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# Artificial Intelligence Adoption as a Mediator of AI Implementation and Financial Accounting Performance

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**ABSTRACT**

**Purpose:** This study examines how the implementation of Artificial Intelligence (AI) in financial accounting systems affects operational efficiency, data security, and workforce skills, with AI adoption as a mediating variable.

**Design/Methodology/Approach:** This study uses a quantitative survey design involving 207 valid respondents from accounting and information technology professionals in Indonesian organizations that use AI-based financial accounting systems. Data were collected through a third-party survey center after a pilot test with 30 respondents. The data were analyzed using Partial Least Squares Structural Equation Modeling with bootstrapping.

**Findings:** The results show that AI implementation has positive direct effects on operational efficiency, data security, and workforce skills. AI adoption significantly mediates the effects of AI implementation on operational efficiency and data security, but does not significantly mediate the effect on workforce skills.

**Research Implications:** The findings show that AI adoption strengthens process and security outcomes, while workforce transformation requires structured training, practical experience, and job redesign. Future research should examine training quality, leadership support, learning culture, and technology readiness. The study contributes to accounting information systems literature by explaining AI adoption as a mediating mechanism, while providing practical insights for organizations implementing AI-based accounting systems.



## INTRODUCTION

Artificial Intelligence (AI) is reshaping financial accounting by changing how organizations process transactions, protect financial data, and develop accounting talent. In financial accounting systems, AI enables faster data processing, improves accuracy, and supports financial analysis by reducing reliance on manual, repetitive procedures. (Ahmad et al., 2021; Chen et al., 2019). In accounting information systems research, AI is not merely viewed as an automation tool, but as a family of intelligent decision-support technologies that can transform data capture, validation, analysis, monitoring, and control activities in accounting processes (Sutton et al., 2016). Prior studies indicate that AI can automate data entry, reconciliation, anomaly detection, and real-time financial reporting, which are core activities in accounting information systems. (Bataineh et al., 2024; Wamba-Taguimdje et al., 2020). Related accounting research also shows that data analytics and machine-learning-based approaches can strengthen fraud prediction, audit monitoring, and financial data evaluation when supported by sufficient data quality and analytical capability (Perols et al., 2017). These changes move accounting work from administrative reporting toward analytical and decision-support functions (Benzerrouk et al., 2023).

The value of AI in financial accounting depends not only on technological availability but also on how far organizations adopt and use it in daily accounting processes. To avoid conceptual ambiguity, this study distinguishes AI implementation from AI adoption. AI implementation refers to the organizational deployment and technical integration of AI-enabled functions within financial accounting systems, including automation, anomaly detection, forecasting, and real-time reporting. AI adoption refers to the extent to which users and organizations accept, trust, routinize, and actually use AI in accounting work practices. AI may improve operational efficiency when firms use it to shorten transaction processing time, reduce manual errors, and accelerate financial reporting (Kaya et al., 2019; Wamba-Taguimdje et al., 2020) (Alles & Gray, 2016; Li et al., 2018). AI may also improve data security when firms use anomaly detection, automated monitoring, encryption support, and risk-based controls in financial data processing (Z. Li, 2018; Manita et al., 2020) (Li et al., 2018; Perols et al., 2017). At the same time, AI changes the skill requirements of accounting workers, as accountants need stronger data analysis, modeling, and technology-based decision-making skills (Benzerrouk et al., 2023; Parasuraman et al., 2018).

Despite these benefits, AI adoption in Indonesia still faces clear implementation barriers. A report by IBM, Advisia Group, and KORIKA (2024) shows that 48% of Indonesian companies face digital skill gaps and 40% face data governance problems. These barriers exist because many organizations still operate with fragmented data, uneven digital proficiency, limited internal data governance, and incomplete visibility of business outcomes from AI initiatives. In Indonesia's digital transformation landscape, these conditions are important because AI-based accounting systems depend on reliable data, disciplined governance, user readiness, and cross-functional coordination among accounting, finance, internal control, and information technology units. These barriers matter because AI delivers practical value only when users integrate it into routine work processes and when organizations are ready to manage the related data, infrastructure, and human resource requirements (Manita et al., 2020; Moll & Yigitbasioglu, 2019). In the accounting context, weak adoption may limit the expected impact of AI on efficiency, data security, and workforce transformation (Bataineh et al., 2024; Wamba-Taguimdje et al., 2020).

