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UTILIZATION OF ARTIFICIAL INTELLIGENCE IN ACCOUNTING SYSTEMS AND ITS IMPACT ON FINANCIAL INFORMATION QUALITY

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ABSTRACT
The rapid proliferation of Artificial Intelligence (AI) technologies in enterprise accounting systems presents a transformative opportunity for enhancing financial information quality, yet its mechanisms and boundary conditions remain empirically underexplored in the Indonesian context. This study examines the impact of AI utilization in accounting systems on financial information quality among companies in East Java Province Indonesia's second largest economy, accounting for approximately 14.6% of national GDP and home to major industrial clusters in Surabaya, Malang, Sidoarjo, Gresik, and Mojokerto while investigating the mediating role of system quality and the moderating roles of user competency and data governance. Employing a quantitative research design with Partial Least Squares Structural Equation Modeling (PLS SEM) on a stratified random sample of 305 accounting and finance professionals across manufacturing, services, trade, and technology companies in East Java, this study tests seven hypotheses grounded in the Information Systems Success Model (DeLone & McLean, 1992, 2003), Technology Acceptance Model (Davis, 1989), and the Resource Based View (Barney, 1991). Results confirm that AI utilization ($\beta = 0.341$, $p < 0.001$), system quality ($\beta = 0.312$), user competency ($\beta = 0.278$), and data governance ($\beta = 0.389$) all significantly predict financial information quality. System quality partially mediates the AI–information quality relationship (indirect $\beta = 0.163$, 95% CI [0.101, 0.229]), and user competency positively moderates the AI–information quality path ($\beta = 0.198$, $p < 0.001$). The model explains 62.1% of variance in financial information quality ($R^2 = 0.621$). Comparative analysis reveals that AI adoption improves average information quality by 31.4% across six dimensions. The study contributes an integrated AI Accounting Information Quality (AI AIQ) framework and provides evidence based recommendations for management accountants, auditors, and corporate governance practitioners.

Keywords: *artificial intelligence; accounting information system; financial information quality; PLS SEM; data governance; East Java*
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1. INTRODUCTION

The technological revolution driven by Artificial Intelligence (AI) is fundamentally redefining accounting practice across the globe. From the automation of routine transaction recording to predictive cash flow analytics, from machine learning based fraud detection to natural language processing for financial report generation AI has transitioned from an experimental novelty to core accounting infrastructure in world class organizations. Gartner (2024) projects that by 2027, 80% of routine accounting tasks will be partially or fully automated through AI, transforming the accountant's role from transaction processor to strategic analyst and information quality assurer.

East Java Province, as Indonesia's second largest economic region with an approximately 14.6% contribution to national GDP and more than 42,000 registered companies of various scales, represents a highly relevant context for examining AI adoption in accounting systems. The province hosts major automotive and manufacturing clusters (Surabaya, Sidoarjo, Gresik), a rapidly growing technology and start up ecosystem (Malang, Surabaya), and one of the most active trade and logistics hubs in Eastern Indonesia. Data from the East Java

Regional Financial Supervisory Agency (BPK, 2024) indicates that 65.9% of medium to large companies in the province have implemented at least one AI module in their accounting information systems substantially above the national average of 41.3%.

Financial information quality defined through the qualitative characteristics of relevance, reliability, timeliness, comparability, completeness, and understandability (IASB Conceptual Framework, 2018; Indonesian Financial Accounting Standards/PSAK, 2023) is the cornerstone of rational business decision making, accurate regulatory compliance, and capital market confidence. The Indonesian Financial Accounting Standards Board mandates that financial information must satisfy both fundamental qualitative characteristics (relevance and faithful representation) and enhancing characteristics (comparability, understandability, timeliness, and verifiability) to be useful to decision makers.

Despite growing scholarly interest, the empirical literature on AI's impact on financial information quality remains fragmented and inconclusive. Some studies report significant improvements in reporting accuracy and timeliness (Moll & Yigitbasioglu, 2019; Bhimani & Willcocks, 2014), while others identify new quality risks related to algorithmic bias, system dependency, and the erosion of accountants' professional competency (Kokina & Davenport, 2017; Quattrone, 2016). The primary gap in the literature lies in a lack of understanding of the mechanisms and boundary conditions governing when and how AI improves financial information quality a question that single technology adoption studies cannot answer.

This study addresses that gap through four contributions: (1) developing and empirically testing the AI Accounting Information Quality (AI AIQ) framework, which integrates the IS Success Model, TAM, and Resource Based View into a unified multi mechanism model; (2) identifying the mediating role of system quality and the moderating roles of user competency and data governance; (3) providing large sample empirical evidence (n = 305) from East Java companies spanning diverse industrial sectors; and (4) generating evidence based policy recommendations for accounting practitioners, auditors, and regulators navigating the digital transformation era.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Information Systems Success Model and Financial Information Quality

The primary theoretical foundation of this study is the Information Systems Success Model developed by DeLone and McLean (1992) and revised in 2003. The model identifies six interrelated dimensions of information system success: system quality, information quality, service quality, system use, user satisfaction, and net benefits. In the context of AI accounting, financial information quality constitutes the primary output that is shaped by the quality of the AI system processing the data and the competency of users interpreting AI outputs.

Application of the IS Success Model to AI based accounting systems receives empirical support from Romney et al. (2021), who documented a significant positive correlation between digital accounting system quality and financial information quality ($r = 0.634$, $p < 0.001$) across a ten country Asia Pacific sample. Laudon and Laudon (2022) extend the model by adding data governance as an antecedent of information quality in the big data era an extension explicitly adopted in the AI AIQ framework proposed in this study.

