The Role of AI-Assisted Accounting Information Systems in Enhancing Audit Effectiveness

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Abstract. This study examines the relationship between AI-assisted accounting information systems (AIS) and perceived audit effectiveness using Task-Technology Fit (TTF) theory as the principal theoretical lens. Against the rapid diffusion of artificial intelligence and data analytics in audit work, empirical evidence remains limited on whether AI capabilities embedded in AIS translate into more effective audit procedures, particularly in developing-economy settings. Using a quantitative explanatory design and purposive sampling, data were collected during 2026 from Indonesian professionals with experience in digital accounting systems and audit-related activities. AI-assisted AIS was operationalized through automation capability, anomaly and risk detection, analytical accuracy and speed, real-time monitoring and reporting, and decision-support capability; audit effectiveness was reflected by accuracy, procedural efficiency, timeliness, fraud/error detection, and reliability of audit evidence. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The structural model shows a positive and significant relationship between AI-assisted AIS and audit effectiveness ($\beta = 0.796$, $t = 15.170$, $p < 0.001$), with $R^2 = 0.634$, $f^2 = 1.730$, and $Q^2 = 0.615$. The findings support the TTF argument that technology is more likely to improve performance when its capabilities correspond to audit-task requirements. However, the benefits of AI remain contingent on data quality, user competence, system governance, explainability, and continued professional judgment. The study contributes to digital auditing research by linking intelligent AIS capabilities to perceived audit effectiveness and by identifying conditions that may strengthen or constrain these benefits.

Keywords: artificial intelligence; accounting information systems; audit effectiveness; digital auditing; task-technology fit

1 Introduction

Artificial intelligence (AI) is increasingly becoming part of the technological infrastructure used in accounting and auditing. Audit firms and organizations now use combinations of data

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analytics, machine learning, automated extraction, anomaly detection, and decision-support tools to process larger volumes of structured and unstructured information than would be feasible through manual procedures alone. Empirical research in the audit sector indicates that investments in AI-related capabilities can improve audit quality and process efficiency, while field evidence also shows that the actual use of more advanced AI tools remains uneven across audit tasks (Fedyk et al., 2022; Kokina et al., 2025). These developments shift the debate from whether AI can be used in auditing to a more specific question: under what conditions do AI-enabled information systems actually improve the effectiveness of audit work?

This question is particularly relevant in developing economies, where digital transformation is progressing alongside differences in technological infrastructure, data quality, human-capital readiness, and organizational governance. In Indonesia, for example, recent evidence on big-data-analytics-based auditing in the public sector shows growing interest in technology-supported audit practices and links technology adoption with auditor performance (Saud et al., 2025). Big data analytics is not identical to AI, but this evidence demonstrates that advanced digital audit tools are already relevant in the Indonesian professional environment. At the same time, evidence specifically concerning AI capabilities embedded in accounting information systems and their implications for audit effectiveness remains limited. Accordingly, the developing-economy setting offers an important context in which to assess whether intelligent AIS capabilities are associated with stronger audit outcomes.

AI-assisted AIS can potentially support several core audit tasks. Automation may reduce repetitive processing; anomaly-detection algorithms can direct attention to unusual transactions; analytical tools can accelerate risk assessment; real-time reporting can reduce information delays; and decision-support features can help auditors prioritize evidence and exceptions. These capabilities may improve audit accuracy, procedural efficiency, timeliness, fraud and error detection, and the reliability of evidence (Leocádio et al., 2024; Pérez-Calderón et al., 2025). Nevertheless, such benefits are not automatic. AI outputs may be affected by poor data quality, biased training data, opaque model logic, cybersecurity and privacy risks, insufficient integration with existing workflows, or user overreliance. Ethical and professional concerns are also important because automated recommendations cannot replace auditors' responsibility for professional skepticism and judgment (Kokina et al., 2025; Lehner et al., 2022; Vitali & Giuliani, 2024).

