment such as risk assessment, substantive testing, and anomaly detection. Empirical research in both AI-based and blockchain-enabled auditing contexts shows that higher trust in technology reduces redundant manual verification, increases reliance on automated analytics, and improves efficiency through streamlined workflows.[41,42] In Indonesia, where audit engagements often involve high volumes of transactions and regulatory scrutiny, confidence in AI tools can help auditors perform more efficiently without compromising quality.

H3a: Auditor confidence in AI tools positively influences audit efficiency.

Perceived usefulness, central to TAM, captures the extent to which auditors believe AI tools enhance their audit performance.[43] Usefulness perceptions are formed when AI demonstrably supports fraud detection, risk prioritization, and evidence gathering areas where human analysis alone may be constrained by time or data complexity.[44] Study in data analytics and cloud-based auditing systems indicate that when technology offers insights that complement or exceed human judgment, decision quality improves significantly.[4] This effect is particularly valuable in high-stakes engagements such as audits of listed companies or government agencies in Indonesia, where decision defensibility is critical for regulatory compliance and public accountability.

H3b: Perceived usefulness of AI tools positively influences audit decision quality.

Perceived usefulness can also reinforce auditor confidence, creating a sequential relationship between the two constructs. Research on intelligent system trust formation suggests that tangible benefits such as reduced error rates, faster data analysis, and improved risk assessment often lead to increased trust over time.[45] In Indonesian auditing, where skepticism toward AI persists and institutional norms still favor human-centric decision-making,[46] demonstrated usefulness serves as a persuasive mechanism for building confidence. The more auditors experience value from AI, the more they are likely to trust its capabilities, accuracy, and alignment with professional standards.

H3c: Perceived usefulness of AI tools positively influences auditor confidence in AI tools.

Together, these hypotheses position auditor confidence and perceived usefulness as essential perceptual bridges between AI adoption and its impact on audit performance. By reinforcing these beliefs through targeted training, transparent system design, and context-appropriate implementation, audit firms can maximize the benefits of AI-powered tools while upholding professional accountability and compliance with auditing standards.

Moderating role of corporate governance

Corporate governance influences not only whether AI-powered audit tools are adopted but also how effectively they are integrated into auditors' work processes.[47] Serving as both a structural and normative control mechanism, governance can facilitate or constrain the translation of technological adoption into improved professional behavior and outcomes. Grounded in Agency Theory, which emphasizes the role of governance in aligning managerial actions with the interests of stakeholders,[48] strong governance enhances accountability, transparency, and strategic alignment, conditions that are particularly conducive to the effective use of AI in auditing. Governance encompasses systems of rules, oversight mechanisms, and practices such as board effectiveness, robust internal controls, audit committee independence, and strict adherence to regulatory requirements.[49] In the Indonesian context, reforms initiated by the Financial Services Authority (OJK) and the adoption of international auditing standards have heightened expectations for transparency and audit quality.[50]

Firms with strong governance structures are more likely to incorporate AI tools within their risk management frameworks, ensure adequate auditor training, and establish clear protocols for responsible usage.[51] Such structures not only promote ethical deployment but also foster greater trust in AI outputs by providing institutional safeguards against misuse.[52] When AI systems are embedded within well-governed organizations, auditors may feel more confident relying on their outputs, knowing that these tools operate within established oversight and compliance parameters. Therefore, governance acts as a reinforcing mechanism, strengthening the positive link between AI adoption and auditor confidence.

H4: Corporate governance positively moderates the relationship between AI-powered audit tool adoption and auditor confidence in AI tools, such that the relationship is stronger in firms with high levels of corporate governance.

By positioning corporate governance as a moderating force, this perspective underscores how organizational context shapes not only the decision to adopt AI but also the extent to which the technology is trusted, integrated, and leveraged to enhance professional judgment in Indonesia's evolving regulatory environment.

Auditor professional reputation

Auditor professional reputation reflects the perceived credibility, ethical conduct, and audit quality as assessed by external stakeholders, including clients, regulators, and the public.[53] It encompasses both the legacy of past performance and the expectations that shape future engagements, client trust, and regulatory endorsement.[54] In this study, professional reputation is positioned as the final outcome variable, shaped by the operational and perceptual impacts of AI-powered audit tools, particularly through gains in audit efficiency and decision quality. Reputation in auditing is sustained through the consistent delivery of timely, high-quality, and defensible audit opinions, aligning with stakeholder theory, which emphasizes fulfilling diverse stakeholder expectations as a means of maintaining legitimacy.[54] In ***Indonesia[55], where audit credibility is under heightened scrutiny due to past scandals,[56] professional reputation serves as a strategic asset.

