ARTIFICIAL INTELLIGENCE ADOPTION AND ITS IMPACT ON ACCOUNTING INFORMATION QUALITY AND ACCOUNTING PROCESS EFFICIENCY

Renna Magdalena[1,*]), Oliandes Sondakh[2]), Olivia Yasmin Pranadia Suyitno[3])

[1)]Pelita Harapan University, Tangerang

[2)] Pelita Harapan University, Surabaya

[3)] Pelita Harapan University, Surabaya

*Email: renna.magdalena@uph.edu

ABSTRACT

Digital transformation and the increasing adoption of Artificial Intelligence AI have reshaped accounting practices toward more automated and data-driven systems. However, their effectiveness in enhancing information quality and process efficiency in Indonesia still requires empirical examination. This study aims to examine the effect of Artificial Intelligence AI adoption on accounting information quality and accounting process efficiency, while considering the mediating role of accounting information quality. The research employs a quantitative approach using purposive sampling combined with snowball sampling, involving 125 respondents. The data are analyzed using Structural Equation Modeling based on Partial Least Squares SEM PLS to test the relationships among the research variables. This study is expected to provide both theoretical and practical contributions to the development of technology-based accounting information systems in Indonesia.

Keywords: Artificial Intelligence, Accounting information quality, Accounting process efficiency, Accounting information systems

1. Introduction

Modernization and digitalization have transformed global business practices by placing technology as a key driver of information processing efficiency, accuracy, and speed. This transformation is further accelerated by the adoption of artificial Intelligence (*A*I) that enables process automation, data analysis at scale, and data-driven decision-making *in real-time*. In Indonesia, the application of AI is seen in various sectors. In the banking and payment systems sector, engineering *machine learning* used to improve anomaly/indication detection capabilities *Fraud* on transactions as well as strengthening strategies *anti-fraud* required by regulators (Amirillah, 2025). On the credit risk management side, *machine learning* is also used in model development, *credit scoring*, and credit risk prediction to support more accurate financing decision-making (Prahastiwi et al., 2025). Meanwhile, in the public sector, AI adoption is seen in service automation and chatbots to improve service efficiency, as well as Natural Language Processing (NLP)-based digital document processing for government document management needs (Tobirin et al., 2024).

The use of artificial Intelligence (AI) in Indonesia continues to increase throughout 2024, with the adoption rate increasing by around 47% compared to the previous year (Beritasatu.com, 2025). However, the results of a recent study from Amazon Web Services (2025) with Strand Partners show that the use of AI in Indonesia is still dominated at the basic level, especially in large companies. In the report *Unlocking Indonesia's AI Potential* (2025), it is stated that around 18 million business actors have leveraged AI for operational efficiency and process automation. However, only about 10% of business actors are strategically utilizing AI in decision-making and the development of new business models.

As the demands for operational efficiency and process automation increase in the business and organizational world, accounting recording systems continue to evolve. In the early 20th century, manual recording was still dominated by physical ledgers and mechanical calculators, before finally entering a phase of significant change in the 1950s–1960s when electronic computers began to be used to process financial data more systematically. This development continued in the early 1970s with the advent of computerized accounting software and the birth of the concept *of Enterprise Resource Planning* through the introduction of SAP (1972), which allowed the automatic integration of accounting with other business operational functions in *real-time*. In the 1980s–1990s, the use of computers extended to small and medium-sized businesses so that financial record-keeping automation was no longer dependent on a *mainframe* system, which was expensive. This digital foundation then develops through the use of *cloud computing, big data analytics, blockchain*, and especially artificial intelligence (*Artificial Intelligence*/AI), which enables the automation of the transaction recording process, account reconciliation, financial reporting, and audit tracking *in real-time* with a much lower rate of human error.

As an example of the application of technology in the government sector accounting system in Indonesia, My Integrated Treasury System (MyIntress), developed by the Directorate General of Treasury of the Ministry of Finance, shows how data integration and the use of modern analytical systems can improve the efficiency of state financial management. MyIntress combines the functions of the OMSPAN and MonSAKTI applications into one *platform* that allows monitoring of State Budget transactions in a systematic, *real-time*, accurate, and *single-source-of-truth* manner. Through features such as *dashboard* Analytics, *early warning system*, and automated data reconciliation, the system reflects the working principles of artificial intelligence/AI in supporting rapid analysis, anomaly detection, and presentation of financial information relevant to decision-making. The implementation of MyIntress also reduces system overlap and duplication of data that were previously obstacles in state financial recording and reporting (djpb.kemenkeu.go.id, 2025).

DeLone and McLean (2003) explain that the quality of the system greatly influences the success of an information system, the quality of information, and the quality of service as key factors, which have an impact on the net benefits (*net benefits*) such as improving organizational performance and efficiency. In the realm of digital accounting, the quality of accounting information is a very crucial aspect because relevant, trustworthy, and timely information will determine the extent to which technology, such as artificial Intelligence (*A*I) and *blockchain*, can provide significant added value in supporting the management decision-making process (Gelinas et al., 2018).

Vasarhelyi, Kogan, and Tuttle (2015) explained that accounting digitization should not only be understood as process automation, but as a transformation towards a financial system based on intelligent data utilization. If the quality of the data used is low or the management of the system is not well designed, then advanced technology risks producing misleading information and lowering the reliability of financial statements. In other words, the quality of accounting information remains a central factor that determines whether new technologies are truly able to improve the performance of accounting systems.