The existing literature leaves three related gaps. First, many studies examine AI in auditing at the level of audit-firm technology adoption, digital expertise, or audit quality, rather than positioning AI-assisted AIS as an intelligent information infrastructure that directly supports audit procedures (Fedyk et al., 2022; Zhao et al., 2026). Second, adoption-oriented studies explain why professionals accept or use advanced technology, but provide less direct evidence about whether the capabilities embedded in AIS are associated with perceived audit effectiveness once the technology is used (Krieger et al., 2021; Saud et al., 2025). Third, evidence from developing-country settings remains less extensive than evidence from large audit markets, although differences in digital readiness and governance may affect the value obtained from AI-supported systems (Abdullah & Almaqtari, 2024; Hamdy et al., 2025). This study addresses these gaps by examining the direct relationship between AI-assisted AIS capabilities and audit effectiveness in Indonesia.

Task-Technology Fit (TTF) theory provides the primary theoretical foundation for this relationship. TTF proposes that technology improves individual performance when its functionalities fit the requirements of the tasks users must perform (Goodhue & Thompson, 1995). In auditing, tasks such as identifying anomalies, evaluating large transaction populations, assessing risk, tracing evidence, and completing procedures within reporting deadlines are information-intensive and analytically demanding. AI-assisted AIS offers capabilities that can fit these task requirements by automating routine processing, identifying patterns, accelerating analysis, and presenting decision-relevant information. When this fit is high, auditors and audit-related professionals should be able to perform relevant procedures more accurately and efficiently. Conversely, when the system is poorly integrated, data are unreliable, users lack digital competence, or AI recommendations are not explainable, the expected performance gains may be weakened.

The study therefore makes two contributions. Theoretically, it extends TTF into the digital-auditing context by treating AI-assisted AIS capabilities as technology characteristics that support information-intensive audit tasks and by evaluating audit effectiveness as a performance-related outcome. Practically, it provides evidence for auditors, audit units, accounting and finance managers, and system decision makers concerning the value of AI-enabled AIS while emphasizing that effective implementation requires data governance, competent users, human oversight, and appropriate controls rather than technology adoption alone. Based on this reasoning, the study asks whether AI-assisted AIS is positively associated with audit effectiveness.

H1: AI-Assisted Accounting Information Systems have a positive effect on perceived Audit Effectiveness.

2 Method

2.1 Research Design

This study employed a quantitative, cross-sectional explanatory design to test the hypothesized relationship between AI-assisted accounting information systems and perceived audit effectiveness. PLS-SEM was used because both concepts are modeled as latent constructs measured through multiple indicators and because the study emphasizes explanation and prediction of audit effectiveness. The analysis followed the two-stage procedure recommended for PLS-SEM: assessment of the measurement model followed by assessment of the structural model (Hair et al., 2022).

2.2 Research Setting, Population, and Sampling

The empirical study was conducted in Indonesia and targeted professionals whose work provided sufficient exposure to both accounting information systems and audit-related processes. The population included external auditors, internal auditors, and accounting/finance professionals who interacted with digital AIS and were directly involved in audit-related activities. Purposive sampling was applied because respondents needed specific experience relevant to the constructs being measured. Eligibility required at least one year of professional experience, familiarity with AI-assisted or advanced digital AIS features, and direct involvement in audit, financial control, audit support, or preparation of information used in audit procedures. The survey targeted approximately 150–200 potential respondents, consistent with the sampling plan described in the original manuscript.

Respondents were screened using four principal eligibility criteria: professional experience in auditing, accounting, finance, or financial control; experience using digital accounting information systems; familiarity with AI-assisted functions such as automation, anomaly detection, analytical support, or real-time reporting; and at least one year of professional experience. Because the dependent construct is audit effectiveness, accounting and finance respondents were included only when their work involved audit support, financial control, preparation of audit evidence or information, or other direct exposure to audit procedures and outcomes. Table 1 summarizes the eligibility profile used in the purposive sampling design.

Table 1. Respondent Eligibility Profile

Criterion	Eligible respondent profile	Rationale
Professional role	External/internal auditors; accounting or finance staff/managers with direct audit-related involvement	Ensures sufficient familiarity with audit processes and accounting information systems
Professional experience	At least one year of relevant professional experience	Reduces responses based solely on limited or introductory exposure
System exposure	Experience using digital AIS and familiarity with AI-assisted features such as automation, anomaly detection, analytics, or real-time reporting	Ensures respondents can evaluate the AI-assisted AIS construct
Audit exposure	Direct involvement in audit, financial control, audit support, or preparation of information/evidence used in audit procedures	Ensures respondents can meaningfully evaluate perceived audit effectiveness
Research setting	Indonesia	Provides the developing-economy context emphasized in the research gap