Existing studies have examined the role of AI in accounting, auditing, and firm performance. However, the literature still pays limited attention to the mechanisms by which AI affects accounting outcomes in developing-country contexts. Prior research reports that AI improves accounting efficiency and information quality (Bataineh et al., 2024; Z. Li, 2018). Other studies emphasize that technology adoption depends on user acceptance, perceived usefulness, infrastructure readiness, and organizational readiness (Moll & Yigitbasioglu, 2019; Van Nguyen & Lu, 2024). However, much of the prior accounting literature discusses AI, big data, or audit analytics either as a technological capability, a professional competency, or an audit innovation. At the same time, fewer studies explicitly distinguish between AI implementation as a technological condition and AI adoption as a behavioral-organizational mechanism. This distinction is critical because implemented AI features may remain underused when employees do not trust the outputs, when accounting routines are not redesigned, or when data governance is too weak to support reliable AI use. However, fewer studies examine whether AI adoption mediates the relationship between AI implementation and three specific accounting outcomes, namely operational efficiency, data security, and workforce skills, especially in Indonesian companies.

From a Stakeholder Theory perspective, AI-based financial accounting systems are relevant because they affect multiple stakeholder interests. Operational efficiency benefits managers and investors by providing faster, more reliable financial information; data security protects regulators, customers, and organizational owners by reducing financial data risk; and workforce skills benefit employees by preparing them for analytical and technology-enabled accounting roles. However, AI may also create stakeholder tensions, especially when efficiency goals increase automation pressure, when stronger data monitoring raises privacy concerns, or when employees are expected to adapt without adequate training. Therefore, the study of AI implementation in financial accounting should not stop at whether the technology exists, but should also examine whether AI is adopted in ways that create balanced value for organizational stakeholders. This argument is consistent with the view that accounting and control innovations become meaningful only when they are embedded in organizational context and work practices (Chenhall, 2003; Chenhall & Moers, 2015; Quattrone & Hopper, 2005).

This study addresses that gap by examining the direct and indirect effects of AI implementation in financial accounting systems. This study offers three main contributions. First, it clarifies the conceptual distinction between AI implementation and AI adoption in financial accounting systems. Second, it extends AI and accounting information systems research by testing AI adoption as a mediating mechanism between AI implementation and three accounting outcomes: operational efficiency, data security, and workforce skills. Third, it provides empirical evidence from Indonesia, a developing country context where AI potential is high but digital skill gaps and data governance barriers remain substantial. Practically, the study helps managers, accounting professionals, and system developers understand that investing in AI technology alone is insufficient; organizations must also strengthen user adoption, data governance, and workforce capability development. The study focuses on six hypotheses. H1a tests whether AI implementation directly improves operational efficiency, measured by transaction processing time, automated data entry, and financial reporting speed. H1b tests whether AI implementation directly improves data security, measured by anomaly detection, data integrity, and automated cyber protection. H1c tests whether AI implementation directly improves workforce skills, measured by data analysis ability, financial modeling capability, and information-based decision-making. H2a, H2b, and H2c test whether AI adoption mediates the effects of AI implementation on operational efficiency, data security, and workforce skills.

## LITERATURE REVIEW

### Stakeholder Theory and AI-Based Financial Accounting Systems

Stakeholder Theory explains that organizations create value by considering the interests of stakeholders such as employees, investors, customers, regulators, and society (Freeman et al., 2021). In financial accounting, Artificial Intelligence (AI) can affect these stakeholders by improving how financial information is processed, protected, and used for decision-making (Bataineh et al., 2024; Wamba-Taguimdje et al., 2020). AI can improve operational efficiency through faster processing and reporting, strengthen data security through anomaly detection and digital controls, and support workforce development by shifting accounting work toward more analytical activities (Kaya et al., 2019; Manita et al., 2020; Parasuraman et al., 2018). These benefits can increase value for managers, investors, regulators, customers, and employees who depend on reliable financial information and effective accounting processes. However, AI adoption may also create stakeholder challenges, such as concerns about job displacement, employee readiness, privacy, and data governance. Therefore, Stakeholder Theory provides a useful perspective for understanding AI implementation as more than a technological decision. Its value depends on how organizations balance efficiency, data protection, and workforce development while ensuring that AI is effectively adopted and integrated into accounting practices.