Although the potential of AI technology is enormous, previous research, such as Alkhajah (2023) and Hasan (2022), tends to discuss the impact of AI on accounting separately and has not simultaneously tested the mediating role of accounting information quality mediation in linking AI adoption to process efficiency, especially in the context of companies in

Indonesia. This gap is important to research because, without understanding such mediation mechanisms, organizations cannot know whether investment in AI infrastructure directly results in efficiencies or whether improving the quality of information is a necessary prerequisite. Therefore, this study is here to fill this gap by testing a partial mediation model that integrates the DeLone and McLean IS Success Model and Resource-Based View in one empirical framework.

This study aims to test the influence of the adoption of *Artificial Intelligence* on the quality of accounting information and the efficiency of the accounting process, taking into account the mediating role of the quality of accounting information on efficiency. This study is expected to make a theoretical and practical contribution to the development of accounting information systems in Indonesia.

2. Literature Review

2.1. DeLone and McLean Information Systems Success Model

DeLone and McLean's (2003) model of information system success is the most widely used theoretical framework in information systems research. This model identifies six interrelated dimensions of information system success: *system quality, information quality, service quality, intention to use/use, user satisfaction,* and *net benefits.* In the context of this study, the DeLone and McLean IS Success Model was used to describe the indirect influence pathway (*indirect effect*) from the adoption of technology to efficiency through information quality. This model argues that a good information system implementation will result in high-quality information (*information quality*), which in turn will provide a net benefit (*net benefits*) for organizations in the form of increasing operational efficiency.

According to DeLone and McLean (2003), *information quality* includes characteristics such as *accuracy*, *timeliness*, *completeness*, *relevance*, and *consistency*. These characteristics are the basis for the development of the constructs *Accounting Information Quality* in this study. Meanwhile, *net benefits* in the context of accounting can be manifested in the form of process efficiency, cost reduction, and increased productivity.

2.2. Resource-Based View (RBV)

Resource-Based View developed by Barney (1991) provides the perspective that an organization's competitive advantage comes from valuable resources and capabilities (*valuable*), rare (*scarce*), difficult to imitate (*inimitable*), and irreplaceable *(non-substitutable*), known as the VRIN criterion. In the context of this study, RBV is used to explain the path of direct influence (*direct effect*) from the adoption of technology to the efficiency of the accounting process. AI adoption can be seen as an investment in technology capabilities that meet the VRIN criteria. AI technology with automation and predictive analytics capabilities is a strategic resource that can directly improve operational efficiency without having to go through improving information quality first.

In contrast to the path described by the DeLone and McLean Model, RBV argues that technology as an organizational capability can have a direct impact on performance. For example, AI features such as *Robotic Process Automation* (RPA) can instantly replace repetitive manual work as well as features *of Machine Learning*, enabling cash flow prediction as well as early identification of potential fraud.

Hypothesis Development

2.3. Artificial Intelligence in Accounting

Artificial Intelligence in accounting includes a wide range of applications such as *Machine Learning* for transaction classification, *Natural Language Processing* for document analysis, and *predictive analytics* for financial forecasting (Zemánková, 2019). AI can automate repetitive tasks such as *data entry*, bank reconciliation, and anomaly detection, freeing accountants to focus on more strategic activities.

Based on the DeLone and McLean IS Success Model; AI features such as anomaly detection and automated validation can improve the accuracy of financial data. Zhang and Xie (2020) stated that AI is able to identify errors and data inconsistencies that may be missed by manual processes, thereby improving the overall quality of accounting information.

H1: Adoption *of Artificial Intelligence* has a Positive Effect on the Quality of Accounting Information

In line with *the Resource-Based View*, AI as a technological capability can directly increase efficiency without having to go through improving information quality. *Robotic Process Automation* (RPA) can replace repetitive manual work, while *Machine Learning* can speed up the analysis and reporting process. Hasan (2022) shows that the implementation of AI can reduce data processing time by up to 80% compared to conventional methods. In line with this, Silooy (2025) found that AI has a positive and significant effect on the efficiency of accounting processes in public accounting firms in Indonesia.

H2: Adoption *of Artificial Intelligence* has a positive effect on the Efficiency of Accounting Processes

2.4. Quality of Accounting Information and Efficiency of Accounting Process

Based on DeLone and McLean IS Success Model, *information quality* is an important antecedent to *net benefits*. In the context of accounting, high-quality information characterized by accuracy, timeliness, completeness, and consistency will simplify the decision-making process and reduce the time required for data verification and correction.

When accounting information is accurate and reliable, staff do not have to spend time double-checking or correcting errors. When information is available on time, the reporting process can be completed faster. Alkhajah (2023) shows that improving the quality of accounting information contributes significantly to overall operational efficiency. Zhang and Xie (2020) also assert that accurate and consistent accounting information allows for a reduction in verification and correction times, thereby increasing the overall speed of the accounting process.

H3: Quality of Accounting Information has a Positive Effect on Accounting Process Efficiency

2.5. The Role of Mediating the Quality of Accounting Information

Integrating DeLone and McLean's IS *Success Model* with *the Resource-Based View* provides a comprehensive understanding of the mechanisms of the influence of technology adoption on efficiency. While RBV explains the direct influence of technology on efficiency, the DeLone and McLean Model explains that the quality of information mediates some of the influence.

