The Effect of Artificial Intelligence Intensity on Audit Quality: Evidence from Accounting Interns in Indonesia

Alyarov Nurbek[1*], Aristanti Widyaningsih[2], Ikin Solikin[3], Inomjon Qudratov[4]
[1,4]Program Studi Akuntansi, Universitas Pendidikan Indonesia
[2,3]Program Studi Magister Ilmu Akuntansi, Universitas Pendidikan Indonesia
nurbekaliorov679@gmail.com*

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Abstrak *: This study examines the effect of artificial intelligence (AI) intensity on audit quality among accounting interns at registered public accounting firms (KAP) in Indonesia. The accelerating deployment of AI technologies — including machine learning, robotic process automation (RPA), data analytics platforms, and anomaly-detection algorithms — has fundamentally restructured audit practice; yet the individual-level implications for early-career auditors operating within AI-augmented environments remain empirically underexplored. Anchored in the Technology Acceptance Model (TAM) and Agency Theory, this study adopts a quantitative, cross-sectional design, collecting primary data from 31 purposively sampled accounting interns through a validated five-point Likert-scale questionnaire. Data were analysed using simple ordinary least squares (OLS) regression in SPSS. Descriptive statistics reveal a moderate level of AI intensity ($M = 3.23$, $SD = 0.71$) and a moderately high level of perceived audit quality ($M = 3.65$, $SD = 0.69$) within the sample. The OLS regression model is statistically significant ($F = 9.636$, $p = 0.004$, $R^2 = 0.249$), and the AI intensity coefficient is positive and significant ($B = 0.485$, $\beta = 0.499$, $t = 3.104$, $p = 0.004$), indicating that each unit increase in AI intensity is associated with a 0.485-unit improvement in perceived audit quality. These results confirm H1 and provide micro-level quantitative evidence that higher AI integration enhances audit outcomes among interns. Concurrently, the study highlights the latent risk of overreliance: uncritical acceptance of AI-generated outputs may erode professional scepticism — a competency that remains irreplaceable in high-stakes financial reporting verification.*

Kata Kunci *: Artificial Intelligence Intensity; Audit Quality; Accounting Interns; Technology Acceptance Model; Indonesia*

INTRODUCTION

The integration of artificial intelligence (AI) into professional accounting and auditing represents one of the most consequential technological inflection points in the history of the profession. Auditing a discipline whose epistemic foundations rest on human scepticism, analytical reasoning, and experiential judgement is undergoing a fundamental paradigm shift toward data-driven, algorithmically enhanced workflows (Fedyk et al., 2022). Machine learning classifiers, natural language processing (NLP) engines, robotic process automation (RPA), and predictive risk-scoring models are now progressively embedded within audit engagement platforms, enabling auditors to process entire transaction populations, detect statistical anomalies imperceptible to manual review, and generate real-time risk stratifications that were previously unattainable at scale (Cao et al., 2015; Vale, 2023).

Yet despite the compelling theoretical efficiency gains AI promises, empirical evidence on its realized impact on audit quality remains decidedly mixed and context-dependent (Appelbaum et al., 2017). Laboratory experiments reveal that auditors augmented by AI-generated outputs do not uniformly achieve superior judgement outcomes; in several instances, AI assistance has been shown to introduce anchoring effects, suppress hypothesis-generation, and attenuate professional scepticism particularly among auditors whose experiential base is insufficient to critically calibrate automated recommendations (Brown-Liburd et al., 2015; MacKenzie et al., 2024).

Accounting interns constitute a strategically important yet empirically underexplored population in this context. They occupy a liminal position between academic preparation and professional practice, absorbing operational audit norms including the appropriate degree of reliance on AI tools during their most formative professional socialisation phase. The habits of technology reliance (or scepticism) formed during internship are likely to persist and intensify across subsequent career stages (Earley, 2015).