### AI Implementation in Financial Accounting Systems

AI implementation refers to the use and integration of intelligent systems in financial accounting processes, including transaction recording, data reconciliation, anomaly detection, forecasting, and financial reporting. It represents the technical and organizational deployment of AI-enabled functions to automate tasks, process financial data, detect irregularities, and support reporting. By processing large volumes of financial data quickly and accurately, AI can reduce repetitive work and human error while supporting timely financial reporting (Ahmad et al., 2021; Bataineh et al., 2024; Chen et al., 2019; Wamba-Taguimdje et al., 2020). However, AI implementation should be distinguished from AI adoption. Implementation refers to the availability and integration of AI capabilities in accounting systems, whereas adoption refers to users' acceptance and actual use of these capabilities in daily accounting activities. This distinction is important because the benefits of AI depend on how effectively it is integrated into organizational routines (Moll & Yigitbasioglu, 2019). In Indonesia, digital skill gaps and data governance challenges may limit the benefits of AI implementation, indicating that technological deployment alone does not guarantee better accounting outcomes (IBM, Advisia Group, & KORIKA, 2024). Therefore, AI implementation needs to be supported by user readiness, appropriate skills, data governance, and trust in AI outputs (Manita et al., 2020; Moll & Yigitbasioglu, 2019). Previous accounting information systems research also emphasizes that the increasing volume and complexity of organizational data require accounting systems to adopt advanced technologies and intelligent decision-support capabilities (Moffitt & Vasarhelyi, 2013; Sutton et al., 2016). Thus, AI implementation provides the technological foundation, while its effective use and adoption determine how far these capabilities generate value for accounting practices.

**AI Implementation and Operational Efficiency**

Operational efficiency in financial accounting refers to the ability to complete accounting processes quickly, accurately, and with efficient use of organizational resources. AI can improve efficiency by automating data entry, transaction processing, reconciliation, and financial reporting, thereby reducing processing time, manual work, and errors (Bataineh et al., 2024; Kaya et al., 2019; Wamba-Taguimdje et al., 2020). AI can also support faster decision-making through data analysis and predictive capabilities (Duong & Vu, 2023). In addition to processing speed, operational efficiency includes better workflow integration, faster exception handling, and coordination among accounting, internal control, and IT functions. Previous studies indicate that the benefits of AI and analytics depend on their integration into organizational routines and accounting processes (Alles & Gray, 2016; Li et al., 2018). Big data analytics can also shift accounting activities toward more analytical and technology-supported work (Richins et al., 2017). Therefore, AI implementation is expected to improve operational efficiency by making accounting processes faster, more accurate, and less dependent on repetitive manual activities.

*H1a: The implementation of AI in financial accounting systems has a positive direct effect on operational efficiency*

**AI Implementation and Data Security**

Data security in financial accounting refers to protecting financial information from unauthorized access, manipulation, leakage, and misuse. AI can strengthen data security through anomaly detection, automated monitoring, risk alerts, and digital audit trails, enabling organizations to identify suspicious activities and potential fraud more quickly (Li, 2018; Manita et al., 2020). AI can also support financial data integrity by improving system monitoring and reducing the risk of undetected manipulation. This role is important because accounting systems handle sensitive financial information, while digital transformation can increase both efficiency and cybersecurity risks (Manita et al., 2020). Effective AI-based security, however, depends on data quality, access governance, system controls, and users' ability to respond to alerts (Dincă et al., 2024; Wamba-Taguimdje et al., 2020). From a stakeholder perspective, strong data security protects the interests of investors, regulators, customers, creditors, and other users who rely on reliable financial information. Therefore, AI

implementation is expected to improve data security when intelligent monitoring, anomaly detection, and automated controls are properly integrated into financial accounting systems.
*H1b: The implementation of AI in financial accounting systems has a positive direct effect on data security*

**AI Implementation and Workforce Skills**

Workforce skills in accounting refer to the ability of accounting professionals to analyze data, use digital technologies, interpret financial information, and support decision-making. AI changes accounting work by reducing routine tasks and increasing the need for analytical, technological, and decision-support skills (Benzerrouk et al., 2023; Parasuraman et al., 2018). As AI becomes part of accounting processes, accountants increasingly need to understand data, interpret AI-generated information, and apply technology in professional judgment (Parasuraman et al., 2018). However, the development of these skills depends on more than AI implementation. Richins et al. (2017) argue that big data analytics can create opportunities or challenges for accountants depending on their analytical capabilities, while Sutton et al. (2016) emphasize the importance of understanding how AI supports judgment and decision-making. Recent evidence also shows that AI adoption in auditing is influenced by technological, organizational, and regulatory conditions (Torroba et al., 2025). Therefore, AI implementation is expected to improve workforce skills by exposing accounting professionals to more analytical and technology-based tasks, although training, practical experience, managerial support, and job redesign remain important for achieving meaningful skill development.
*H1c: The implementation of AI in financial accounting systems has a positive direct effect on workforce skills*

**AI Adoption as a Mediating Mechanism**

AI adoption refers to the extent to which users and organizations accept, use, and integrate AI into accounting processes. In this study, AI adoption is viewed as a behavioral and organizational mechanism that translates implemented AI capabilities into actual accounting outcomes. The availability of AI technology does not automatically improve performance; its benefits depend on whether users understand, trust, and consistently use the technology in their daily work (Moll & Yigitbasioglu, 2019; Van Nguyen & Lu, 2024). Previous studies also suggest that technology creates greater value when it is embedded in organizational routines, supported by appropriate governance, and used by competent professionals (Alles & Gray, 2016; Chenhall, 2003; H. Li et al., 2018; Quattrone & Hopper, 2005). Therefore, this study distinguishes AI implementation from AI adoption: implementation represents the availability and integration of AI capabilities in accounting systems, while adoption reflects users' acceptance, actual use, trust, and routinization of those capabilities. This distinction supports the role of AI adoption as a mediator through which AI implementation contributes to operational efficiency, data security, and workforce skills.