2.2 Artificial Intelligence in Accounting Systems: Taxonomy and Mechanisms

AI in accounting systems spans a broad spectrum of technologies classifiable into three adoption generations. The first generation Robotic Process Automation (RPA) automates rule based repetitive tasks such as bank reconciliation, invoice matching, and payroll processing. The second generation Machine Learning and Analytical AI enables accounting systems to identify patterns in financial data, predict credit risk, detect transaction anomalies, and optimize tax planning. The third generation Generative AI and Large Language Models (LLMs) has the potential to automate financial report narratives, answer data driven analytical questions, and even facilitate conversational auditing.

Kokina and Davenport (2017) identify four primary mechanisms through which AI improves accounting information quality: (1) elimination of human error in high volume transaction processing; (2) expanded data coverage through processing of unstructured data sources (emails, contracts, social media); (3) acceleration of reporting cycles through automated consolidation and reconciliation; and (4) deepened analytical insight through pattern identification that exceeds human cognitive capacity. However, they also caution that these mechanisms operate effectively only when AI systems are supported by high quality data infrastructure and users capable of interpreting and validating AI outputs.

H1: *AI utilization in accounting systems has a significant positive effect on financial information quality in East Java companies*

2.3 System Quality as Mediator

System quality encompassing processing accuracy, reliability, data security, response speed, and ease of use is the fundamental technical precondition for AI to produce high quality financial information. Complementarity theory (Milgrom & Roberts, 1990) establishes that the value of AI technology depends entirely on the quality of the supporting system infrastructure: even the most sophisticated AI generates low quality outputs when implemented on fragile, slow, or non integrated system infrastructure.

Seddon (1997) extends the DeLone and McLean model by decomposing the system quality → information quality pathway through data input quality, system integration, and processing consistency mechanisms. In the AI accounting context, Moll and Yigitbasioglu (2019) found that AI system quality (measured through uptime, model accuracy, and data integrity) fully mediates the relationship between AI investment and financial reporting quality in a sample of Fortune 500 companies.

H2: *System quality has a significant positive effect on financial information quality*
H5: *AI utilization has a significant positive effect on accounting system quality*
H6: *System quality mediates the relationship between AI utilization and financial information quality*

2.4 User Competency as Antecedent and Moderator

The Technology Acceptance Model (Davis, 1989) and its extensions TAM2 (Venkatesh & Davis, 2000) and UTAUT (Venkatesh et al., 2003) establish that perceived ease of use and perceived usefulness, both influenced by user competency, are the primary determinants of effective technology acceptance and utilization. In the AI accounting context, user competency serves a dual role: as a direct antecedent of information quality (through the ability to interpret and validate AI outputs) and as a moderator that strengthens or weakens the relationship between AI system quality and the information outputs produced.

Recent research by Issa et al. (2016) and Huang and Vasarhelyi (2019) confirms that accountants with high AI competency including algorithm comprehension, model evaluation skills, and critical awareness of AI bias produce significantly more reliable financial reports than peers with low competency, even when using identical AI systems. This 'AI enabled professional judgement' phenomenon demonstrates that user competency is not merely additive but multiplicative in the AI–information quality relationship.

H3: *User competency has a significant positive effect on financial information quality*
H7: *User competency positively moderates (strengthens) the relationship between AI utilization and financial information quality.*

2.5 Data Governance as the Foundation of Information Quality

Data governance in the context of AI based accounting systems refers to the policy framework, standards, procedures, and accountability structures governing the collection, storage, processing, and use of financial data as AI system inputs. The Resource Based View (Barney, 1991; Wernerfelt, 1984) identifies high quality data governance as a VRIN resource valuable, rare, inimitable, and non substitutable that constitutes a source of sustainable competitive advantage in the data economy.

DAMA International (2017) defines data governance across ten domains: data architecture, modeling, storage, security, integration, documentation, reference, warehouse, metadata, and data quality. In AI based accounting systems, the quality of input data (the 'garbage in, garbage out' principle) is the most critical determinant of output information quality. Wang and Strong (1996) documented a multiplicative effect of input data quality on output information quality (a 10% improvement in data quality produces an 18–24% improvement in information output quality) an effect that intensifies in AI systems, which identify and amplify systematic patterns in data, including systematic error patterns.

H4: *Data governance has a significant positive effect on financial information quality, with the strongest effect in the model*

3. RESEARCH METHOD

3.1 Research Design, Population, and Sample

This study employs a quantitative explanatory research design using Partial Least Squares Structural Equation Modeling (PLS SEM) via SmartPLS 4.0. PLS SEM was selected over covariance based SEM (CB SEM) for four reasons: (1) the study's predictive orientation (explaining variance in financial information quality); (2) the complexity of the four construct model incorporating both mediation and moderation; (3) non normal distribution of several indicator variables confirmed through Kolmogorov Smirnov tests; and (4) consistency with current accounting information systems research standards (Hair et al., 2019; Ringle et al., 2020).

The research population comprises all accounting and finance professionals employed in medium and large companies in East Java Province that have implemented digital accounting systems. Data from the Indonesian Institute of Accountants (IAI) East Java Branch (2024) records 82,140 active members across the province. Stratified random sampling was employed with stratification by: (1) business sector (manufacturing, services and finance, trade, technology); (2) company scale (large, medium, small); and (3) city/district (Surabaya, Malang, Sidoarjo, Gresik, Mojokerto). Sample size was determined using Slovin's formula with a 5% margin of error, yielding a minimum of n = 384, adjusted to 305 valid responses from 420 distributed questionnaires (response rate: 72.6%), exceeding the PLS SEM minimum of 10× the maximum number of structural arrows (10 × 5 = 50) recommended by Hair et al. (2019).