This study conceptualises AI intensity as the degree and frequency with which AI-based tools are integrated into the audit workflow encompassing both the breadth of AI deployment across audit phases and the depth of individual reliance on AI-generated outputs for judgement and decision-making (Vale, 2023). Audit quality, the dependent variable, is operationalised following DeAngelo's (1981) canonical formulation as the joint probability that material misstatements will be both detected and reported, supplemented by cognitive quality dimensions including professional scepticism, evidence reliability, and judgement accuracy (Brown-Liburd et al., 2015).

The theoretical relationship between these constructs is grounded in two complementary frameworks. The Technology Acceptance Model (TAM) predicts that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) jointly determine users' behavioural intention to utilise and rely upon technological systems (Davis, 1989, as cited in Fedyk et al., 2022). Agency Theory further supports this prediction: AI intensity shifts audit verification from probabilistic sampling toward comprehensive population testing, thereby reducing information asymmetry between auditor and management (Fedyk et al., 2022).

Using primary data from 31 accounting interns at Indonesian KAPs and a simple OLS regression framework, this study pursues three specific objectives: (1) to empirically test whether AI intensity has a positive and significant effect on audit quality among accounting interns; (2) to analyse the magnitude and direction of that effect, including its theoretical mediation through TAM and Agency Theory pathways; and (3) to derive actionable implications for audit firms, accounting educators, and professional regulators in Indonesia regarding the optimisation of AI adoption while preserving the cognitive competencies that underpin lasting audit quality.

RESEARCH METHOD

Research Design and Approach

This study employs a quantitative, cross-sectional research design with a causal-explanatory approach. A quantitative design is appropriate because the research objective testing a directional causal hypothesis between operationally defined, measurable constructs requires the systematic collection of numerical data subject to inferential statistical analysis (Appelbaum et al., 2017). The cross-sectional time-horizon reflects practical constraints on intern accessibility and is consistent with existing single-period studies examining individual auditor technology adoption (Earley, 2015).

Population, Sample and Sampling Procedure

The target population comprises accounting students currently enrolled in, or who have recently completed, structured internship programmes at registered public accounting firms (Kantor Akuntan Publik, KAP) in Indonesia. Respondents were selected using purposive sampling (non-probability). The two inclusion criteria were: (1) the respondent must currently be, or must within the preceding twelve months have been, employed as an intern at a KAP registered with the Indonesian Institute of Certified Public Accountants (IAPI); and (2) the respondent must have been directly exposed to, or personally operated, at least one AI-enabled or automated audit tool during their internship engagement.

Data collection was conducted through a structured electronic questionnaire distributed via the researchers' professional audit networks and LinkedIn communities between January and March 2025. A total of 31 valid, complete responses were returned. It is acknowledged that this sample size falls below the conventional minimum of 50 observations recommended for regression studies, which constitutes a material limitation on statistical power and generalisability.

Research Instrument

Primary data were collected using a structured, self-administered electronic questionnaire comprising eight Likert-scale items distributed across the two constructs of interest. Response options were coded on a five-point scale (1 = Strongly Disagree; 5 = Strongly Agree). Table 1 presents the full item battery.

Table 1. Research Instrument: Variable Indicators and Item Battery

No.	Variable	Questionnaire Item	Scale
1	*AI Intensity (Independent Variable, X)*	X1: My audit firm frequently deploys AI-based tools to analyse large volumes of financial transaction data.	Ordinal (Likert 1–5)
		X2: I regularly rely on AI tools to identify unusual patterns or anomalies embedded in transaction populations.	

No.	Variable	Questionnaire Item	Scale
		X3: The use of AI substantially reduces manual testing burdens and improves the efficiency of my audit work.	
		X4: AI-based tools are systematically integrated across multiple stages of our audit engagement process.	
2	*Audit Quality (Dependent Variable, Y)*	Y1: The use of AI tools materially improves the accuracy and completeness of audit findings I produce.	Ordinal (Likert 1–5)
		Y2: AI-assisted procedures enhance the overall reliability and defensibility of my audit conclusions.	
		Y3: AI integration improves the timeliness and thoroughness of audit completion without sacrificing quality.	
		Y4: I consciously maintain professional scepticism and critically evaluate AI-generated outputs rather than accepting them without independent verification.	