**AI Adoption as a Mediator between AI Implementation and Operational Efficiency**

AI implementation provides tools that can improve accounting processes, but its benefits depend on whether accounting staff actually use them. When users adopt AI for transaction processing, data entry, reconciliation, and reporting, organizations can achieve faster and more efficient accounting processes (Bataineh et al., 2024; Wamba-Taguimdje et al., 2020). In contrast, limited adoption may leave AI features underused and reduce their expected benefits (Moll & Yigitbasioglu, 2019). Previous studies also show that technology creates greater value when it is integrated into organizational routines and used in daily work practices (Alles & Gray, 2016; Li et al., 2018). Therefore, AI adoption is expected to mediate the relationship

between AI implementation and operational efficiency by converting available AI capabilities into actual improvements in accounting processes.
*H2a: AI adoption mediates the effect of AI implementation in financial accounting systems on operational efficiency*

**AI Adoption as a Mediator between AI Implementation and Data Security**

AI implementation can strengthen data security through anomaly detection, monitoring of unusual transactions, and automated controls, but these benefits depend on users' actual adoption of AI-based security functions (Li, 2018; Manita et al., 2020). Users need to consistently use the system, respond to alerts, and apply AI-generated control information to protect financial data. When adoption is low, AI security features may be underused and their benefits may be limited (Wamba-Taguimdje et al., 2020). Previous studies show that data analytics can improve fraud prediction and financial monitoring, particularly when supported by appropriate organizational use and governance (Perols et al., 2017; Li et al., 2018). Therefore, AI adoption is expected to mediate the relationship between AI implementation and data security by ensuring that AI-based security capabilities are consistently used and integrated into accounting control practices.
*H2b. AI adoption mediates the effect of AI implementation in financial accounting systems on data security*

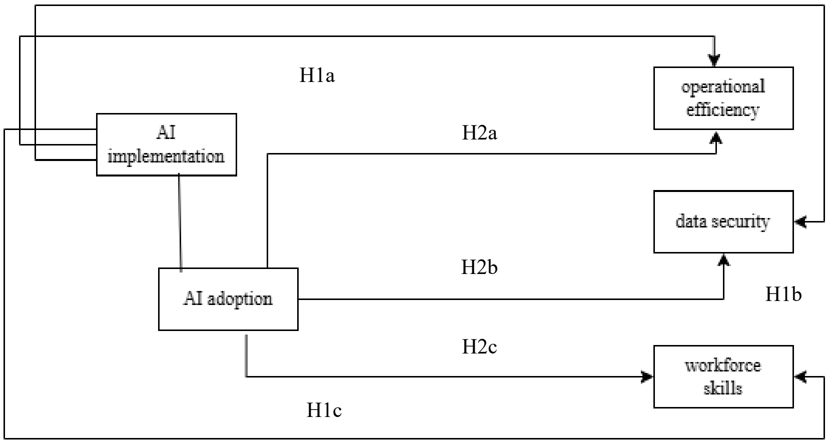
**AI Adoption as a Mediator between AI Implementation and Workforce Skills**

AI implementation can support workforce skill development by shifting accounting work from routine tasks toward data analysis, interpretation, and technology-supported decision-making (Benzerrouk et al., 2023; Parasuraman et al., 2018). However, these benefits depend on whether employees actually adopt and use AI in their daily work. Frequent use of AI may provide opportunities to develop skills in data analysis, financial modeling, and decision support (Haddad et al., 2020; Parasuraman et al., 2018). Previous studies indicate that AI and data analytics require accountants to develop new competencies and that adoption is influenced by technological, organizational, and environmental factors (Richins et al., 2017; Torroba et al., 2025). Nevertheless, workforce skill development may require more than regular AI use because it also depends on training, practical experience, continuous learning, and the ability to interpret and critically evaluate AI-generated outputs (Sutton et al., 2016). Therefore, AI adoption is expected to mediate the relationship between AI implementation and workforce skills, although this effect may be weaker or more dependent on organizational support than its effects on operational efficiency and data security.
*H2c: AI adoption mediates the effect of AI implementation in financial accounting systems on workforce skills*