AI-driven efficiency, achieved through faster audits with optimal resource use, signals technological competence, enhances client satisfaction, and reinforces a firm's innovative capacity. Empirical evidence demonstrates that such efficiency positively influences client evaluations and market perceptions of audit quality,[57] supporting the proposition that:

H5a: Audit efficiency positively influences auditor professional reputation.

Similarly, improvements in audit decision quality bolster professional reputation by strengthening the accuracy, insightfulness, and defensibility of audit opinions.[58] High decision quality reflects the auditor's ability to make well-reasoned judgments, particularly in complex areas such as fraud detection, estimation, and going concern evaluations.[7] AI tools enhance these capabilities by enabling full-population testing,

identifying subtle anomalies, and integrating evidence from multiple data sources, thereby increasing the robustness of conclusions. In Indonesia's evolving regulatory climate, where audit quality is under close observation, the consistent delivery of high-quality decisions significantly elevates both firm-level and individual auditor standing.

H5b: Audit decision quality positively influences auditor professional reputation.

These two performance pathways, efficiency and decision quality represent the operational mechanisms through which AI adoption translates into stronger external perceptions of auditors. In a profession where trust is the currency, the capacity to deliver audits that are both timely and technically sound translates into enduring professional recognition. As Indonesian audit firms advance in their digital transformation, investments in AI-enabled capabilities have the potential to generate not only operational efficiencies but also reputational dividends.

Methodology

This study employed a quantitative, explanatory research design to examine the influence of organizational and technological enablers on auditor professional reputation through the adoption of AI-powered audit tools. The study also explored the mediating roles of auditor confidence and perceived usefulness of AI tools, with corporate governance serving as a moderating variable. The conceptual framework was grounded in the Technology Acceptance Model (TAM), Resource-Based View (RBV), and Institutional Theory, allowing for a multidimensional exploration of how AI integration shapes performance and trust in the auditing profession.

The study targeted external auditors from public accounting firms in Indonesia, particularly those affiliated with the Indonesian Institute of Certified Public Accountants (IAPI) and listed in the Financial Services Authority (OJK) directory. Participants were required to have active audit engagement experience and familiarity with AI-enabled audit tools. A purposive sampling method was used, and between January and March 2025, 400 structured questionnaires were distributed digitally. A total of 320 valid responses were collected, yielding an 80% response rate with a demographic breakdown of 60% male and 40% female. Most respondents (56.2%) had over five years of experience. Job roles were fairly balanced: 53.1% were junior auditors, while 46.9% held senior or managerial positions. Regarding firm size, 57.8% worked at small firms (≤50 employees), and 42.2% at larger firms. Notably, 65.6% reported moderate to high exposure to AI audit tools, indicating increasing technological engagement.

A structured questionnaire was developed using previously validated 7-point Likert scales (1 = strongly disagree to 7 = strongly agree). Technology Readiness was measured using items from Uren & Edwards,[59] e.g., "My organization is well-equipped with technology to support AI audit tools." Top Management Support was adapted from Cheng et al.[60], while Innovation Climate followed Popa et al.[17], with items like "Our firm encourages innovative thinking." Vendor Ecosystem was measured using Raji et al.[61], including "We have strong partnerships with external AI audit technology vendors." The independent variable, AI-Powered Audit Tool Adoption, included items such as "We have adopted AI tools to assist in auditing processes." Mediators included Auditor Confidence (e.g., "I am confident in the accuracy of audit outputs") and Perceived Usefulness (e.g., "AI tools are useful in improving the quality of my audit work"). Audit Efficiency and Audit Decision Quality were measured using scales from Larmande & Lesage[62] and Rajabalizadeh & Schadewitz,[63] including items like "AI tools help reduce audit time" and "AI tools support better-informed decisions." The moderator, Corporate Governance, was adapted from Khanchel,[64] and the final outcome, Auditor Professional Reputation, was assessed through statements like "Clients perceive our audit team as credible and trustworthy." For more constructs detailed, please refer to Appendix.

Prior to full deployment, a pilot test was conducted with 30 external auditors to validate the clarity, readability, and internal consistency of the questionnaire items. Feedback was used to improve item formulation and ensure alignment with the Indonesian context. The final version of the questionnaire was distributed online, and all respondents provided informed consent. Anonymity and confidentiality were guaranteed.