Note: Variable scores are computed as arithmetic means across their respective four items. Scale classification corrected from 'Nominal' to 'Ordinal (Likert 1–5)' consistent with measurement theory conventions (Appelbaum et al., 2017).

Data Analysis Procedure

Data were processed and analysed in SPSS (version 26) following a sequential five-stage procedure: Stage 1 Descriptive analysis; Stage 2 Validity testing via Pearson bivariate correlation ($r > 0.30$ threshold); Stage 3 Reliability assessment via Cronbach's Alpha ($\alpha \geq 0.70$); Stage 4 Classical assumption testing including Kolmogorov-Smirnov normality test, Variance Inflation Factor (VIF < 10) for multicollinearity, and Glejser test for heteroscedasticity ($p > 0.05$); Stage 5 Simple OLS regression analysis, constituting the primary test of H1.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 2 presents descriptive statistics for AI Intensity (X) and Audit Quality (Y) based on the full sample of N = 31 valid observations.

Table 2. Descriptive Statistics (N = 31)

Variable	N	Minimum	Maximum	Mean	Std. Deviation
AI Intensity (X)	31	1.50	4.50	3.2339	0.71279
Audit Quality (Y)*	31	1.25	5.00	3.6452	0.69154
Valid N (listwise)	31				

**Labelled 'Auditor_Performance' in the SPSS output file; harmonised to 'Audit Quality' in alignment with the theoretical construct. Source: Primary data, processed with SPSS v.26.*

The descriptive results warrant careful substantive interpretation. AI Intensity records a mean of 3.23 (SD = 0.71) on a five-point scale, situating the sample at a moderate level of AI integration. This score representing 64.7% of the scale maximum indicates that AI tools are meaningfully present in the intern-level audit workflow at the sampled KAPs, but have not yet achieved the deep, pervasive integration characteristic of fully digitised engagement platforms. The standard deviation of 0.71 indicates moderate cross-respondent variability, confirmed by the observed range of 1.50 to 4.50. This heterogeneity likely reflects differences in KAP size, technology investment levels, and engagement type across the sample, consistent with the uneven AI adoption trajectory documented in the Indonesian professional services sector (Vale, 2023). Notably, no respondent recorded the scale minimum of 1.00, suggesting that at least minimal AI exposure is now a baseline feature of internship assignments at registered KAPs.

Audit Quality records a higher mean of 3.65 (SD = 0.69), indicating that interns in the sample perceive their audit outputs as moderately to substantially quality-compliant. The wider observed range (1.25 to 5.00) compared to AI Intensity reflects greater heterogeneity in quality self-assessments, potentially attributable to variation in supervisor rigour, client complexity, and the inherently subjective nature of intern quality self-evaluation. The positive differential between the Audit Quality mean (3.65) and the AI Intensity mean (3.23) is consistent with the baseline-quality effect anticipated by Agency Theory: even at moderate AI adoption levels, the quality floor is elevated above the AI intensity floor, suggesting that conventional audit procedures and professional training independently sustain a baseline quality level independent of AI intensity (DeAngelo, 1981). Both distributions approximate symmetry around their respective means, supporting the normality of residuals assumption required for valid OLS inference.

Model Summary

Table 3 presents the model summary statistics for the simple OLS regression of Audit Quality on AI Intensity.

Table 3. OLS Regression Model Summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	0.499[a]	0.249	0.224	0.60937

a. Predictors: (Constant), AI Intensity. Dependent Variable: Audit Quality.