**Conceptual Framework**

The conceptual framework examines the relationship between AI implementation and three accounting outcomes: operational efficiency, data security, and workforce skills. AI implementation is expected to directly improve these outcomes through automation, anomaly detection, data processing, and analytical support (Bataineh et al., 2024; Li, 2018; Parasuraman et al., 2018). AI adoption is positioned as a mediator because the benefits of AI depend on users' acceptance and actual use in accounting activities (Moll & Yigitbasioglu, 2019; Wamba-Taguimdje et al., 2020). The framework distinguishes AI implementation, which refers to the availability and integration of AI capabilities in accounting systems, from AI adoption, which reflects their acceptance and use in daily accounting practices. This distinction is important because AI may be implemented without being fully adopted by users. Based on Stakeholder Theory and accounting information systems literature, the framework explains how AI can create value through improved operational efficiency, data security, and workforce skills. Figure 1 presents the conceptual framework of the study.

**Figure 1.** Conceptual Framework of AI Implementation, AI Adoption, and Accounting Outcomes




Source: (Moll & Yigitbasioglu, 2019; Wamba-Taguimdje et al., 2020)

## METHODS

This study uses a quantitative cross-sectional survey to examine the effects of Artificial Intelligence (AI) implementation in financial accounting systems on operational efficiency, data security, and workforce skills, with AI adoption as a mediating variable. The population consisted of accounting and information technology professionals in Indonesian organizations using AI-enabled financial accounting systems. Respondents were selected purposively based on three criteria: their organization had used AI-enabled accounting systems for at least one year, they were directly involved in accounting, auditing, financial data management, or accounting information systems, and they understood digital transformation in their organization. Data were collected through an online questionnaire distributed with the assistance of a third-party survey center. The questionnaire used a five-point Likert scale and contained 24 indicators covering five constructs: AI implementation (6 indicators), AI adoption (5), operational efficiency (4), data security (4), and workforce skills (5). The measurement items were adapted from previous studies on accounting information systems, AI, audit analytics, and technology adoption (Alles & Gray, 2016; H. Li et al., 2018; Moffitt & Vasarhelyi, 2013; Perols et al., 2017; Sutton et al., 2016). Content validity was reviewed by relevant experts, followed by a pilot test with 30 respondents to improve item clarity and consistency. The main survey produced 207 valid responses, which were considered adequate for PLS-SEM. AI implementation represents the deployment of AI capabilities in accounting systems, while AI adoption reflects users' acceptance and actual use of these capabilities. Operational efficiency measures improvements in accounting processing and reporting, data security reflects protection and integrity of financial information, and workforce skills represent improvements in analytical and technology-related capabilities. All constructs were measured reflectively. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0. The measurement model was assessed using outer loadings, Cronbach's Alpha, Composite Reliability, AVE, Fornell-Larcker, and HTMT, while the structural model was evaluated using path coefficients, p-values, $R^2$, VIF, $f^2$, $Q^2$, and PLSpredict. Mediation was tested using bootstrapping with 5,000 resamples, with AI adoption examined as the mediator between AI implementation and the three outcome variables. Significant direct and indirect effects were interpreted as partial mediation, whereas a significant indirect effect with a non-significant direct effect indicated full mediation. Data were screened for incomplete, duplicate, and ineligible responses before analysis. Common method bias was addressed through respondent anonymity, careful questionnaire design, and full-collinearity VIF. Participation was voluntary, and respondent and organizational information was kept confidential and reported in aggregate form.

## RESULT

### Respondent Profile

The final dataset consists of 207 valid responses from accounting and information technology professionals working in Indonesian organizations that use AI-based financial accounting systems. Table 1 presents the distribution of respondents by industry sector. The respondent distribution indicates that the sample covers several industries with different levels of digitalization and accounting process complexity. Food and beverages, automotive, electronics, pharmaceuticals, mining and energy, textiles, chemicals and petrochemicals, and building materials are represented in the dataset. This sectoral variation is useful because AI-based accounting systems may be implemented differently across operational environments.

**Table 1.** Respondent Distribution by Industry Sector

| No. | Industry Sector | Frequency | Percentage |
|---|---|---|---|
| 1 | Food and beverages | 36 | 17.39% |
| 2 | Automotive | 34 | 16.43% |
| 3 | Electronics | 30 | 14.49% |
| 4 | Pharmaceuticals, including herbal products | 28 | 13.53% |
| 5 | Mining and energy | 26 | 12.56% |
| 6 | Textiles and accessories | 24 | 11.59% |
| 7 | Chemicals and petrochemicals | 20 | 9.66% |
| 8 | Building materials | 9 | 4.35% |
| Total | | 207 | 100.00% |

Source: Primary data processed by the authors, 2026

Although the sample covers multiple sectors, the distribution is not intended to represent all Indonesian industries proportionally. Therefore, sectoral comparison should be interpreted with caution and treated as a direction for future research rather than as a core claim of this study.