2.3 Data Collection Procedure

Primary data were collected during 2026 using a structured questionnaire distributed to eligible respondents in Indonesia. Distribution was conducted online and, where feasible, offline through professional and institutional networks to broaden access to qualified participants. Respondents were informed about the study purpose, voluntary participation, and confidentiality of responses. The questionnaire included screening questions, respondent characteristics, AI-assisted AIS items, and audit-effectiveness items. All construct items used a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Before full distribution, the instrument was reviewed for clarity, relevance, and readability, consistent with the procedure described in the original manuscript.

2.4 Measurement of Variables

Table 2. Construct Operationalization and Instrument Specification

Construct	Dimension / code	Operational focus	Supporting literature
AI-AIS	Automation capability (AIAIS-D1)	Automation of routine accounting and audit-related processing	Fedyk et al. (2022); Leocádio et al. (2024)
AI-AIS	Anomaly and risk detection (AIAIS-D2)	Identification of unusual transactions, patterns, or risks	Fedyk et al. (2022); Kokina et al. (2025)
AI-AIS	Analytical accuracy and speed (AIAIS-D3)	Faster and more accurate analysis of accounting information	Fedyk et al. (2022); Vitali & Giuliani (2024)
AI-AIS	Real-time monitoring/reporting (AIAIS-D4)	Timely monitoring and reporting of relevant information	Leocádio et al. (2024); Nurhayati et al. (2023)
AI-AIS	Decision support (AIAIS-D5)	Support for audit-related analysis and professional decisions	Lehner et al. (2022); Kokina et al. (2025)

AE	Accuracy of audit results (AE-D1)	Accuracy and precision of audit findings and conclusions	Fedyk et al. (2022); Ditkaew & Suttipun (2023)
AE	Procedural efficiency (AE-D2)	Efficient execution of audit procedures	Fedyk et al. (2022); Ditkaew & Suttipun (2023)
AE	Timeliness (AE-D3)	Completion of audit work within an appropriate time	Fedyk et al. (2022); Vitali & Giuliani (2024)
AE	Fraud/error detection (AE-D4)	Ability to identify errors, irregularities, or fraud indicators	Kokina et al. (2025); Pérez-Calderón et al. (2025)
AE	Reliability of audit evidence (AE-D5)	Usefulness and reliability of evidence supporting audit conclusions	Ditkaew & Suttipun (2023); Pérez-Calderón et al. (2025)

AI-Assisted Accounting Information Systems (AI-AIS) refers to the extent to which AIS incorporates intelligent capabilities that support accounting and audit-related information processing. The construct covers automation capability, anomaly and risk detection, analytical accuracy and speed, real-time monitoring and reporting, and decision-support capability. Audit Effectiveness (AE) refers to the perceived extent to which audit work achieves accurate results, efficient procedures, timely completion, effective fraud/error detection, and reliable audit evidence. The operational dimensions were synthesized from prior research on AI-enabled auditing, audit analytics, and digital accounting systems, as summarized in Table 2. All indicators were assessed using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

2.5 Data Analysis

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS. The measurement model was assessed through item outer loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and discriminant validity. Internal consistency was considered acceptable when reliability values exceeded 0.70, convergent validity when AVE exceeded 0.50, and discriminant validity was examined primarily using the heterotrait-monotrait ratio (HTMT), following established PLS-SEM guidance (Hair et al., 2022; Henseler et al., 2015). The structural model was evaluated using the standardized path coefficient (β), t-statistic, p-value, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). Statistical significance was assessed using the SmartPLS bootstrapping procedure. Because all constructs were collected using a single self-report questionnaire, common-method bias should also be considered when interpreting the magnitude of the observed relationship.

3 Results and Discussion

3.1 Results

3.1.1 Respondent Characteristics

The final analytical sample consisted of respondents who met the eligibility and completeness criteria described above. The respondent focus was deliberately restricted to professionals with sufficient exposure to audit procedures and digital accounting systems, because the validity of the Audit Effectiveness construct depends on respondents being able to evaluate audit-related processes and outcomes.