This mediation logic assumes that AI adoption not only directly automates processes (*direct effect* based on RBV) but also improves the quality *of output* information that, in turn, simplifies subsequent processes (*indirect effect* based on the D&M Model). Thus, the quality of accounting information serves as an intermediary mechanism that explains in part the relationship between technology adoption and efficiency. A similar mediation pattern has been found in information systems research, where the quality of system output acts as a mediator between technology adoption and organizational performance (DeLone & McLean, 2003; Gelinas et al., 2018).

H4: Quality of Accounting Information Mediates the Influence of *Artificial Intelligence* Adoption on Accounting Process Efficiency

3. Research Method

3.1. Research Design

This study uses a quantitative approach with a *cross-sectional* survey design. This method was chosen because the purpose of the study was to test the causal relationship between independent variables (adoption of AI technology), mediating variables (quality of accounting information), and dependent variables (efficiency of accounting processes).

3.2. Population and Sample

The research population is accounting practitioners working in companies in Indonesia that have adopted digital technology in their accounting systems. The inclusion criteria for respondents include: (1) working in accounting/finance for at least 1 year, (2) having experience using accounting software or ERP systems, and (3) being familiar with AI concepts in the context of work.

Sampling techniques use *purposive sampling* with the above criteria, combined with *snowball sampling* to expand the reach of respondents. Based on the rule of thumb for PLS-SEM (Hair et al., 2019), the minimum sample size is 10 times the number of the largest structural paths leading to a particular construct. With 2 maximum paths to one construct (EF), the minimum sample is 20. However, to ensure adequate statistical power, the sample target was set at 100 respondents. In its implementation, this study succeeded in gathering as many as 125 respondents who met all inclusion criteria, so as to exceed the required minimum limit and provide more adequate statistical power.

3.3. Variables and Measurements

This study uses four main constructs measured by a 5-point Likert scale:

Table 3.1 Research Variables

Variable	Operational Definition	Number of Items	Source
AI Adoption (AI)	Rate of use of AI features in accounting systems, such as automatic classification, anomaly detection, automatic reconciliation, and predictive analysis	7 items	Zhang & Xie (2020); Hasan (2022)

Accounting Information Quality (AQ)	Perception of the quality of accounting information, which includes accuracy, timeliness, ease of understanding, reliability, completeness, and consistency	7 items	DeLone & McLean (2003); Alkhajah (2023)
Accounting Efficiency (EF)	Perceived improved efficiency of accounting processes, including recording speed, reporting time, error reduction, and resource savings	7 items	Zhang & Xie (2020); Silooy (2025)

3.4. Research Model

This research model combines the perspective of the DeLone and McLean IS Success Model (an indirect path through information quality) and *the Resource-Based View* (direct path from technology adoption to efficiency) in a single framework, the *Partial Mediation Model*:

Figure 3.1 Partial Mediation Model

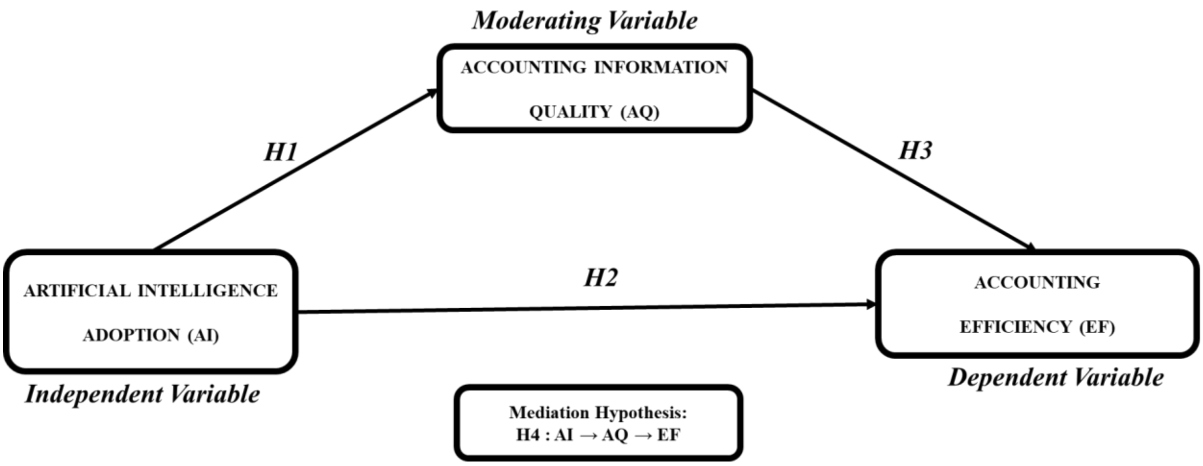

Table 3.2 Summary of Research Hypotheses

Code	Hypothesis Statement	Types of Effects	Theoretical Foundations
H1	AI Adoption Has a Positive Effect on Accounting Information Quality	Direct	D&M IS Success Model
H2	AI Adoption Has a Positive Effect on Accounting Process Efficiency	Direct	Resource-Based View

H3	Quality of Accounting Information has a Positive Effect on Accounting Process Efficiency.	Direct	D&M IS Success Model
H4	Quality of Accounting Information mediates the influence of AI on Efficiency.	Indirect	D&M IS Success Model

3.5. Data collection techniques

Data is collected through an online questionnaire distributed through the Google Forms platform. The questionnaire is disseminated through professional networks (LinkedIn), accounting professional associations, and emails to contacts in various companies. The data collection period is planned for 4-6 weeks.