### Measurement Model Assessment

The measurement model was assessed using Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE). Table 2 presents the reliability and convergent validity results.

As shown in Table 2, all Cronbach's Alpha values range from 0.846 to 0.891, and all Composite Reliability values range from 0.895 to 0.916. These results indicate satisfactory internal consistency reliability. The AVE values range from 0.646 to 0.695, exceeding the commonly accepted threshold of 0.50. This shows that each construct explains an adequate proportion of variance in its indicators. The results also support the empirical distinction among AI implementation, AI adoption, operational efficiency, data security, and workforce skills, which is important because AI implementation and AI adoption are conceptually related but theoretically different constructs.

These reliability and validity findings provide adequate support for proceeding to the structural model assessment. However, because reliability and AVE alone do not fully establish discriminant validity, the revised manuscript should also report the HTMT values and, where relevant, the Fornell-Larcker criterion in an additional table or appendix.

**Table 2.** Reliability and Convergent Validity

| Construct | Number of Indicators | Cronbach's Alpha | Composite Reliability | AVE |
|---|---|---|---|---|
| AI implementation | 6 | 0.891 | 0.916 | 0.646 |
| AI adoption | 5 | 0.872 | 0.907 | 0.662 |
| Operational efficiency | 4 | 0.854 | 0.901 | 0.695 |
| Data security | 4 | 0.846 | 0.895 | 0.681 |
| Workforce skills | 5 | 0.863 | 0.902 | 0.648 |

Source: SmartPLS output based on primary data processed by the authors, 2026

### $R^2$ and Inner Model Collinearity

$R^2$ was used to assess the model's explanatory power for each endogenous construct. The Variance Inflation Factor (VIF) was used to assess multicollinearity within the model. Table 3 presents the $R^2$ and VIF results.

**Table 3.** $R^2$ and Inner Model VIF

| Endogenous Construct | $R^2$ | Predictor Variable | VIF Value |
|---|---|---|---|
| AI adoption | 0.42 | AI implementation | 1 |
| Operational efficiency | 0.52 | AI implementation | 1.45 |
| Operational efficiency | 0.52 | AI adoption | 1.31 |
| Data security | 0.48 | AI implementation | 1.32 |
| Data security | 0.48 | AI adoption | 1.36 |
| Workforce skills | 0.5 | AI implementation | 1.28 |
| Workforce skills | 0.5 | AI adoption | 1.33 |

Source: SmartPLS output based on primary data processed by the authors, 2026

The $R^2$ values indicate that the model has meaningful explanatory power. AI implementation explains 42% of the variance in AI adoption, while AI implementation and AI adoption jointly explain 52% of operational efficiency, 48% of data security, and 50% of workforce skills. These results show that AI implementation and adoption contribute substantially to accounting outcomes, although other factors such as leadership support, organizational culture, data governance, system maturity, training, and job redesign may also influence these outcomes. The VIF values range from 1.00 to 1.45, indicating no serious multicollinearity and supporting the distinction between AI implementation and AI adoption. In addition to $R^2$ and VIF, the structural model was assessed using effect size ($f^2$), predictive relevance ($Q^2$), and PLSpredict to evaluate the substantive contribution and predictive capability of the model. These assessments provide a more complete evaluation of the model beyond statistical significance (Hair et al., 2019, 2022).

### Direct Effect Path Coefficients

The direct effects test examined the effect of AI implementation on operational efficiency, data security, and workforce skills. Table 4 presents the path coefficients for H1a, H1b, and H1c. Table 4 shows that AI implementation has a positive and significant effect on operational efficiency, data security, and workforce skills. The strongest direct coefficient is found for workforce skills (β = 0.29), followed by operational efficiency (β = 0.28), and data security (β = 0.18).

**Table 4.** Direct Effect Path Coefficients

| Hypothesis | Path | β | t-statistic | p-value | Decision |
|---|---|---|---|---|---|
| H1a | AI implementation → Operational efficiency | 0.28 | 3.41 | <0.01 | Supported |
| H1b | AI implementation → Data security | 0.18 | 2.21 | <0.05 | Supported |
| H1c | AI implementation → Workforce skills | 0.29 | 3.62 | <0.01 | Supported |

Source: SmartPLS output based on primary data processed by the authors, 2026

These results suggest that AI implementation is associated not only with process and control improvements but also with changes in human capabilities. However, the smaller coefficient for data security indicates that security outcomes may depend more heavily on governance, control discipline, cybersecurity infrastructure, and user response than on AI implementation alone.