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4. The measurement model was evaluated for reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted), and discriminant validity (Fornell—Larcker and HTMT ratio). The structural model was tested using bootstrapping with 5,000 subsamples to assess the significance of hypothesized paths, mediating and moderating effects. Full collinearity variance inflation factors (VIF) were also used to examine potential common method bias.

Table 1. Descriptive statistics of constructs.

Construct	Mean	Std. Deviation	Minimum	Maximum
Technology Readiness	4.97	0.89	2	7
Top Management Support	5.04	0.68	3	7
Innovation Climate	5.19	1.29	2	7
Vendor Ecosystem	5.54	0.69	3	7
AI-Powered Audit Tool Adoption	4.92	0.84	2	7
Auditor Confidence in AI Tools	5.06	0.95	3	7
Perceived Usefulness of AI Tools	5.12	0.88	3	7
Audit Efficiency	5.23	0.91	3	7
Audit Decision Quality	5.45	1.01	2	7
Corporate Governance	5.33	0.74	3	7
Auditor Professional Reputation	5.27	0.86	3	7

Result and discussion

Descriptive statistics

Table 1 presents the descriptive statistics for all constructs. Mean scores ranged from 4.92 to 5.45 on a 7-point Likert scale, reflecting generally positive perceptions of AI adoption and organizational readiness. Audit Decision Quality had the highest mean ($M = 5.45$, SD = 1.01), while AI Tool Adoption had the lowest ($M = 4.92$, SD = 0.84), suggesting uneven implementation across firms. Constructs such as Technology Readiness, Vendor Ecosystem, and Corporate Governance were

Table 2. Reliability.

Construct	Item	Loading Factor	Cronbach Alpha	CR	AVE
Technology Readiness	TE1	0.81	0.85	0.88	0.72
	TE2	0.87			
	TE3	0.75			
	TE4	0.81			
Top Management Support	TO1	0.83	0.89	0.88	0.70
	TO2	0.89			
	TO3	0.77			
	TO4	0.83			
	TO5	0.95			
Innovation Climate	IN1	0.82	0.86	0.89	0.68
	IN2	0.88			
	IN3	0.76			
	IN4	0.82			
Vendor Ecosystem	VE1	0.79	0.86	0.88	0.70
	VE2	0.85			
	VE3	0.73			
AI Tool Adoption	AI1	0.80	0.86	0.89	0.72
	AI2	0.86			
	AI3	0.74			
	AI4	0.80			
Auditor Confidence	AC1	0.83	0.87	0.90	0.74
	AC2	0.89			
	AC3	0.77			
	AC4	0.83			
Perceived Usefulness	PU1	0.85	0.88	0.90	0.71
	PU2	0.91			
	PU3	0.79			
	PU4	0.85			
	PU5	0.97			
Audit Efficiency	AE1	0.81	0.85	0.88	0.68
	AE2	0.87			
	AE3	0.75			
Audit Decision Quality	AD1	0.83	0.85	0.88	0.70
	AD2	0.89			
	AD3	0.77			
	AD4	0.83			
Corporate Governance	CG1	0.81	0.85	0.88	0.72
	CG2	0.87			
	CG3	0.75			
	CG4	0.81			
Auditor Reputation	AR1	0.83	0.88	0.90	0.74
	AR2	0.89			
	AR3	0.77			
	AR4	0.83			
	AR5	0.95			

rated highly, offering early evidence of AI maturity and organizational support among Indonesian auditors.

Measurement model

The reliability and validity of the measurement model were evaluated using multiple criteria, including indicator loadings, internal consistency, convergent validity, and discriminant validity. Table 2 presents the outer loadings, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) for all constructs. As shown, all indicator loadings exceeded the threshold of 0.70, indicating satisfactory indicator reliability.[64] Cronbach's Alpha and CR values for each construct were above 0.70, confirming the internal consistency of the measurement scales. Furthermore, AVE values ranged from 0.68 to 0.74, exceeding the recommended minimum of 0.50, which supports convergent validity.

Discriminant validity was assessed using the Fornell—Larcker criterion and the Heterotrait—Monotrait (HTMT) ratio, following the recommendations of Fornell & Larcker, and Hair, Henseler.[65–67]

As shown in Table 3, the square root of the AVE values (bolded diagonal elements) for all constructs is greater than their corresponding inter-construct correlations. For example, the square root of AVE for Technology Readiness (0.849) exceeds its correlations with other constructs such as Top Management Support (0.57), Innovation Climate (0.63), and Vendor Ecosystem (0.59). Similarly, Auditor Confidence (0.860), Perceived Usefulness (0.843), Corporate Governance (0.849), and Auditor Reputation (0.860) all show higher diagonal values than any of their off-diagonal correlations. This indicates that each construct shares more variance with its own indicators than with those of any other construct, thereby satisfying the Fornell—Larcker discriminant validity criterion.