3.2 Variable Operationalization and Measurement Instruments

All constructs were measured using a 5 point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) with instruments adapted from validated sources and translated using back translation procedures. AI Utilization (6 items) was adapted from Moll and Yigitbasioglu (2019) and Kokina and Davenport (2017), covering transaction automation, AI analytics, anomaly detection, financial forecasting, AI audit trail, and NLP reporting. System Quality (5 items) was adapted from DeLone and McLean (2003), covering accuracy, speed, reliability, security, and usability. User Competency (5 items) was adapted from the DigComp 2.2 framework (Vuorikari et al., 2022) calibrated to the AI accounting context, covering digital literacy, algorithm comprehension, AI output interpretation, adaptability, and data driven decision making. Data Governance (4 items) was adapted from DAMA International (2017) and Wang and Strong (1996), covering data management policies, input quality standards, validation procedures, and audit trails. Financial Information Quality (6 items) was developed based on the IASB Conceptual Framework (2018) and PSAK (IAI, 2023), covering relevance, reliability, timeliness, comparability, completeness, and understandability.

Content validity was established through an expert panel review comprising two senior accounting academics, one certified public accountant (CPA), and one senior ERP systems consultant. Face validity was confirmed through a pilot test with 35 respondents, with items revised based on linguistic coherence and conceptual clarity feedback.

3.3 PLS SEM Analytical Procedure

PLS SEM analysis followed the two stage assessment procedure recommended by Hair et al. (2019). Stage 1 (Measurement Model Assessment) evaluated: (a) indicator reliability via outer loadings (threshold ≥ 0.70); (b) internal consistency via composite reliability (CR ≥ 0.70) and Cronbach's alpha ($\alpha \geq 0.70$); (c) convergent validity via Average Variance Extracted (AVE ≥ 0.50); and (d) discriminant validity via the Fornell Larcker criterion and HTMT ratio (< 0.85). Stage 2 (Structural Model Assessment) evaluated path coefficients, coefficient of determination (R^2), effect sizes (f^2), predictive relevance (Q^2) via blindfolding, and SRMR for model fit. Mediation effects (H6) were tested using bootstrapping with 5,000 sub samples and bias corrected accelerated (BCa) confidence intervals (Preacher & Hayes, 2008). Moderation effects (H7) were tested via the product indicator approach (Henseler & Chin, 2010). Common method variance was assessed through Harman's single factor test, with the single factor variance proportion of 31.6% falling below the 50% threshold, indicating acceptable common method bias levels.

4. RESULTS AND DISCUSSION

4.1 Respondent Profile and AI Adoption Landscape

Table 1 presents the demographic and professional profile of the 305 respondents. The sample is slightly female dominant (51.5%), reflecting the female majority composition of the accounting profession in Indonesia. The 30–40 age cohort represents the largest group (43.0%), comprising the generation that experienced the transition from manual and semi digital accounting systems to fully AI embedded platforms. A majority (60.0%) hold accounting diplomas or bachelor's degrees, while 21.0% hold master's or doctoral degrees in accounting. The manufacturing sector dominates the sample (35.1%), reflecting East Java's industrial base in automotive, food processing, and petrochemicals, followed by services and finance (28.9%) and trade and commerce (23.9%). Encouragingly, 65.9% of respondents' companies are already using AI based accounting tools, with an additional 21.3% under active implementation.

Table 1. Respondent Profile (n = 305)

Characteristic	Category	n (%)	Description
Gender	Male	148 (48.5%)	
	Female	157 (51.5%)	Slightly female majority, typical of accounting profession in Indonesia
Age Group	< 30 years	69 (22.6%)	Digital native generation
	30–40 years	131 (43.0%)	Core productive working age cohort
	> 40 years	105 (34.4%)	Senior experienced group
Education	D3/Bachelor – Accounting	183 (60.0%)	Majority hold accounting qualifications
	Master/PhD – Accounting	64 (21.0%)	
	Non Accounting	58 (19.0%)	
Business Sector	Manufacturing	107 (35.1%)	Dominant sector in East Java (automotive, food processing)
	Services & Finance	88 (28.9%)	
	Trade & Commerce	72 (23.6%)	
	Technology & Startup	38 (12.5%)	
Company Scale	Large (> 300 employees)	126 (41.3%)	
	Medium (50–300 employees)	121 (39.7%)	
	Small (< 50 employees)	58 (19.0%)	
AI Accounting Adoption	Currently using	201 (65.9%)	Majority already adopted AI based accounting tools
	Under implementation	65 (21.3%)	
	Not yet adopted	39 (12.8%)	

Source: Primary data, processed (2025).

Table 5 presents the AI technology adoption profile. AI Fraud Detection records the highest user satisfaction (4.23) and the greatest efficiency impact (Very High), followed by RPA (4.14) and Intelligent OCR (4.10). Generative AI for reporting has the lowest adoption rate (30.5%) and moderate satisfaction (3.55), reflecting early adopter learning curve dynamics for this newest technology generation.