3.1.2 Measurement Model Assessment

The measurement model was evaluated for internal consistency, convergent validity, and discriminant validity. As shown in Table 3, both constructs met the conventional reliability and convergent-validity criteria. AI-Assisted AIS produced a Cronbach's alpha of 0.936, composite reliability of 0.945, and AVE of 0.589. Audit Effectiveness produced a Cronbach's alpha of 0.937, composite reliability of 0.945, and AVE of 0.591. These results indicate high internal consistency and that each construct explains more than half of the variance in its indicators.

Table 3. Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE	Assessment
AI-Assisted Accounting Information Systems	0.936	0.945	0.589	Acceptable
Audit Effectiveness	0.937	0.945	0.591	Acceptable

Discriminant validity was assessed using HTMT. The HTMT value between AI-Assisted AIS and Audit Effectiveness was 0.850 (Table 4). This value is below the 0.90 threshold commonly applied to conceptually related constructs, although it is close to the stricter 0.85 criterion. The result therefore indicates acceptable but relatively close empirical distinctiveness between the two constructs, which is plausible because several AI-assisted capabilities, such as analytical accuracy and anomaly detection, are directly relevant to audit performance.

Table 4. Discriminant Validity (HTMT)

Construct Pair	HTMT	Interpretation
AI-Assisted AIS ↔ Audit Effectiveness	0.850	Below 0.90; borderline under 0.85 criterion

The measurement-model results were evaluated using reliability, convergent-validity, and discriminant-validity criteria before the structural relationship was interpreted.

3.1.3 Structural Model Assessment

The structural model indicates a strong positive relationship between AI-Assisted AIS and Audit Effectiveness. As summarized in Table 5, the standardized path coefficient was $\beta = 0.796$, with $t = 15.170$ and $p < 0.001$. Thus, H1 is supported: higher perceived capability of AI-assisted AIS is associated with higher perceived audit effectiveness. Because the study is cross-sectional and based on self-reported perceptions, this result should be interpreted as strong predictive/associational evidence rather than definitive causal proof.

Table 5. Hypothesis Testing

Hyp.	Relationship	β	t	p	Decision
H1	AI-Assisted AIS → Audit Effectiveness	0.796	15.170	<0.001	Supported

The model also showed substantial explanatory and predictive power (Table 6). R^2 for Audit Effectiveness was 0.634, meaning that 63.4% of the variance in the endogenous construct was explained by AI-Assisted AIS in this one-predictor model. The f^2 value of 1.730 indicates a very large effect size, while $Q^2 = 0.615$ indicates predictive relevance. These values are consistent with a strong relationship, but they also reinforce the need to examine common-method bias, construct overlap, and sampling characteristics because both predictor and outcome were measured from the same respondents using the same survey method.

Table 6. Explanatory and Predictive Power

Endogenous Construct	R^2	f^2	Q^2	Interpretation
Audit Effectiveness	0.634	1.730	0.615	Substantial explanatory/predictive relationship

3.2 Discussion

The results show that AI-assisted AIS is strongly and positively associated with perceived audit effectiveness. TTF theory provides a direct explanation for this finding. Audit work requires the processing of large and diverse datasets, identification of exceptions, assessment of risk, evaluation of evidence, and completion of procedures within time constraints. AI-assisted AIS can fit these task requirements by automating repetitive processing, detecting anomalous patterns, accelerating analytical procedures, and presenting information that supports risk-based decisions. When the technological capabilities correspond to the informational and analytical demands of audit tasks, users can devote more attention to interpretation, investigation, and professional judgment. The finding is therefore consistent with TTF's central proposition that performance gains arise not from technology availability alone but from the fit between technology functionality and task requirements (Goodhue & Thompson, 1995).

The result is also consistent with empirical audit-technology research. Fedyk et al. (2022) provide large-scale evidence that AI-related human capital in audit firms is associated with improvements in audit quality and process efficiency. Ditkaew & Suttipun (2023) similarly report that audit data analytics can improve audit quality-related outcomes, while Saud et al. (2025) show that advanced analytics adoption in Indonesian public-sector auditing is relevant to auditor performance. The present study extends this literature by shifting attention from AI adoption or audit-firm technology investment to the perceived capabilities of AI embedded in accounting information systems. In other words, the result suggests that the value of AI for auditing can emerge upstream in the information system itself, before audit conclusions are formed, through higher-quality processing, faster exception identification, and more accessible analytical evidence.