The HTMT results presented in Table 4 further support discriminant validity. All HTMT ratios are below the conservative threshold of 0.85 and well below the more liberal criterion of 0.90.[66] For instance, the HTMT value between AI Tool Adoption and Perceived Usefulness is 0.85, between Audit Efficiency and Audit Decision Quality is 0.79, and between Corporate Governance and Auditor Reputation is 0.71, all within acceptable limits.

These findings confirm that the constructs are not excessively correlated and that each captures a unique conceptual domain. Therefore, the measurement model satisfies the recommended standards for discriminant validity in PLS-SEM.

To examine the potential issue of multicollinearity among predictor constructs, the Variance Inflation Factor (VIF) values were assessed. All VIF values were below the recommended threshold of 3.3, indicating that multicollinearity was not a concern in this study. Notably, the highest VIF value observed was for AI Tool Adoption (2.95), which still falls within an acceptable range.

Table 3. Fornell—Larcker Criterion.

	TR	TMS	IC	VE	AI	AC	PU	AE	ADQ	CG	AR
TR	0.849										
TMS	0.57	0.837									
IC	0.63	0.61	0.825								
VE	0.59	0.56	0.58	0.837							
AI	0.52	0.54	0.55	0.57	0.849						
AC	0.48	0.49	0.52	0.50	0.46	0.860					
PU	0.45	0.50	0.51	0.48	0.49	0.58	0.843				
AE	0.46	0.51	0.50	0.49	0.51	0.56	0.59	0.825			
ADQ	0.44	0.47	0.48	0.46	0.48	0.54	0.57	0.61	0.837		
CG	0.41	0.45	0.44	0.45	0.47	0.50	0.52	0.53	0.51	0.849	
AR	0.47	0.49	0.46	0.47	0.53	0.55	0.56	0.58	0.55	0.54	0.860

Table 4. Heterotrait-monotrait ratio (HTMT).

	TR	TMS	IC	VE	AI	AC	PU	AE	ADQ	CG	AR
TR	1.00										
TMS	0.57	1.00									
IC	0.88	0.52	1.00								
VE	0.81	0.56	0.49	1.00							
AI	0.74	0.59	0.52	0.69	1.00						
AC	0.74	0.43	0.76	0.73	0.46	1.00					
PU	0.58	0.54	0.58	0.41	0.85	0.77	1.00				
AE	0.88	0.85	0.71	0.65	0.83	0.65	0.73	1.00			
ADQ	0.87	0.52	0.71	0.51	0.53	0.75	0.71	0.79	1.00		
CG	0.52	0.47	0.66	0.72	0.72	0.61	0.67	0.74	0.66	1.00	
AR	0.64	0.64	0.44	0.49	0.80	0.70	0.69	0.68	0.77	0.71	1.00

Table 5. Model fit indicators.

Fit Indicator	Value
SRMR	0.068
NFI	0.923
Chi-square	1015.34
Chi-square/df	2.41
d_ULS	0.601
d_G	0.428

Structural measurement

The model demonstrated moderate to substantial explanatory power, with R^2 values ranging from 0.42 to 0.55 (Table 5).[66] It explained 42% of the variance in AI Tool Adoption, 51% in Auditor Confidence, and 47% in Perceived Usefulness, indicating that factors like Technology Readiness, Top Management Support, Innovation Climate, and Vendor Ecosystem are meaningful predictors. Additionally, the model accounted for 55% of Audit Efficiency, 49% of Audit Decision Quality, and 53% of Auditor Professional Reputation, confirming its strength in capturing the link between AI adoption, auditor perceptions, audit quality, and professional reputation.

To assess model adequacy, several fit indices were examined. The SRMR value of 0.068 is below the 0.08 threshold, indicating good model fit. The NFI score of 0.923 exceeds the recommended 0.90, further confirming model adequacy. Other indices, including the Chi-square/df ratio (2.41), d_ULS (0.601), and d_G (0.428), also fall within acceptable limits. Collectively, these results support the structural model's validity and reinforce confidence in the subsequent hypothesis testing and interpretation.