**Mediation Effects**

The mediation test examined whether AI adoption mediates the relationship between AI implementation and the three outcome variables. Bootstrapping with 5,000 resamples was used to test the indirect effects. Table 5 presents the mediation results for H2a, H2b, and H2c.

**Table 5.** Mediation Effect Results

| Hypothesis | Indirect Path | β | t-statistic | p-value | Decision |
|---|---|---|---|---|---|
| H2a | AI implementation → AI adoption → Operational efficiency | 0.21 | 2.54 | <0.05 | Supported |
| H2b | AI implementation → AI adoption → Data security | 0.23 | 2.76 | <0.05 | Supported |
| H2c | AI implementation → AI adoption → Workforce skills | 0.14 | 1.62 | >0.05 | Not supported |

Source: SmartPLS output based on primary data processed by the authors, 2026

The mediation results show that AI adoption significantly mediates the effects of AI implementation on operational efficiency and data security. However, AI adoption does not significantly mediate the relationship between AI implementation and workforce skills. This means that adoption is an effective mechanism for translating AI implementation into technical and control-related outcomes, but it is not sufficient to explain the transformation of human capabilities.

To assess the strength of mediation, the Variance Accounted For (VAF) was calculated as the indirect effect divided by the total effect. The total effect was estimated as the sum of the direct and indirect effects. Because the final total effect values should ideally be taken directly from SmartPLS output, the VAF values below should be verified against the final bootstrapping output before submission.

**Table 6.** VAF and Type of Mediation

| Hypothesis | Direct Effect | Indirect Effect | Estimated Total Effect | VAF | Type of Mediation |
|---|---|---|---|---|---|
| H2a | 0.28 | 0.21 | 0.49 | 42.86% | Partial mediation |
| H2b | 0.18 | 0.23 | 0.41 | 56.10% | Partial mediation |
| H2c | 0.29 | 0.14 | N/A | 32.56% | No mediation |

Source: SmartPLS output based on primary data processed by the authors, 2026

The VAF for H2a is 42.86%, indicating that AI adoption accounts for a moderate proportion of the effect of AI implementation on operational efficiency. Because both the direct and indirect effects are significant, this relationship indicates partial mediation. The VAF for H2b is 56.10%, indicating that AI adoption accounts for more than half of the total effect of AI implementation on data security. This also indicates partial mediation, as both the direct and indirect paths remain significant. For H2c, the indirect effect is not statistically significant; therefore, VAF is not interpreted, and AI adoption cannot be considered a mediating mechanism between AI implementation and workforce skills.

## DISCUSSION

The findings show that AI implementation positively affects operational efficiency, data security, and workforce skills. AI adoption also mediates the effects of AI implementation on operational efficiency and data security, but not on workforce skills. These results indicate that AI creates value in accounting through both direct technological capabilities and actual user adoption, although the mechanisms differ between process, control, and human-capability outcomes.

The positive effect of AI implementation on operational efficiency indicates that AI can reduce manual work, accelerate accounting processes, and improve the timeliness of financial reporting. This finding is consistent with previous studies showing that AI, automation, and analytics can improve accounting and audit processes by supporting transaction processing, reconciliation, anomaly detection, and reporting (Alles & Gray, 2016; Bataineh et al., 2024; H. Li et al., 2018; Kaya et al., 2019; Moffitt & Vasarhelyi, 2013; Sutton et al., 2016; Wamba-Taguimdje et al., 2020). However, AI should not be viewed as the only source of efficiency. Process maturity, leadership support, workflow standardization, and organizational readiness may also influence how effectively AI improves accounting performance.

AI implementation also has a positive effect on data security, suggesting that AI can strengthen financial information protection through anomaly detection, monitoring, and data integrity controls. This result is consistent with research showing that analytics and AI can support fraud prediction, audit monitoring, and financial information quality (Li, 2018; Manita et al., 2020; Perols et al., 2017). Nevertheless, AI-based security depends on more than technological capabilities. Effective access control, audit trails, cybersecurity infrastructure, data governance, and appropriate responses to system alerts remain important for achieving strong security outcomes.

The positive relationship between AI implementation and workforce skills indicates that AI exposure encourages accounting professionals to develop analytical, data-related, and technology-supported capabilities. This finding supports previous research suggesting that technological transformation is changing accounting work from routine processing toward analysis and decision support (Benzerrouk et al., 2023; Parasuraman et al., 2018; Richins et al., 2017). However, AI implementation does not automatically guarantee deep professional development. Skill improvement may depend on training, practical experience, mentoring, managerial support, and job redesign. Thus, the positive effect should be understood as evidence that AI creates opportunities for skill development rather than as proof that technology alone transforms employee capabilities.