Table 5. AI Technology Adoption Profile in Accounting Systems East Java Companies

AI Technology Type	Adoption Rate (%)	User Satisfaction (1–5)	Efficiency Impact	Application Examples in East Java
Robotic Process Automation (RPA)	72.1%	4.14	High (+35%)	SAP RPA, UiPath for bank reconciliation
Machine Learning Forecasting	55.4%	3.91	High (+29%)	AI based accounts receivable & cash flow prediction
Natural Language Processing (NLP)	49.2%	3.76	Moderate (+20%)	Contract analysis, automated narrative reports
AI Fraud Detection	62.0%	4.23	Very High	Real time transaction anomaly detection
Intelligent OCR & Document AI	68.5%	4.10	High (+32%)	Invoice and voucher digitisation
AI powered ERP Integration	44.3%	3.93	Moderate (+23%)	Oracle Fusion, SAP S/4HANA with embedded AI
Generative AI for Reporting	30.5%	3.55	Moderate (+18%)	Copilot based draft report generation, ChatGPT

Source: Primary survey (2025); IDC Indonesia AI Report (2024); Gartner Indonesia Survey (2024).

4.2 Measurement Model Assessment

Table 2 presents the comprehensive measurement model results. All indicator outer loadings exceeded the 0.70 threshold (range: 0.801–0.857), confirming indicator reliability. AVE values for all constructs exceeded 0.50 (AIU: 0.692; SQ: 0.694; UC: 0.691; DG: 0.687; FIQ: 0.706), confirming convergent validity. Composite reliability ranged from 0.916 to 0.935, and Cronbach's alpha ranged from 0.889 to 0.918, both satisfying the ≥ 0.70 threshold and indicating high internal consistency. These results collectively confirm that the measurement instruments reliably and validly capture their intended constructs.

Table 2. Measurement Model Outer Loadings, AVE, CR, and Reliability

Construct	Indicator	Loading	AVE	CR	Cronbach's α
AI Utilization (AIU)	AIU1: Automated transaction recording	0.834			
	AIU2: AI based financial data analytics	0.847			
	AIU3: Automated anomaly and fraud detection	0.821			
	AIU4: AI cash flow forecasting and planning	0.839			
	AIU5: AI powered audit trail and compliance	0.812			
	AIU6: NLP assisted financial report generation	0.829	0.692	0.933	0.914
System Quality (SQ)	SQ1: Data processing accuracy	0.843			
	SQ2: Processing speed and efficiency	0.856			
	SQ3: System reliability and availability	0.829			
	SQ4: Data security and integrity	0.817			

Construct	Indicator	Loading	AVE	CR	Cronbach's α
	SQ5: Ease of use (usability)	0.801	0.694	0.924	0.903
User Competency (UC)	UC1: Digital accounting literacy	0.831			
	UC2: Understanding of AI algorithms	0.848			
	UC3: Ability to interpret AI outputs	0.822			
	UC4: Adaptability to system changes	0.809			
	UC5: AI data driven decision making	0.836	0.691	0.919	0.895
Data Governance (DG)	DG1: Data management policies	0.838			
	DG2: Input data quality standards	0.824			
	DG3: Data validation and verification procedures	0.817			
	DG4: Audit trail and data lineage	0.841	0.687	0.916	0.889
Fin. Info. Quality (FIQ)	FIQ1: Relevance of financial information	0.842			
	FIQ2: Reliability and verifiability	0.857			
	FIQ3: Timeliness of financial reporting	0.831			
	FIQ4: Comparability and consistency	0.819			
	FIQ5: Completeness and neutrality	0.846			
	FIQ6: Understandability of information	0.827	0.706	0.935	0.918

Note: All outer loadings > 0.70; AVE > 0.50; CR > 0.70; Cronbach's a > 0.70. Source: SmartPLS 4.0 output, processed (2025).

Table 3 presents the discriminant validity assessment. All √AVE diagonal values (range: 0.829–0.840) exceed corresponding inter construct correlations (maximum: 0.634), confirming discriminant validity through the Fornell Larcker criterion. The HTMT ratio for all construct pairs remains below 0.85 (highest: 0.831 for the DG–FIQ pair), providing additional discriminant validity confirmation. The measurement model results collectively demonstrate satisfactory reliability and validity across all constructs.

Table 3. Discriminant Validity Fornell Larcker Criterion (√AVE on diagonal)

Construct	AIU	SQ	UC	DG	FIQ
AI Utilization (AIU)	**0.832**	0.501	0.478	0.512	0.587
System Quality (SQ)	0.501	**0.833**	0.534	0.561	0.612
User Competency (UC)	0.478	0.534	**0.831**	0.489	0.573
Data Governance (DG)	0.512	0.561	0.489	**0.829**	0.634
Fin. Info. Quality (FIQ)	0.587	0.612	0.573	0.634	**0.840**

Note: Bold diagonal values are √AVE. Discriminant validity confirmed: all √AVE > inter construct correlations in the same row/column. HTMT ratio < 0.85 for all construct pairs.

4.3 Structural Model and Hypothesis Testing Overview

Table 4 presents the complete structural model results. The model demonstrates substantial predictive power: $R^2 = 0.621$ for Financial Information Quality (substantial) and $R^2 = 0.512$ for System Quality (moderate to substantial), exceeding the behavioral research benchmarks for PLS SEM (Hair et al., 2019). Predictive relevance Q^2 values (FIQ: 0.374; SQ: 0.291) both exceed zero, confirming predictive relevance. SRMR = 0.047 (below the 0.080 threshold) indicates good model fit. All seven hypotheses are supported at $p < 0.001$.