Hypothesis testing

Table 6 presents the results of hypothesis testing from the structural model. The findings confirm that Top Management Support (H1b: $\beta = 0.34$, $p < .001$) and Innovation Climate (H1c: $\beta = 0.29$, $p < .001$) significantly promote the adoption of AI-powered audit tools, indicating the importance of leadership commitment and an innovation-friendly culture. In contrast, Technological Readiness (H1a: $\beta = 0.08$, $p = .215$) and Vendor Ecosystem Support (H1d: $\beta = 0.07$, $p = .293$) were not significant, suggesting that infrastructure and external partnerships alone may be insufficient to drive adoption in the Indonesian audit context. AI adoption was found to significantly influence both mediators: Auditor Confidence (H2a: $\beta = 0.39$, $p < .001$) and Perceived Usefulness (H2b: $\beta = 0.36$, $p < .001$). In turn, these mediators positively impacted audit outcomes, Confidence enhanced Audit Efficiency (H3a: $\beta = 0.41$, $p < .001$), while Usefulness improved Audit Decision Quality (H3b: $\beta = 0.37$, $p < .001$). The interaction between Corporate Governance and AI Adoption (H4) was also significant ($\beta = 0.12$, $p = .043$), confirming that strong governance amplifies the positive effect of AI on auditor confidence. Finally, both Audit Efficiency (H5a: $\beta = 0.35$, $p < .001$) and Audit Decision Quality (H5b: $\beta = 0.38$, $p < .001$) significantly contributed to Auditor Professional Reputation. These results validate the proposed model and emphasize that internal support and user perception are central to effective AI adoption, with measurable impacts on audit performance and professional standing.

To test the moderating role of corporate governance (CG) on the relationship between AI tool adoption and auditor confidence, an interaction term (AI Adoption × Corporate Governance) was included in the structural model. The results ($\beta = 0.12$, $t = 2.03$, $p = .043$) shown in Table 5 confirm a positive and significant moderation effect, supporting H4.

This suggests that corporate governance strengthens the relationship between AI adoption and auditor confidence. In firms with robust governance, characterized by active oversight, clear ethical standards, and strong compliance mechanisms, auditors are more likely to trust and rely on AI tools. Good governance likely enhances perceived data integrity, algorithm transparency, and accountability, thereby reducing risks and increasing trust in AI systems. As illustrated in the

Table 6. Hypothesis testing result.

Hypothesis	Path	Coeff.	t-value	p-value	Result
H1a	TR → AI	0.08	1.24	0.215	Not significant
H1b	TMS → AI	0.34	5.48	0.000	Significant
H1c	IC → AI	0.29	4.83	0.000	Significant
H1d	VE → AI	0.07	1.05	0.293	Not significant
H2a	AI → AC	0.39	6.72	0.000	Significant
H2b	AI → PU	0.36	6.15	0.000	Significant
H3a	AC → AE	0.41	7.01	0.000	Significant
H3b	PU → DQ	0.37	6.44	0.000	Significant
H4	CG × AI → AC	0.12	2.03	0.043	Significant
H5a	AE → PR	0.35	5.49	0.000	Significant
H5b	DQ → PR	0.38	6.02	0.000	Significant