3.6. Data Analysis Techniques

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 software. PLS-SEM was chosen because: (1) it is suitable for predictive models and theory development, (2) it does not require the assumption of data normality, (3) it can handle complex models with many constructs and indicators, and (4) it is effective for relatively small sample sizes (Hair et al., 2019).

4. Results and Discussion

4.1. Respondent Profile

This study involved 125 respondents who had diverse demographic and professional backgrounds. The characteristics of the respondents were analyzed based on the length of work experience, position, and industry sector. Based on the length of work experience, most of the respondents had 2-5 years of work experience, which was 50 people (40.0%). Furthermore, respondents with 6-10 years of work experience were 39 people (31.2%), 25 people (20.0%) had more than 10 years of experience, and 11 respondents had less than 2 years of experience (8.8%). The data shows that the majority of respondents have had enough work experience to understand professional practice in their field. When viewed from job positions, respondents were dominated by Accounting Staff as many as 53 people (42.4%), followed by Supervisors as many as 37 people (29.6%), and Managers as many as 22 people (17.6%). In addition, there are 8 Finance Staff (6.4%), and 1 person each (0.8%) who serve as Work Team Chairs, Tax Staff, Banking, Admin Staff, and Tax Consultant. Based on the industrial sector, respondents came from various fields of work. The Trade sector was the most dominant with 35 respondents (28.0%), followed by the Services sector with 34 respondents (27.2%), and the Manufacturing sector with 30 respondents (24.0%). Furthermore, the Finance/Banking sector amounted to 20 respondents (16.0%), while Government Agencies had as many as 4 respondents (3.2%), and 1 respondent each (0.8%) came from the Tax Consultant and Trade and Services sectors.

4.2. Statistics Descriptive

Descriptive statistics were used to describe the tendency of respondents' responses to the research variables measured using the Likert scale. A mean value close to the maximum score indicates that the respondent has a positive perception of the variables being studied (Alkharusi, 2022). This study involved 125 respondents with a measurement scale of 1 to 5 on all research variables. The variables studied consisted of Artificial Intelligence (AI) Adoption variables, Accounting Information Quality (AQ), and Accounting Efficiency (EF).

Table 4.1 Descriptive Statistics

Variable	N	Scale min	Scale max	Mean	Standard Deviation
Adopt Artificial Intelligence (AI)	125	1	5	4.462	0.586
Accounting Information Quality (AQ)	125	1	5	4.427	0.582
Accounting Efficiency (EF)	125	1	5	4.362	0.574

Source: Research Results, 2026 (Data Processed)

Based on Table 4.1 Descriptive Statistics, the analysis results show that the Artificial Intelligence (AI) Adoption variable has a mean value of 4.462 with a standard deviation of 0.586. The Accounting Information Quality (AQ) variable had a mean of 4.427 with a standard deviation of 0.582, while the Accounting Efficiency (EF) variable had a mean of 4.362 with a standard deviation of 0.574. An average score above 4 indicates that respondents tend to give a high rating to these three variables.

In addition, a relatively small standard deviation value (below 1) indicates that respondents' answers are fairly consistent and do not have a large difference. This descriptive analysis shows that in general, respondents have a positive perception of the application of AI, the quality of accounting information, and the efficiency of the accounting process.

4.3. Measurement Model (Outer Model)

4.3.1. Convergent Validity

Convergent validity was tested using outer loading and Average Variance Extracted (AVE). The indicator is valid if the outer loading > 0.70, and the construct meets the convergent validity if the AVE > 0.50 (Fornell & Larcker, 1981). The following are presented the values of outer loading and AVE for each indicator in the research variables in Table 4.2.

Table 4.2 Outer Loading

Variable	Indicator	Outer Loading
Adopt Artificial Intelligence (AI)	AI. 1	0.790
	AI. 2	0.813
	AI. 3	0.772
	AI. 4	0.734
	AI. 5	0.755
	AI. 6	0.787
	AI. 7	0.781

Accounting Information Quality (AQ)	AQ. 1	0.715
	AQ. 2	0.776
	AQ. 3	0.761
	AQ. 4	0.811
	AQ. 5	0.870
	AQ. 6	0.847
	AQ. 7	0.770
Accounting Efficiency (EF)	EF. 1	0.741
	EF. 2	0.768
	EF. 3	0.759
	EF. 4	0.729
	EF. 5	0.744
	EF. 6	0.781
	EF. 7	0.731

Source: Research Results, 2026 (Data Processed)

Based on the results of the data processing, all indicators in the three constructs met the outer loading criteria > 0.70: AI (0.734–0.813), AQ (0.715–0.870), and EF (0.729–0.781). Thus, all indicators are declared to be valid in a convergent manner.

Table 4.3 *Average Variance Extracted* (AVE)

Variable	**Average Variance Extracted (AVE)**
Adopt Artificial Intelligence (AI)	0.603
Accounting Information Quality (AQ)	0.631
Accounting Efficiency (EF)	0.564

Source: Research Results, 2026 (Data Processed)

In Table 4.3. The results of the AVE test showed that all constructs had a value above 0.50, which indicates that each construct was able to explain more than 50% of the variance of its indicators. Thus, the constructs in this study have a good level of convergent validity.

4.3.2. Discriminant Validity

Discriminant validity testing (*discriminant validity*) is done to ensure that each construct in the research model has a clear difference and does not overlap with other constructs. This test was conducted using the Fornell–Larcker Criteria and the Heterotrait–Monotrait Ratio (HTMT).