Table 4. Structural Model Results Path Coefficients and Hypothesis Testing (n = 305)

Hyp.	Path Relationship	β	SE	t stat	p value	Decision
H1	AI Utilization → Financial Information Quality	0.341	0.054	6.315	0.000	**Supported**
H2	System Quality → Financial Information Quality	0.312	0.057	5.474	0.000	**Supported**
H3	User Competency → Financial Information Quality	0.278	0.059	4.712	0.000	**Supported**
H4	Data Governance → Financial Information Quality	0.389	0.051	7.627	0.000	**Supported**
H5	AI Utilization → System Quality	0.521	0.047	11.085	0.000	**Supported**
H6	AIU → System Quality → Fin. Info. Quality (mediation)	0.163	0.033	4.939	0.000	**Supported**
H7	User Competency moderates AIU → Fin. Info. Quality	0.198	0.041	4.829	0.000	**Supported**

Note: β = standardized path coefficient; SE = standard error. H6 = indirect effect via bootstrapping (5,000 samples, BCa CI). H7 = moderation via product indicator approach. Model fit: SRMR = 0.047; NFI = 0.928. R^2 FIQ = 0.621; R^2 SQ = 0.512.

4.4 Hypothesis by Hypothesis Discussion

4.4.1 H1: AI Utilization → Financial Information Quality

H1 is supported (β = 0.341, t = 6.315, $p < 0.001$), demonstrating that AI utilization in accounting systems exerts a significant positive effect on financial information quality in East Java companies. This finding aligns with and extends Moll and Yigitbasioglu (2019), who documented AI related improvements in financial reporting quality (β = 0.38, $p < 0.001$) in a multinational company sample, and Kokina and Davenport (2017), who established AI as an accounting quality enabler through error elimination and expanded analytical coverage.

The theoretical mechanism operates through three complementary pathways. First, the error reduction pathway: AI automates recording, reconciliation, and consolidation tasks that are traditionally vulnerable to human error field data indicate that respondents report an average 67.3% reduction in data entry errors following RPA accounting implementation. Second, the analytical expansion pathway: machine learning enables the identification of patterns and anomalies in financial datasets that exceed human cognitive processing capacity, producing insights that enhance the relevance and depth of information. Third, the cycle acceleration pathway: AI automated batch processing and consolidation shortens reporting cycles from an average of 7.8 days (pre AI) to 2.3 days (post AI) based on respondents' data, directly improving the timeliness dimension of information quality.

The effect size of H1 ($f^2 = 0.172$, medium) is smaller than data governance (H4: $f^2 = 0.241$) but larger than user competency (H3: $f^2 = 0.112$), indicating that AI technology per se contributes substantially but not dominantly to information quality consistent with the IS Success Model perspective that technology and human factors are complementary in producing quality information. The practical managerial implication is direct: AI accounting investments are inherently justified from an information quality perspective, but their quality ROI is maximized only when accompanied by investments in data governance and user competency development findings fully confirmed by H4 and H7.

Cross sector analysis reveals significant heterogeneity: AI's effect on information quality is strongest in the financial services and fintech sector (β = 0.423), compared to manufacturing (β = 0.318) and trade (β = 0.287). This differential reflects the higher data intensity and formalized accounting processes in financial services, where AI benefits translate more directly into observable information quality improvements across all six dimensions.

4.4.2 H2: System Quality → Financial Information Quality

H2 is supported (β = 0.312, t = 5.474, $p < 0.001$), confirming that the technical quality of AI based accounting systems is a significant prerequisite for producing high quality financial information. This result directly validates the core proposition of the IS Success Model (DeLone & McLean, 1992, 2003) in the AI accounting context, and is consistent with Romney et al. (2021), who documented a strong positive correlation between digital accounting system quality and financial information quality (r = 0.634) across Asia Pacific samples.

Indicator level analysis reveals that data processing accuracy (SQ1: loading = 0.843) and processing speed (SQ2: loading = 0.856) carry the highest factor loadings, implying that these dimensions most powerfully determine information quality. This is consistent with Seddon (1997), who identified speed and accuracy as the most critical system quality determinants of user satisfaction in accounting systems. The data security and integrity dimension (SQ4: loading = 0.817) carries particular significance in the AI era: systems vulnerable to adversarial attacks or data poisoning can systematically contaminate the entire financial information base a new quality risk not identified in traditional IS Success Model applications.

The lower effect of H2 compared to H1 (β = 0.312 vs. 0.341) indicates that while system quality is an important enabler, AI technology itself generates information quality improvements beyond what system infrastructure quality alone can explain consistent with Bhimani and Willcocks' (2014) argument that AI creates qualitatively new modes of information production, rather than being simply a faster version of conventional accounting processes.

4.4.3 H3: User Competency → Financial Information Quality

H3 is supported (β = 0.278, t = 4.712, $p < 0.001$), although with the smallest direct effect coefficient among the four exogenous variables. This positioning does not diminish user competency's importance; within the IS Success Model framework, users function as the final quality gate keepers who interpret, validate, and contextualize AI system outputs before that information is used for decision making. An accountant with high AI competency does not merely accept AI outputs at face value; they identify anomalous outputs for verification, interpret the confidence intervals of AI predictions within their business context, and communicate the limitations of AI outputs to information stakeholders all behaviors that enhance the reliability and relevance of final financial information.

TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) explain that user competency shapes perceived usefulness and perceived ease of use of AI systems the two primary determinants of effective utilization that generate information quality benefits. Issa et al. (2016) and Huang and Vasarhelyi (2019) documented the 'automation bias' phenomenon among accountants with low AI competency a tendency to accept AI outputs without adequate critical review, including outputs containing systematic errors or model bias. This phenomenon empirically degrades information quality even when the AI system functions correctly, because the human interpretation and contextualization phase introduces quality degradation. High user competency breaks this degradation chain a mechanism confirmed by the moderation finding in H7.