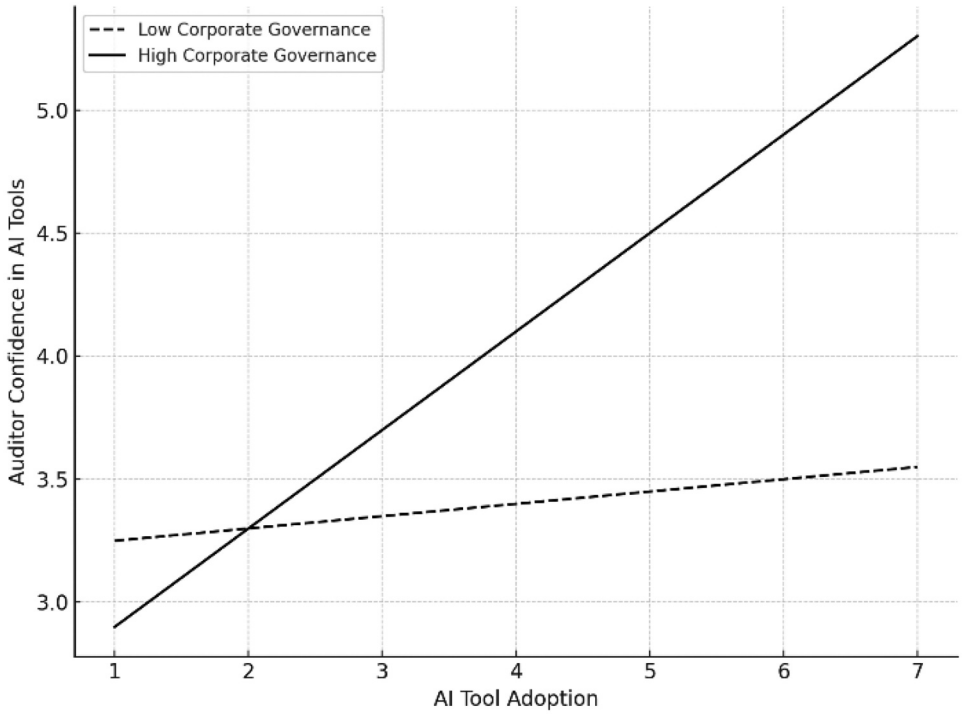


Figure 2. Interaction effect of corporate governance.

moderation graph (Figure 2), the relationship between AI adoption and auditor confidence is notably stronger under high governance conditions, while it weakens considerably in low-governance settings. This aligns with prior research underscoring governance as a critical enabler of digital innovation acceptance. In Indonesia, where governance practices are inconsistent across firms, these findings imply that adopting AI alone is insufficient; a supportive institutional framework is equally vital to foster auditor trust and effective tool utilization.

Discussion

This study examined the adoption and effectiveness of AI-powered audit tools in Indonesia, focusing on organizational antecedents, cognitive-perceptual mediators, the moderating role of corporate governance, and their combined influence on auditor professional reputation. The results contribute to understanding how emerging technologies reshape auditing practices within developing economies where digital transformation coexists with regulatory and cultural constraints.

Top Management Support and Innovation Climate were identified as the strongest predictors of AI tool adoption, demonstrating that visible leadership endorsement and an experimentation-oriented culture remain decisive in legitimizing technological change. These findings echo previous research in accounting information systems that highlights leadership commitment and openness to innovation as essential preconditions for digital transformation.[68] The results also extend global discussions by suggesting that in the Indonesian auditing context, psychological and cultural enablers outweigh purely technical considerations. In contrast, Technology Readiness and Vendor Ecosystem Support were not significant predictors, indicating a divergence from classical Technology—Organization—Environment (TOE) assumptions. This pattern reflects an environment in which basic digital infrastructure is already present, but formal adoption depends more on leadership advocacy and collective learning orientation than on external support or hardware maturity. Similar observations were made by Widuri,[69] who found that Indonesian auditors emphasize contextual fit such as language localization and regulatory compatibility over generic technological capacity. Hence, the determinants of AI adoption in auditing appear to be socially and institutionally embedded rather than purely technological.

The mediating roles of Auditor Confidence and Perceived Usefulness clarify the cognitive mechanisms through which AI adoption translates into improved audit outcomes. Confidence significantly enhanced Audit Efficiency, whereas Perceived Usefulness strengthened Audit Decision Quality, aligning with the Technology Acceptance Model (TAM).[11] These results corroborate global evidence that user beliefs mediate the

effectiveness of AI-based systems. Gursoy similarly argued that AI acceptance involves a combination of cognitive and affective trust; users must believe not only that AI improves performance but also that it behaves predictably and ethically.[24] This study extends that logic to professional auditing by demonstrating that confidence and perceived usefulness operate as sequential, mutually reinforcing drivers of performance in highly regulated, judgment-intensive settings. Unlike consumers in Gursoy et al.'s study, auditors evaluate AI tools within accountability and assurance frameworks, suggesting that trust formation in professional contexts is mediated by organizational ethics and compliance structures rather than convenience or enjoyment.

Corporate Governance was shown to moderate the link between AI adoption and Auditor Confidence, underscoring governance as a trust-enabling infrastructure. Auditors embedded in firms with strong ethical oversight, transparent decision protocols, and clear accountability reported greater confidence in AI outputs. This finding complements the argument by Cheong that transparency and institutional safeguards are fundamental to AI trustworthiness.[70] Conversely, weak governance environments diminished the positive effects of AI adoption, illustrating that technological advancement without ethical control may exacerbate uncertainty rather than alleviate it.

Finally, both Audit Efficiency and Audit Decision Quality were found to significantly enhance Auditor Professional Reputation, reaffirming that technological competence and high-quality decision-making jointly underpin professional credibility.[71] These outcomes mirror prior evidence that innovation adoption in auditing strengthens client trust and perceived legitimacy when coupled with responsible governance and sound judgment. In Indonesia's evolving audit landscape, however, the study suggests that symbolic adoption of AI without the psychological readiness, ethical training, and institutional integrity to sustain it may fail to produce substantive gains. Strengthening governance frameworks, embedding AI ethics within professional standards, and fostering localized vendor partnerships can therefore bridge the persistent gap between adoption and performance. In doing so, Indonesian audit firms can transform AI integration from a procedural compliance exercise into a source of sustainable professional advantage and reputational capital.