Based on the Fornell–Larcker criteria, the square root value of AVE in each construct must be greater than the correlation value between other constructs. Meanwhile, in the HTMT method, the construct is declared to meet the discriminant validity if the HTMT ratio value is less than 0.90. The following are presented the Fornell–Larcker and Heterotrait–Monotrait Ratio (HTMT) values of each research construct:

Table 4.4 Fornell–Larcker

	Adopt Artificial Intelligence (AI)	Accounting Information Quality (AQ)	Accounting Efficiency (EF)
Adopt Artificial Intelligence (AI)	0.777	-	-
Accounting Information Quality (AQ)	0.718	0.794	-
Accounting Efficiency (EF)	0.654	0.661	0.751

Source: Research Results, 2026 (Data Processed)

Based on the table above, it can be seen that the total square root value of AVE in each construct is higher than the correlation value between constructs, so based on the Fornell–Larcker criterion, it can be concluded that each construct has a good degree of discrimination and can distinguish itself from other constructs.

Table 4.5 Heterotrait–Monotrait Ratio

	Adopt Artificial Intelligence (AI)	Accounting Information Quality (AQ)	Accounting Information Quality (AQ)
Adopt Artificial Intelligence (AI)			
Accounting Information Quality (AQ)	0.771		
Accounting Efficiency (EF)	0.733	0.737	

Source: Research Results, 2026 (Data Processed)

Based on the test results using the Heterotrait-Monotrait Ratio (HTMT) method, all the values of the ratio between constructs are below the threshold limit of 0.90. The HTMT value between Artificial Intelligence (AI) Adoption and Accounting Information Quality (AQ) is 0.771, between AI and Accounting Efficiency (EF) is 0.733, and between AQ and EF is 0.737. Since all of these values are less than 0.90, it can be concluded that each construct has an adequate level of discrimination, and there is no problem of discriminant validity.

Based on the results of the test using the Fornell–Larcker and HTMT criteria, it can be concluded that all constructs in this study, namely AI Adoption, Accounting Information Quality, and Accounting Efficiency, have met the discriminatory validity. The square root value of AVE is greater than the correlation between constructs, as well as HTMT values smaller than 0.90, indicating that each latent variable has empirically distinct characteristics and no construct overlap occurs.

4.3.3. Internal Consistency: Cronbach's Alpha dan Composite Reliability (>0.70)

Reliability is tested using Cronbach's Alpha and Composite Reliability. A ≥ value of 0.70 is considered adequate, ≥ 0.80 indicates good reliability, and ≥ 0.90 is very high (Hair et al., 2019).

Table 4.6 ***Cronbach's Alpha and Composite Reliability Tests***

	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)

Adopt Artificial Intelligence (AI)	0.892	0.896	0.914
Accounting Information Quality (AQ)	0.902	0.902	0.923
Accounting Efficiency (EF)	0.871	0.871	0.900

Source: Research Results, 2026 (Data Processed)

Based on Table 4.6, the entire construct has a Cronbach's Alpha and Composite Reliability above 0.80, indicating good reliability. Thus, the research instrument was declared reliable and worthy of further analysis. These values show that each indicator in each construct has a good level of internal consistency and is able to measure latent variables stably and consistently.

4.4. Model Structural (Inner Model)

4.4.1. Collinearity: Variance Inflation Factor/VIF (<5)

The multicollinearity test used the Variance Inflation Factor (VIF). The model is free from multicollinearity problems if the VIF value is < 5 (Hair et al., 2019).

Table 4.7 Variance Inflation Factor (VIF) Test

	Adopt Artificial Intelligence (AI)	**Accounting Information Quality (AQ)**	**Accounting Efficiency (EF)**
Adopt Artificial Intelligence (AI)	-	1.000	2.062
Accounting Information Quality (AQ)	-	-	2.062
Accounting Efficiency (EF)	-	-	-

Source: Research Results, 2026 (Data Processed)

Based on the results of the test above, it was found that the VIF value was < 5, which indicates that the level of multicollinearity is still in the acceptable category and does not cause significant distortion to the results of the analysis (Hair et al., 2019). Thus, the variables in this research model can be declared free from serious multicollinearity problems, so that the results of parameter estimation and hypothesis testing can be interpreted accurately and reliably. Therefore, the research model has met the assumptions of multicollinearity and is feasible to proceed to the next stage of analysis.

4.4.2. R^2 (Coefficient of Determination)

The R^2 value measures the ability of independent variables to explain the variation of dependent variables. Categories: R^2 = 0.75 (substantial), 0.50 (moderate), 0.25 (weak) (Hair et al., 2019).

Table 4.8 Determination Coefficient Test

	R-square	R-square adjusted
Accounting Information Quality (AQ)	0.515	0.511
Accounting Efficiency (EF)	0.504	0.495

Source: Research Results, 2026 (Data Processed)

Based on the results of data processing, the R^2 value for the Accounting Information Quality (AQ) variable was 0.515 and the adjusted R^2 value was 0.511. This shows that the Artificial Intelligence (AI) adoption variable is able to explain 51.5% of the variation in the Quality of Accounting Information, while the remaining 48.5% is explained by other variables outside the research model. With values above 0.50, the model's ability to explain AQ is included in the moderate category.

Furthermore, the R^2 value for the Accounting Efficiency (EF) variable is 0.504, with the adjusted R^2 being 0.495. AI Adoption and Accounting Information Quality are simultaneously able to explain 50.4% of the variation in Accounting Efficiency. In comparison, the remaining 49.6% are influenced by other factors not studied in this model. This value is also in the moderate category.