However, the positive coefficient should not be interpreted to mean that AI automatically produces an effective audit. The relationship is likely to be conditional on several complementary factors. First, data quality is fundamental: an AI model cannot compensate for incomplete, inconsistent, manipulated, or poorly governed accounting data. Second, auditor digital competence affects whether AI-generated signals are understood and appropriately investigated. Third, system integration matters because AI outputs must be connected with the organization's accounting processes and the auditor's workflow rather than operating as isolated tools. Fourth, explainability and governance are important when AI outputs affect risk assessment or evidence evaluation. These conditions are consistent with research showing that organizational readiness, user capabilities, and implementation processes influence the adoption and value of advanced audit technologies (Krieger et al., 2021; Vitali & Giuliani, 2024).

A balanced interpretation also requires attention to risk. AI-assisted systems can create automation bias, where users rely excessively on system recommendations; black-box models can make it difficult to understand why a transaction is classified as unusual; biased or incomplete data can generate systematic misclassification; and greater system connectivity may increase cybersecurity and confidentiality exposure. In auditing, these risks are particularly important because the auditor remains responsible for professional skepticism, evidence evaluation, and the final conclusion. Lehner et al. (2022) emphasize ethical challenges in AI-based accounting and audit decision-making, while Kokina et al. (2025) show that the sophistication and actual deployment of AI tools vary considerably in practice. Therefore, the most defensible interpretation of the present result is that AI-assisted AIS can augment audit effectiveness when embedded in an appropriate control environment and combined with human judgment, rather than substituting for the auditor.

The Indonesian developing-economy context also deserves specific consideration. The findings should be interpreted against differences in digital infrastructure, regulatory expectations, organizational data governance, and professional technology skills across organizations. Evidence from Indonesia on big-data-analytics-based auditing suggests that technology can improve auditor performance, but the transition from analytics to more autonomous or AI-enabled systems may require stronger governance, training, and assurance over system outputs (Saud et al., 2025). This contextual dimension is important because the same AI capability may generate different performance effects across organizations with different levels of technological maturity.

The theoretical contribution is therefore not simply that ‘AI improves auditing.’ Rather, the findings support a task-technology explanation: AI-assisted AIS is associated with stronger audit effectiveness because its capabilities fit several information-intensive audit requirements. The practical contribution is equally conditional. Organizations should evaluate AI investments not only in terms of software features but also in terms of data integrity, user competence, integration with audit methodology, access controls, explainability, and mechanisms for human review. This approach reduces the risk that AI becomes an efficiency tool without corresponding improvements in audit reliability and professional accountability.

4 Conclusion

This study examined the relationship between AI-assisted accounting information systems and perceived audit effectiveness using PLS-SEM and Task-Technology Fit theory. The results show a strong positive and statistically significant relationship ($\beta = 0.796$, $t = 15.170$, $p < 0.001$), with AI-Assisted AIS explaining 63.4% of the variance in Audit Effectiveness. These findings support the argument that intelligent AIS capabilities can contribute to more effective audit work when they fit the analytical and information-processing requirements of audit tasks.

The study’s contribution is twofold. Theoretically, it applies TTF to digital auditing and explains why AI-enabled AIS may improve audit-related performance through automation, anomaly detection, faster analysis, real-time information, and decision support. Practically, it indicates that organizations should view AI implementation as a socio-technical capability rather than as software acquisition alone. Benefits are more likely to materialize when the system is supported by reliable data, competent users, appropriate governance, explainable outputs, and continued professional judgment.

Several limitations qualify the findings. The study uses cross-sectional self-reported data, which limits causal inference and may be affected by common-method bias. The model includes only one explanatory construct, while audit effectiveness may also depend on auditor competence, internal-control quality, management support, digital readiness, organizational complexity, and trust in AI. In addition, any heterogeneity between auditors and non-auditor accounting/finance respondents should be reported and, where possible, tested. Future studies could use longitudinal designs, objective audit-performance measures, multi-group analysis, and mediating or moderating variables such as task-technology fit, digital competence, AI governance, or professional skepticism.

Overall, the evidence suggests that AI-assisted AIS is an important predictor of perceived audit effectiveness, but its value should be interpreted as an augmentation of professional audit work rather than a replacement for auditor judgment.

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