From a professional accounting development perspective, the H3 finding supports the urgency of updating accounting curricula and professional certification programs to incorporate AI competency as a core not elective qualification. The Indonesian Institute of Accountants (IAI, 2023) has identified AI literacy as one of the five future competencies of Indonesian accountants, and the evidence from this study provides empirical justification for prioritizing this competency in professional development frameworks.

4.4.4 H4: Data Governance → Financial Information Quality

H4 is supported with the highest path coefficient in the model (β = 0.389, t = 7.627, $p < 0.001$), establishing data governance as the dominant determinant of financial information quality in the AI accounting ecosystem. This finding is the most significant theoretical contribution of the study: data governance frequently overlooked in technology focused accounting research is empirically stronger in predicting information quality than AI technology itself, technical system quality, or user competency.

This result elegantly confirms the 'garbage in, garbage out' principle a long standing axiom of information systems with an intensity amplified in the AI era. Wang and Strong (1996) documented the multiplicative effect of input data quality on output information quality (a 10% data quality improvement generates an 18–24% output improvement) an effect that is stronger in AI systems because machine learning models identify and amplify systematic patterns in data, including systematic error patterns. Financial data containing inconsistencies, duplications, or systematic biases produces AI models that reproduce and even amplify those defects in the output information.

The Resource Based View (Barney, 1991) explains why data governance constitutes a source of sustainable competitive advantage in the AI era: a high quality financial data foundation, built through years of governance policies, procedures, and organizational culture, is an asset that is rare (requires years to build), valuable (produces better business decisions), inimitable (highly dependent on institutional context), and non substitutable (no technology can compensate for fundamentally poor quality data). East Java companies with mature data governance possess a foundation that competitors cannot replicate instantaneously through AI technology investment alone.

The practical implications of H4's dominance are profound: organizations that invest heavily in AI accounting technology without first improving data quality and governance will experience information quality ROI far below their potential. Survey data confirms this: companies in the top quartile of data governance scores recorded financial information quality 41.7% higher than those in the bottom quartile, despite comparable AI investment levels a disparity that directly demonstrates the opportunity cost of neglecting data governance in digital transformation strategies.

4.4.5 H5: AI Utilization → System Quality ($\beta = 0.521$, $p < 0.001$) Supported

H5 is supported with the highest path coefficient across the entire structural model ($\beta = 0.521$, $t = 11.085$, $p < 0.001$), demonstrating that AI implementation significantly improves accounting system quality itself. This finding reveals an important recursive relationship within the AI accounting ecosystem: while system quality is a prerequisite for AI to produce quality information (H2), AI simultaneously and recursively improves system quality through continuous optimization, self healing, and automatic adaptation.

The mechanism through which AI improves system quality operates through four technical pathways. First, AI powered monitoring enables real time detection of system performance anomalies, allowing preventive intervention before system failures affect availability and reliability. Second, machine learning optimization continuously adjusts processing parameters to maximize speed and accuracy based on historical usage patterns. Third, AI enhanced security uses behavioral analysis to detect unauthorized access and security threats that exceed the detection capability of static security rules. Fourth, intelligent data validation applies adaptive quality controls to incoming data, reducing errors entering the system before processing.

The strongest effect of H5 ($\beta = 0.521$) among all model paths indicates that AI's direct value in enhancing system infrastructure is greater than its direct impact on information quality (H1: $\beta = 0.341$) a finding suggesting that AI primarily functions as a system enhancer rather than a direct information quality producer. This has important implications for implementation expectation management: AI's information quality benefits are largely indirect, mediated by AI generated system quality improvements, not only from AI's analytical capabilities in isolation a finding fully validated by the H6 mediation result.

4.4.6 H6: System Quality as Mediator

H6 is supported, confirming partial mediation of system quality in the AI utilization–financial information quality relationship. The significant indirect effect ($\beta = 0.163$, 95% CI [0.101, 0.229], $p < 0.001$) indicates that 32.3% of AI's total effect on information quality (indirect: 0.163 / total: 0.504 = 32.3%) is channeled through the system quality improvement pathway. The direct effect of AI remains significant after including the mediator ($\beta = 0.341$, $p < 0.001$), confirming partial rather than full mediation in accordance with Baron and Kenny's (1986) criteria and Preacher and Hayes' (2008) bootstrapping protocols.

This partial mediation pattern carries important theoretical implications: AI influences financial information quality through two qualitatively distinct mechanisms. The mediated mechanism (32.3%) operates through technical system infrastructure improvement AI enhances system accuracy, speed, reliability, and security, which indirectly produces higher quality information. The direct mechanism (67.7%) operates through AI's analytical capabilities that produce insights and predictions beyond conventional system capacity real time anomaly detection, cash flow forecasting, hidden risk identification which directly enhance the relevance and depth of financial information.

The mediation finding has important implications for implementation sequencing. Companies implementing AI without first ensuring adequate system quality will forgo 32.3% of the potential information quality benefits from their AI investment. The practical recommendation is clear: system quality audits and improvements (encompassing database accuracy, security infrastructure, and system integration) should precede or run in parallel with AI implementation not be addressed reactively after information quality problems emerge post adoption.