4.4.3. f^2 (Effect Size)

The value of f^2 measures the magnitude of the contribution of exogenous variables. Categories: f^2 = 0.02 (small), 0.15 (medium), 0.35 (large) (Hair et al., 2019).

Table 4.9 Effect Size Test

Variabel	f-square
Adopsi Artificial Intelligence (AI) → Accounting Information Quality (AQ)	1.062
Adopsi Artificial Intelligence (AI) → Accounting Efficiency (EF)	0.134
Accounting Information Quality (AQ) →Accounting Efficiency (EF)	0.153

Source: Research Results, 2026 (Data Processed)

Based on the results of *the effect size* (f^2) test, the influence of Artificial Intelligence (AI) Adoption on Accounting Information Quality (AQ) was 1.062, which was included in the category of large influence because it exceeded 0.35, this shows that AI has a very dominant contribution in explaining AQ variations, as well as being a major factor influencing the increase in AQ in research models.

Meanwhile, the influence of AI on Accounting Efficiency (EF) of 0.134 is categorized as a small to moderate influence, which means its contribution to EF is relatively limited. The influence of AQ on EF of 0.153 is included in the category of moderate influence, so it can be concluded that the quality of accounting information has a significant role in improving accounting efficiency in this research model.

4.4.4. Q^2 (Predictive Relevance)

The value of Q^2 (Stone–Geisser) measures the predictive relevance of the model. A Q^2 value of > 0 indicates the model has adequate predictive capabilities (Hair et al., 2019).

Table 4.10 Q² Values

Indicator	Q² predict
AQ. 1	0.456
AQ. 2	0.259
AQ. 3	0.245
AQ. 4	0.249
AQ. 5	0.211
AQ. 6	0.276
AQ. 7	0.245
EF. 1	0.154
EF. 2	0.093
EF. 3	0.153
EF. 4	0.163
EF. 5	0.172
EF. 6	0.147
EF. 7	0.107

Source: Research Results, 2026 (Data Processed)

Based on the results of the data processing, all indicators in the Accounting Information Quality (AQ) construct have a Q^2 predict value that is greater than zero, with a value range between 0.211 and 0.456. The highest value is found in the AQ.1 indicator of 0.456, which shows that the model has good predictive ability in explaining the QA variable.

Similarly, in the Accounting Efficiency (EF) construct, all indicators show a positive Q^2 predict value, which ranges from 0.093 to 0.172. Although some values are at relatively lower levels than AQ, they are still greater than zero, so the model still has predictive relevance to the EF variable.

4.5. Hypothesis

Path Coefficient is used to show the direction and magnitude of the influence between variables in a structural model. The significance test of the path coefficient was carried out through a bootstrapping procedure with 5,000 *sub-samples*. This method is used to derive the *t-statistic* and *p-value*, so that it can be determined whether the relationship between variables in the model is statistically significant.

Based on the criteria put forward by Hussein (2015), a relationship is stated to be significant if the value of *the t-statistic* is greater than 1.96 and the value *of the p-value* is less than 0.05 at a significance level of 5%. If the score obtained does not meet these criteria, then the hypothesis submitted is declared unacceptable or not supported empirically.

Table 4.11 Path Coefficient

Hipotesis	Variable Relationships	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Remarks
H1	**AI → AQ**	0.718	0.703	0.091	7.915	0.000	Signifikan
H2	**AI → EF**	0.370	0.324	0.131	2.830	0.005	Signifikan
H3	**AQ → EF**	0.396	0.367	0.109	3.621	0.000	Signifikan

Source: Research Results, 2026 (Data Processed)

The Effect of *Artificial Intelligence Adoption* on the Quality of Accounting Information

Based on the results of the hypothesis test, the relationship between Artificial Intelligence (AI) Adoption and Accounting Information Quality (AQ) has a path coefficient value of 0.718, with a t-statistic of 7.915 and a p-value of 0.000. A t-value greater than 1.96 and a p-value smaller than 0.05 indicate that the influence is statistically significant. The positive path coefficient shows that the higher the level of AI adoption in the accounting process, the higher the quality of the accounting information produced. This shows that the use of AI technology is able to improve the accuracy, timeliness, and relevance of accounting information through automation processes, faster data analysis, and reduced human error. The research conducted by Alkhajah (2023) discusses how the development of digital technology, including Artificial Intelligence, affects modern accounting practices. The results of the study show that AI is able to improve the quality of accounting information through the automation of the recording process, faster data analysis, and improved accuracy of financial statements. In addition, this is also strengthened by research conducted by Davenport and Ronanki (2018), which explains that AI in organizations is able to improve the quality of information through more accurate and faster data analysis, which supports managerial decision-making. Thus, the H1 hypothesis that AI adoption has a positive effect on the quality of accounting information is acceptable.

This finding is also reinforced by an *effect size* (f^2) value of 1.062, which falls into the large category, far exceeding the threshold of 0.35 proposed by Cohen (in Hair et al., 2019). These figures indicate that AI adoption is not only statistically significant but also has a dominant, substantial contribution in explaining variations in the quality of accounting information, making it the strongest predictor in this research model. The result is in line with the View of DeLone and McLean (2003) that system quality is a direct antecedent of information *quality*. In the context of this study, the adoption of AI that includes *machine learning*, NLP, and predictive analytics features serves as a system quality enhancer that directly drives *information quality dimensions* such as accuracy, timeliness, completeness, and consistency. These findings also extend the research results of Zhang and Xie (2020) and Zemánková (2019) into the context of companies in Indonesia, which show that the relationship between AI and information quality is consistent across geographical and industrial contexts.