The mediation results further show that AI adoption significantly mediates the relationship between AI implementation and operational efficiency. This finding indicates that AI produces greater process benefits when users accept and integrate AI into their daily accounting activities. The VAF of 42.86% indicates partial mediation, meaning that AI implementation improves efficiency both directly through system capabilities and indirectly through user adoption. This result supports the argument that technology creates greater organizational value when it becomes part of routine work practices rather than remaining a technical feature of the system (Moll & Yigitbasioglu, 2019; Wamba-Taguimdje et al., 2020). Therefore, organizations should not only invest in AI systems but also ensure that employees understand, trust, and consistently use them.

AI adoption also significantly mediates the relationship between AI implementation and data security, with a VAF of 56.10%, indicating that more than half of the total effect is transmitted through adoption. This finding suggests that AI-based security capabilities become more effective when users actively use, monitor, and respond to system outputs. AI-enabled anomaly detection and automated alerts may have limited value if users ignore alerts or fail to follow appropriate control procedures. Therefore, data security depends on the combination of technological capability and user behavior, supported by effective governance and internal controls.

In contrast, AI adoption does not significantly mediate the relationship between AI implementation and workforce skills. This finding suggests that using AI systems is not sufficient to produce deeper human-capability development. Employees may use AI for routine tasks without understanding the underlying analytical processes, may rely passively on AI recommendations, or may have limited opportunities to engage in more advanced activities such as financial modeling and decision support. This result is consistent with the argument that the benefits of data analytics and AI depend on the development of appropriate professional capabilities (Richins et al., 2017; Sutton et al., 2016). Therefore, workforce transformation requires complementary mechanisms such as structured training, continuous learning, mentoring, and job redesign. The non-significant mediation thus represents an important boundary of AI adoption: adoption appears to translate more readily into process and control improvements than into deeper employee capability development.

From a Stakeholder Theory perspective, the findings indicate that AI implementation can create value for multiple stakeholders by improving accounting efficiency, protecting financial information, and supporting workforce development (Freeman et al., 2021). Managers and investors benefit from faster and more reliable information, while regulators, creditors, customers, and other stakeholders benefit from stronger data protection and information integrity. Employees may also benefit from opportunities to develop technology-related skills. However, AI transformation may create competing interests, particularly when automation raises concerns about job displacement or when increased monitoring creates privacy concerns. Therefore, AI adoption should be managed not only as a technological investment but also as a process of balancing organizational and stakeholder interests.

The findings have several practical implications. Organizations should integrate AI into core accounting activities such as transaction processing, reconciliation, reporting, anomaly detection, and data monitoring while simultaneously encouraging user adoption. Managers should provide training and practical experience to ensure that employees understand and effectively use AI outputs. Data governance should also be strengthened through clear access controls, audit trails, security monitoring, and procedures for responding to AI-generated alerts. More importantly, workforce development should go beyond technical system training by including analytical reasoning, financial modeling, interpretation of AI outputs, and continuous learning. These measures are particularly relevant for organizations facing differences in digital readiness and data governance maturity.

Several limitations should be considered when interpreting the findings. The cross-sectional design limits causal interpretation, while the use of self-reported data may introduce subjective evaluation and common method bias. The purposive sample of Indonesian organizations using AI-enabled accounting systems also limits generalizability to other countries and organizations at different stages of AI adoption. In addition, the model focuses on AI adoption as the main mediating mechanism and does not include other factors that may influence workforce development. Future research should therefore use longitudinal designs and combine survey responses with objective indicators such as system usage data, audit logs, or accounting performance measures. Future studies could also examine the roles of training quality, leadership support, digital maturity, data governance, organizational learning, and job redesign as mediators or moderators of AI-related accounting outcomes.

## CONCLUSION

This study concludes that AI implementation in financial accounting systems improves operational efficiency, data security, and workforce skills. AI adoption further strengthens the effects of AI implementation on operational efficiency and data security but does not significantly mediate workforce skills. This finding indicates that while AI can improve accounting processes and financial controls, workforce development requires additional support through training, practical experience, organizational learning, mentoring, and job redesign. Theoretically, the study contributes to the accounting information systems literature by distinguishing AI implementation from AI adoption and highlighting adoption as an important mechanism through which AI generates accounting value. Practically, organizations should focus not only on implementing AI but also on encouraging user adoption, strengthening data governance, and developing employee capabilities. The study is limited by its cross-sectional design, self-reported data, purposive sampling, and focus on Indonesian organizations, which may limit causal interpretation and generalizability. Future research should use longitudinal and cross-country approaches and incorporate objective organizational data to further examine how AI implementation and adoption influence accounting outcomes and workforce capabilities over time.

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