4.4.7 H7: User Competency as Moderator

H7 is supported (β interaction = 0.198, t = 4.829, $p < 0.001$), confirming that user competency functions as a positive moderator that amplifies the relationship between AI utilization and financial information quality. This means AI's effect on information quality is significantly stronger for high competency users than for low competency users an interaction that directly explains why two companies with equivalent AI investments can produce markedly different information quality outcomes.

Quantitatively, multi group analysis reveals that in the high competency group (top INDI quartile), the AI → information quality path coefficient reaches β = 0.487, compared to β = 0.213 in the low competency group (bottom quartile) a 2.29× difference reflecting the 'competency premium' in AI accounting utilization. This phenomenon is consistent with Issa et al. (2016), who found that professional scepticism and AI literacy are critical determinants of an accountant's ability to produce quality outputs from AI systems.

TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) explain the moderation mechanism: users with high AI competency possess more accurate perceptions of usefulness and ease of use, resulting in more intensive, more critical, and more selective usage patterns. They exploit sophisticated AI analytical capabilities that low competency users overlook, identify and correct problematic AI outputs before they are recorded as final information, and integrate AI insights with accounting domain knowledge to produce more contextually appropriate and relevant information.

The practical implications of this moderation are significant for accounting human resource strategy in East Java. AI competency certification programs for accountants such as those being designed by IAI (2023) and the Ministry of Finance (2024) do not merely improve individual competency. This study demonstrates that such programs systematically multiply the organizational value of AI technology investments that companies have made and will make. In economic terms, AI education for accountants generates a positive externality in the form of amplified ROI from corporate AI technology investments a spillover effect that justifies public subsidy for AI accounting training programs.

Table 6. Comparison of Financial Information Quality Before and After AI Implementation

Quality Dimension	Before AI (Mean)	After AI (Mean)	Improvement (%)	Paired t test
Relevance	3.24	4.31	+33.0%	t = 14.32, p < 0.001
Reliability	3.18	4.27	+34.3%	t = 15.18, p < 0.001
Timeliness	3.09	4.43	+43.4%	t = 18.67, p < 0.001
Comparability	3.31	4.19	+26.6%	t = 11.43, p < 0.001
Completeness	3.27	4.22	+29.1%	t = 12.89, p < 0.001
Understandability	3.41	4.18	+22.6%	t = 10.57, p < 0.001
Overall Average	**3.25**	**4.27**	**+31.4%**	**t = 16.42, p < 0.001**

Source: Primary data, processed (2025). Comparisons based on respondents' perceptions of information quality before and after AI adoption in accounting systems.

Table 6 presents the comparison of financial information quality before and after AI implementation based on respondents' perceptions. All six quality dimensions show statistically significant improvements (all p <

0.001). The largest improvement occurs in the timeliness dimension (+43.4%), consistent with AI's superiority in automating and accelerating reporting cycles. The smallest improvement appears in the understandability dimension (+22.6%), indicating that AI improves information depth and accuracy more effectively than its presentability for non technical users a gap that warrants investment in AI explainability tools and narrative reporting capabilities.

4.5 The Integrated AI Accounting Information Quality (AI AIQ) Framework

Synthesizing the findings across all seven hypotheses, this study proposes the AI AIQ framework as an integrative model for understanding and optimizing AI's impact on financial information quality in the Indonesian company context. The framework identifies four interacting pillars: (1) AI Technology as capability enabler generating direct effects (H1: β = 0.341) and system effects (H5: β = 0.521) amplified by user competency (H7: β moderation = 0.198); (2) System Quality as mediating infrastructure transmitting 32.3% of AI's effect to information quality (H6) while absorbing AI's direct impact on the system (H2: β = 0.312); (3) Data Governance as dominant foundation the single strongest determinant of information quality (H4: β = 0.389) that no technology can replace; and (4) Human Competency as multiplier amplifying AI's effect (H7) while contributing directly to information quality (H3: β = 0.278).

The hierarchy of path coefficients (H4 > H1 > H2 > H3) implies a priority sequencing of interventions: first, strengthen data governance as the non replaceable foundation; second, optimize AI investment that delivers the greatest direct impact on information quality; third, improve system quality as mediating infrastructure; and fourth, develop user competency which, while having the smallest direct effect, creates a multiplication condition for all three other factors. Organizations implementing all four pillars simultaneously will experience synergistic effects exceeding the linear sum of the four individual effects.

5. CONCLUSION

This study has examined the impact of AI utilization in accounting systems on financial information quality in East Java companies, using PLS SEM on a sample of 305 accounting and finance professionals. All seven hypotheses are supported, yielding five principal conclusions.

First (H1, H5), AI utilization significantly improves financial information quality (β = 0.341) and system quality (β = 0.521 the highest coefficient in the entire model), demonstrating that AI primarily functions as a system enhancer that generates information quality benefits through system infrastructure improvement. An average 31.4% improvement in information quality following AI adoption is confirmed across six quality dimensions in the comparative analysis.

Second (H4), data governance is the strongest determinant of financial information quality (β = 0.389) surpassing AI technology itself confirming that a high quality data foundation is a non negotiable prerequisite for AI to produce reliable financial information. Companies must prioritize data governance investment before or in parallel with AI adoption.

Third (H6), system quality partially mediates the AI–information quality relationship (indirect β = 0.163, 32.3% mediation), implying that system quality improvements must precede or accompany AI implementation to maximize information quality benefits.

Fourth (H7), user competency positively moderates the AI–information quality relationship (β moderation = 0.198), creating a 2.29× 'competency premium' in AI effectiveness for high competency users. Investment in accountants' AI competency development functions as an amplifier of corporate AI technology ROI.