The Effect of *Artificial Intelligence* Adoption on Accounting Process Efficiency

The test results showed that the relationship between Artificial Intelligence (AI) Adoption and Accounting Process Efficiency (EF) had a path coefficient value of 0.370, with a t-statistic of 2.830 and a p-value of 0.005. The value met the significance criteria because the t-value > 1.96 and the p-value < 0.05, so this relationship was statistically significant. Positive coefficients indicate that increased adoption of AI can improve the efficiency of accounting processes. In line with the findings by Silooy, Marissa (2025), who stated that AI has a significant positive influence on the Efficiency of Accounting Processes. The application of AI in accounting systems allows organizations to increase productivity as well as reduce data processing time in accounting activities. Thus, the H2 hypothesis that AI adoption has a positive effect on the efficiency of accounting processes is acceptable.

The Effect of Accounting Information Quality on the Efficiency of the Accounting Process

The test results showed that the relationship between Accounting Information Quality (AQ) and Accounting Process Efficiency (EF) had a path coefficient value of 0.396, with a t-statistic of 3.621 and a p-value of 0.000. This value shows that this relationship is statistically significant because it meets the criteria of t-statistic > 1.96 and p-value < 0.05. The positive coefficient shows that the better the quality of accounting information produced by the accounting system, the more efficient the accounting process that takes place in the organization. Accurate, relevant, and timely information can speed up the decision-making process, minimize errors, and reduce the need for re-verification processes. Thus, the H3 hypothesis, which states that the quality of accounting information has a positive effect on the efficiency of the accounting process, is acceptable.

4.6. Mediation Test

The mediation effect was tested using the bootstrapping method by calculating specific indirect effects. Medias' is declared significant if the confidence interval does not pass zero. The type of mediation is determined based on the criteria of Zhao et al. (2010), namely complementary mediation (partial), competitive mediation, indirect-only mediation (full), or direct-only non-mediation.

Table 4.12 Uji Indirect Effects (Specific Indirect Effects)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P va ues
AI → AQ → EF	0.284	0.262	0.096	2.970	0.00

Source: Research Results, 2026 (Data Processed)

Based on the results of data processing, the indirect effect of Artificial Intelligence (AI) Adoption on Accounting Efficiency (EF) through Accounting Information Quality (AQ) has a coefficient of 0.284 with a t-statistic value of 2.970 and a p-value of 0.003. In the PLS-SEM analysis, indirect effect testing was performed using the bootstrapping technique, and a mediating relationship was declared significant if the t-statistic value was greater than 1.96 and the p-value was less than 0.05 at a significance level of 5% (Hair et al., 2019).

Because the t-statistic value > 1.96 and the p-value < 0.05, the indirect effect was declared significant. Accounting Information Quality (AQ) significantly mediates the relationship between Artificial Intelligence (AI) Adoption and Accounting Efficiency (EF). In the context of accounting information systems, the quality of information produced by digital technology acts as a mechanism that bridges the use of technology with improving the performance or efficiency of organizational processes.

Referring to the criteria put forward by (Zhao et al., 2010), the type of mediation is determined by comparing the significance of direct and indirect influences in the structural model. This approach classifies mediation into several categories, such as *complementary mediation, competitive mediation, indirect-only mediation*, and *direct-only non-mediation*.

In this study, the direct influence of AI on EF was also previously proven to be significant, and the indirect influence through AQ was also significant and had the same (positive) direction. Therefore, the type of mediation that occurs is complementary mediation (*partial mediation*), which is a condition where direct and indirect influences are both significant and have a corresponding relationship direction (Zhao et al., 2010).

These *complementary mediation findings* have important theoretical implications. From the perspective of *the Resource-Based View* (Barney, 1991), the adoption of AI as a valuable and difficult-to-replicate technological capability has been proven to improve process efficiency directly through the automation of repetitive tasks such as *data entry* and reconciliation. However, DeLone and McLean (2003) are also valid: some of the influence of AI on the efficiency of work is through indirect channels, i.e., by first improving the quality of the information produced. These two mechanisms do not negate each other, but are *complementary*, so that the total influence of AI on efficiency (*direct* + *indirect*) is greater than if only one of the paths works. Quantitatively, the indirect influence of AI on EF through AQ of 0.284 adds to the total influence outside of direct influence by 0.370, bringing the total contribution of AI to overall efficiency to 0.654. The practical implication: organizations that only invest in AI infrastructure without paying attention to the quality of the information it generates will miss out on some of the potential efficiencies that should have been achieved. On the other hand, organizations that optimize both paths simultaneously, both in terms of technology capabilities and the quality of their information output, will benefit from maximum efficiency.

5. Conclusion

Based on the results of the data analysis that has been carried out, this study shows that the adoption of Artificial Intelligence (AI) has a positive and significant influence on the quality of accounting information. The use of AI technology in accounting systems can increase the accuracy, timeliness, and relevance of the information generated. The automation process and AI's ability to process data quickly and systematically allow for the reduction of human error and increase the reliability of financial information. In addition, this study also found that the quality of accounting information has a positive and significant effect on the efficiency of the accounting process, which shows that accurate, relevant, and timely information can support the smooth accounting process and accelerate decision-making in the organization.