Implications

This study advances the theoretical understanding of AI adoption in auditing by integrating insights from the Technology Acceptance Model (TAM), the Technology-Organization-Environment (TOE) framework, and corporate governance literature. It extends TAM by positioning auditor confidence and perceived usefulness as complementary mediators, demonstrating how cognitive trust and perceived value jointly influence AI effectiveness in judgment-intensive audit tasks. The findings also refine the TOE framework by revealing that internal enablers particularly top management support and an innovation-oriented culture are more influential in driving AI adoption in Indonesia than technological readiness or vendor support. Furthermore, corporate governance emerges as a key moderating factor that not only safeguards compliance but also strengthens trust and amplifies the benefits of AI adoption. By linking these factors to auditor professional reputation, the study offers a stakeholder-centered perspective on digital transformation in auditing.

From a practical standpoint, the results highlight that in Indonesia's early-stage digital auditing environment, internal support systems are more decisive than mere tool availability. Public accounting firms should prioritize leadership-driven initiatives where senior partners actively endorse AI usage and model its integration into audit workflows. This can be operationalized through structured change management programs, visible leadership engagement in AI-driven projects, and clear communication of AI's value to staff at all levels.

The strong role of innovation climate suggests that firms should invest in continuous learning ecosystems that normalize experimentation with AI tools. This includes providing regular skills-based training on AI-enabled audit procedures, scenario-based workshops that simulate complex decision-making with AI assistance, and mentorship programs that pair technology-savvy auditors with less experienced staff. Training should not be limited to technical operation but also cover critical interpretation of AI outputs, ethical considerations, and risk management, ensuring auditors remain in control of professional judgments.

For regulators, the findings indicate a need to embed AI adoption guidelines within professional auditing standards, particularly those related to data governance, accountability, and transparency. Regulatory bodies could also sponsor national competency certification programs for AI-enabled auditing, ensuring a consistent baseline of skills across the profession and reducing inter-firm disparities in readiness.

For technology vendors, the lack of significant impact from vendor support signals a need for localized, audit-specific AI solutions. Vendors should invest in tools that are compliant with Indonesian accounting

and auditing standards, offer full Bahasa Indonesia interfaces, and provide customizable modules that align with local audit methodologies. Partnerships with local professional associations can help vendors deliver co-developed training resources, joint pilot projects, and post-implementation support tailored to Indonesian audit environments.

Finally, given the significant moderating role of corporate governance, both firms and regulators should work to strengthen governance frameworks by embedding AI oversight into audit committees, formalizing ethical review processes for AI use, and ensuring transparency in AI-assisted decision-making. Such measures will not only enhance adoption outcomes but also position auditors to gain in professional reputation, client trust, and competitive advantage in a rapidly evolving audit market.

Limitations and future recommendations

Finally, this study also acknowledges the theoretical limitations of employing the Technology Acceptance Model (TAM) as the principal framework. Although TAM provides a parsimonious and empirically validated structure for analyzing technology acceptance, it may not fully capture the complex cognitive and ethical processes involved in adopting autonomous systems. As highlighted by Gursoy et al. [24] users' perceptions of artificial intelligence often extend beyond usefulness and ease of use to include trust, perceived autonomy, and moral comfort. In the auditing context, such dimensions may influence how professionals interpret algorithmic recommendations or assess accountability. Moreover, this study did not account for auditors' "folk theories" or intuitive beliefs about AI's human-like agency and decision logic, which could shape their confidence and resistance. Future research should therefore integrate constructs such as perceived transparency, anthropomorphism, and ethical alignment to refine AI adoption theories in professional settings.

Conclusion

This study investigated the adoption of AI-powered audit tools in Indonesia, focusing on organizational enablers, cognitive-perceptual mediators, corporate governance as a moderator, and their combined influence on audit efficiency, audit decision quality, and auditor professional reputation. The findings demonstrate that top management support and an innovation-friendly culture are decisive drivers of AI adoption, outweighing the effects of technology readiness and vendor ecosystem support. This underscores that in Indonesia's evolving audit environment, leadership commitment and cultural receptivity are more influential than infrastructure availability alone.