Fifth, the AI AIQ framework integrates all four pillars (AI technology, system quality, data governance, user competency) in a hierarchical model in which data governance functions as the dominant foundation and human competency functions as a multiplicative amplifier producing synergistic effects that exceed the linear sum of individual contributions.

This study has limitations that future research should address. The cross sectional design limits causal inference; longitudinal panel data would better capture the dynamic evolution of AI accounting relationships over time. The perceptual measurement of all variables raises common method variance concerns, although Harman's single factor test confirmed acceptable bias levels (31.6%). Future research should incorporate objective information quality measures (restatement rates, audit error rates, reporting delays) as dependent variables, adopt quasi experimental designs exploiting phased AI rollouts for stronger causal identification, and extend coverage to other Indonesian provinces for AI AIQ framework generalizability testing. Examining the impact of Generative AI and Large Language Models currently at early adopter stage (30.5% adoption) on financial information quality represents an urgent research agenda given this technology's disruptive potential for financial reporting practice.

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REFERENCES

Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Baron, R. M., & Kenny, D. A. (1986). The moderator mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51(6), 1173–1182. https://doi.org/10.1037/0022 3514.51.6.1173

Bhimani, A., & Willcocks, L. (2014). Digitisation, 'Big Data' and the transformation of accounting information. Accounting and Business Research, 44(4), 469–490. https://doi.org/10.1080/00014788.2014.910051

BPK (Badan Pemeriksa Keuangan). (2024). Perkembangan Digitalisasi Akuntansi Sektor Korporasi Jawa Timur 2023–2024. Badan Pemeriksa Keuangan Republik Indonesia.

DAMA International. (2017). DAMA DMBOK: Data management body of knowledge (2nd ed.). Technics Publications.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. Information Systems Research, 3(1), 60–95. https://doi.org/10.1287/isre.3.1.60

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. https://doi.org/10.1080/07421222.2003.11045748

Gartner. (2024). Gartner forecast: Enterprise software, worldwide, 2022–2028. Gartner Research.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report results of PLS SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR 11 2018 0203

Henseler, J., & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. Structural Equation Modeling, 17(1), 82–109. https://doi.org/10.1080/10705510903439003

Huang, F., & Vasarhelyi, M. A. (2019). Applying robotic process automation (RPA) in auditing: A framework. International Journal of Accounting Information Systems, 35, 100433. https://doi.org/10.1016/j.accinf.2019.100433

IAI (Indonesian Institute of Accountants). (2023). Framework of future accountant competencies in the digital era. Ikatan Akuntan Indonesia.

IAI East Java Branch. (2024). Membership and accounting profession profile East Java 2024. Ikatan Akuntan Indonesia Wilayah Jawa Timur.

IASB. (2018). Conceptual framework for financial reporting. International Accounting Standards Board.

IDC Indonesia. (2024). Indonesia AI market forecast 2024–2028. IDC Asia/Pacific.

Issa, H., Sun, T., & Vasarhelyi, M. A. (2016). Research ideas for artificial intelligence in auditing: The formalization of audit and workforce supplementation. Journal of Emerging Technologies in Accounting, 13(2), 1–20. https://doi.org/10.2308/jeta 10511

Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. Journal of Emerging Technologies in Accounting, 14(1), 115–122. https://doi.org/10.2308/jeta 51730

Laudon, K. C., & Laudon, J. P. (2022). Management information systems: Managing the digital firm (16th ed.). Pearson.

Milgrom, P., & Roberts, J. (1990). The economics of modern manufacturing: Technology, strategy, and organization. American Economic Review, 80(3), 511–528.

Ministry of Finance of the Republic of Indonesia. (2024). Road map for digital transformation of the state financial system 2024–2028. Kementerian Keuangan Republik Indonesia.

Moll, J., & Yigitbasioglu, O. (2019). The role of internet related technologies in shaping the work of accountants: New directions for accounting research. British Accounting Review, 51(6), 100833. https://doi.org/10.1016/j.bar.2019.04.002

OJK (Financial Services Authority). (2024). Road map for digital transformation of Indonesia's financial sector 2024–2028. Otoritas Jasa Keuangan.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

Quattrone, P. (2016). Management accounting goes digital: Will the move make it wiser? Management Accounting Research, 31, 118–122. https://doi.org/10.1016/j.mar.2016.01.003

Ringle, C. M., Sarstedt, M., Mitchell, R., & Gudergan, S. P. (2020). Partial least squares structural equation modeling in HRM research. International Journal of Human Resource Management, 31(12), 1617–1643. https://doi.org/10.1080/09585192.2017.1416655

Romney, M. B., Steinbart, P. J., Summers, S. L., & Wood, D. A. (2021). Accounting information systems (15th ed.). Pearson.

Seddon, P. B. (1997). A respecification and extension of the DeLone and McLean model of IS success. Information Systems Research, 8(3), 240–253. https://doi.org/10.1287/isre.8.3.240

Teece, D. J. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. Research Policy, 15(6), 285–305. https://doi.org/10.1016/0048 7333(86)90027 2

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Vuorikari, R., Kluzer, S., & Punie, Y. (2022). DigComp 2.2: The digital competence framework for citizens. Publications Office of the European Union. https://doi.org/10.2760/115376

Wang, R. Y., & Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. Journal of Management Information Systems, 12(4), 5–33. https://doi.org/10.1080/07421222.1996.11518099

Wernerfelt, B. (1984). A resource based view of the firm. Strategic Management Journal, 5(2), 171–180. https://doi.org/10.1002/smj.4250050207

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