Furthermore, the results of the study show that the adoption of AI also directly affects the efficiency of the accounting process, as well as has an indirect influence through the quality of accounting information as a mediating variable. The results of the mediation test showed that the quality of accounting information significantly mediated the relationship between AI adoption and the efficiency of the accounting process, with the complementary mediation (partial mediation) type. These findings suggest that the efficiency of accounting processes can be improved directly through the application of AI technology, without having to always rely on improving the quality of accounting information as a key prerequisite. However, information quality still makes an additional contribution to strengthening these relationships. Quantitatively, the AI → AQ path coefficient of 0.718 ($f^2 = 1.062$) reflects a very dominant influence, while the total AI contribution to efficiency reaches 0.654 when direct (0.370) and indirect (0.284) paths are combined.

This research has several limitations that need to be considered. First, the cross-sectional survey design does not allow for strong causality inference, so the relationships between variables are associative. Second, the use of purposive sampling combined with snowball sampling limits the generalization of the findings to a wider population. Third, self-reported data have the potential to contain common method bias, which is reflected in the mean value of all variables that are grouped above 4.3 on a scale of 5. Fourth, this model only explains about

50% of the efficiency variation ($R^2 = 0.504$), suggesting that there are still other relevant factors that have not been included in the model.

Based on these limitations, future research is recommended to: (1) use longitudinal designs to observe changes in AI adoption and their impact on efficiency over time; (2) expand geographical coverage to other ASEAN countries to test the consistency of findings across contexts; (3) add moderation variables such as company size, industry sector, or organizational digital maturity level; and (4) considering the use of objective data (e.g. financial statement data from the IDX) as a complement to perception data to reduce the potential for common method bias.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to the Faculty of Economics and Business, Universitas Pelita Harapan (FEB UPH), for the institutional support and academic environment that facilitated the completion of this research. The authors also extend their appreciation to the Office of Research and Publication (ORP), Universitas Pelita Harapan, for the research facilitation and support provided throughout the process of this study.

REFERENCES

Alkhajah, M. (2023). Financial Accounting in the Digital Era: Literature Review. International Journal of Professional Business Review, 8(4), e01234.

Alkharusi, H. (2022). A descriptive analysis and interpretation of data from Likert scales in educational and psychological research. Indian Journal of Psychology and Education. 12(2). 13-16.

Amirillah, C. D. R. (2025). Detecting Fraudulent Transactions in the Banking Sector. National Journal of Electrical Engineering and Information Technology, 14(2).983.

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. Journal of Management, 17(1), 99–120.

News One. (2025, August 11). Increasingly in Demand, AI Adoption in Indonesia Grows 47 Percent Annually. Beritasatu.com. Accessed on February 04, 2026. https://www.beritasatu.com/ekonomi/2912337/makin-diminati-adopsi-ai-di-indonesia-tumbuh-47-persen-secara-tahunan

Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the real world. Harvard Business Review, 96(1), 108–116.

Directorate General of Treasury. (2025, December 31). *My Integrated Treasury System (MyIntress).* Ministry of Finance of the Republic of Indonesia.

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. Journal of Management Information Systems, 19(4), 9–30.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50.

Gelinas, U. J., Dull, R. B., & Wheeler, P. R. (2018). Accounting Information Systems (11th International ed.). Cengage Learning.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2-24.

Hamid, R. S., & Anwar, S. M. (2019). *Variant-based structural equation modeling (SEM): Basic concepts and applications of the SmartPLS 3.2.8 program in business research*. PT Incubator Penulis, Indonesia.
Hasan, A. R. (2022). Artificial Intelligence (AI) in Accounting & Auditing: A Literature Review. Open Journal of Business and Management, 10, 440–465.
Hussein, A. S. (2015). Business and management research using partial least squares (PLS) with SmartPLS 3.0. Brawijaya University.
Prahastiwi, N. A., Lubis, M., & Fakhrurroja, H. (2025). The ensemble supervised machine learning for a credit scoring model in a digital banking institution. Indonesian Journal of Artificial Intelligence and Data Mining, 8(2).
Silooy, M. (2025). The Influence of Artificial Intelligence (AI), Information Technology Capabilities, and Employee Training on Accounting Proccess Efficiency at Public Accounting Firms in Ambon City. International Journal of Business Accounting Management Social Science, 1(2), 67–77. https://doi.org/10.64530/ijbams.v1i2.26
Ma'rup, M., Tobirin, & Rokhman, A. (2024). Utilization of Artificial Intelligence (AI) chatbots in improving public services: A meta-analysis study. Open Access Indonesia Journal of Social Sciences, 7(4), 1610–1618. https://doi.org/10.37275/oaijss.v7i4.255
Vasarhelyi, M. A., Kogan, A., & Tuttle, B. M. (2015). Big data in accounting: An overview. Accounting Horizons, 29(2), 381–396. https://doi.org/10.2308/acch-51071
Yusuf, M. F. M., Garusu, I. A., & Rauf, D. M. (2024). System for the application of artificial Intelligence in accounting. *Scientific Journal of Social Sciences and Education*, 2(2), 1–7.
Zemánková, A. (2019). Artificial Intelligence and Blockchain in Audit and Accounting: Literature Review. WSEAS Transactions on Business and Economics, 16, 568-581.
Zhang, Y., & Xie, F. (2020). The Impact of Artificial Intelligence and Blockchain on the Accounting Profession. IEEE Access, 8, 110461-110477.
Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. Journal of Consumer Research, 37(2), 197–206.