Auditor confidence and perceived usefulness emerged as key mechanisms through which AI adoption translates into improved audit outcomes, confirming the centrality of human factors in technology effectiveness. Corporate governance enhanced the positive influence of AI adoption on auditor confidence, emphasizing its role as a trust-building and performance-enabling structure.

Both audit efficiency and audit decision quality significantly enhanced auditor professional reputation, illustrating the reputational value of technological competence. For practice, these results highlight the need for leadership-driven strategies, governance strengthening, tailored training programs, and locally adapted AI solutions. By aligning technology adoption with supportive organizational and institutional conditions, Indonesian audit firms can unlock AI's potential for higher performance and sustainable professional credibility.

Author contributions

CRediT: **Yasri Tarawiru:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing; **Hasdiana:** Data curation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing; **Yusran Bachtiar:** Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing; **Parman:** Supervision, Validation, Writing – original draft, Writing – review & editing.

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Data availability statement

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Appendix. Measurement items and sources

Construct	Item Code	Measurement Item	Primary Source
Technology Readiness	TE1	My organization is well-equipped with technology to support AI audit tools.	Uren & Edwards (2023)
	TE2	Our firm has sufficient IT infrastructure and data capacity for AI deployment.	
	TE3	Our organization's systems are compatible with AI audit technologies.	
	TE4	Employees in our firm possess adequate digital skills to operate AI-based tools.	
Top Management Support	TO1	Top management actively encourages the use of AI in auditing.	Cheng et al. (2024)
	TO2	Senior leadership provides sufficient resources for AI implementation.	
	TO3	Top management clearly communicates the strategic value of AI adoption.	
	TO4	Top management participates in AI-related decision-making processes.	
	TO5	Leadership commitment motivates employees to engage with AI tools.	
Innovation Climate	IN1	Our firm encourages innovative thinking and experimentation.	Popa et al. (2017)
	IN2	Employees are supported when testing new technologies.	
	IN3	Mistakes in technological experimentation are treated as learning opportunities.	
	IN4	Innovative ideas are recognized and rewarded in our firm.	
Vendor Ecosystem	VE1	We maintain strong partnerships with AI audit technology vendors.	Raji et al. (2022)
	VE2	Vendors provide timely updates and technical assistance.	
	VE3	Vendors offer training and knowledge-sharing opportunities for AI tools.	
AI Tool Adoption	AI1	We have adopted AI tools to assist in auditing processes.	Seethamraju & Hecimovic (2023)
	AI2	AI tools are integrated into our regular audit workflow.	
	AI3	We use AI for data analysis and risk identification in audits.	
	AI4	AI applications support decision-making during audit engagements.	
Auditor Confidence	AC1	I am confident in the accuracy of audit outputs generated by AI tools.	Li & Goel (2025)
	AC2	I trust AI tools to provide reliable audit evidence.	
	AC3	I believe AI tools comply with professional and ethical standards.	
	AC4	I feel comfortable relying on AI-generated insights in audit judgments.	
Perceived Usefulness	PU1	AI tools are useful in improving the quality of my audit work.	Davis (1989)
	PU2	AI enhances the effectiveness of my audit tasks.	
	PU3	AI applications improve the accuracy of audit judgments.	
	PU4	Using AI helps detect anomalies and potential fraud more efficiently.	
	PU5	AI tools provide valuable support for complex audit decisions.	
Audit Efficiency	AE1	AI tools help reduce audit time and effort.	Larmande & Lesage (2023)
	AE2	AI facilitates faster data processing during audits.	
	AE3	AI reduces manual procedures and repetitive audit tasks.	
Audit Decision Quality	AD1	AI tools support better-informed audit decisions.	Rajabalizadeh & Schadewitz (2025)
	AD2	AI enhances the consistency and reliability of audit judgments.	
	AD3	AI improves auditors' ability to detect material misstatements.	
	AD4	AI enables more defensible and transparent audit conclusions.	
Corporate Governance	CG1	Our firm has established clear governance procedures for AI use.	Khanchel (2007)
	CG2	The audit committee oversees the ethical use of AI technologies.	
	CG3	Governance mechanisms ensure transparency in AI-assisted decisions.	
	CG4	Oversight systems promote accountability in technological applications.	
Auditor Reputation	AR1	Clients perceive our audit team as credible and trustworthy.	Rothenberg (2020)
	AR2	Our firm is recognized for high technological competence.	
	AR3	Our audit opinions are perceived as accurate and reliable.	
	AR4	AI adoption enhances our firm's professional reputation.	
	AR5	Our audits reflect high standards of ethics and professionalism.	