The Pearson correlation coefficient R = 0.499 indicates a moderate positive linear association between AI Intensity and Audit Quality, statistically and substantively significant at the conventional threshold. This correlation magnitude exactly at the conventional boundary between 'moderate' and 'strong' effect sizes per Cohen's (1988) benchmarks implies that AI intensity is a meaningful, though not dominant, determinant of perceived audit quality in this sample. The coefficient of determination R^2 = 0.249 indicates that AI Intensity accounts for approximately 24.9% of the total variance in Audit Quality. While this explanatory proportion is substantively important in a bivariate model with a single predictor, it simultaneously and importantly reveals that 75.1% of audit quality variance is attributable to factors outside the model's specification including, most plausibly, individual auditor competence, the quality of engagement supervision, organisational audit culture, time pressure conditions, and client complexity. The Adjusted R^2 of 0.224, which penalises R^2 for the number of predictors relative to sample size (here n = 31, k = 1), remains positive and close to the unadjusted value, confirming that the explanatory power of the model is genuine and not an artefact of overfitting. The standard error of the estimate (SEE = 0.609) quantifies the average magnitude of prediction error in Audit Quality units: on a five-point scale, this corresponds to approximately 12.2% of the scale range, which is acceptable for a parsimonious single-predictor model.

ANOVA — Overall Model Significance

Table 4 presents the ANOVA decomposition of the total variance in Audit Quality.

Table 4. Analysis of Variance (ANOVA[a])

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	3.578	1	3.578	9.636	0.004[b]
Residual	10.769	29	0.371		
Total	14.347	30			

a. Dependent Variable: Audit Quality. b. Predictors: (Constant), AI Intensity.

ANOVA F-statistic of 9.636 with 1 numerator and 29 denominator degrees of freedom yields a p-value of 0.004, decisively rejecting the null hypothesis that the regression slope is zero at both the $\alpha = 0.05$ and $\alpha = 0.01$ significance levels. This confirms that the observed linear relationship between AI Intensity and Audit Quality is not attributable to sampling error. The variance decomposition further illuminates the model's fit structure: the Regression Sum of Squares of 3.578 represents the portion of total Audit Quality variance (14.347) explained by AI Intensity a ratio of 24.9%, arithmetically consistent with $R^2 = 0.249$. The Residual Mean Square of 0.371 provides the error variance estimate underlying the regression's standard error computations. Together, these ANOVA results satisfy the minimum inferential conditions required to proceed with coefficient-level interpretation.

Coefficient Analysis and Hypothesis Testing

Table 5 presents the unstandardised and standardised regression coefficients for the simple OLS model, constituting the primary empirical test of H1.

Table 5. Regression Coefficients (Dependent Variable: Audit Quality)[a]

Model	B (Unstandardised)	Std. Error	β (Standardised)	t	Sig.
(Constant)	2.078	0.516	—	4.024	0.000
AI Intensity	0.485	0.156	0.499	3.104	0.004

a. Dependent Variable: Audit Quality. Source: Primary data, processed with SPSS v.26.

$$\hat{Y}\ (\text{Audit Quality}) = 2.078 + 0.485 \cdot X\ (\text{AI Intensity})$$

The intercept ($B_0 = 2.078$; SE = 0.516; t = 4.024; p = 0.000) is highly statistically significant, indicating that even in the hypothetical absence of AI tool use when AI Intensity = 0 the expected Audit Quality score is 2.078 on the five-point scale. This non-trivial baseline reflects the independent quality contribution of conventional audit procedures, professional training programmes, regulatory standards, and supervisor oversight all of which sustain a foundational audit quality floor that exists independently of AI augmentation. This finding aligns with DeAngelo's (1981) observation that audit quality is structurally embedded in the institutional and professional context of the engagement, not solely in the technological tools employed.

The slope coefficient for AI Intensity (B_1 = 0.485; SE = 0.156; ß = 0.499; t = 3.104; p = 0.004) is positive, statistically significant at α = 0.01, and of substantively meaningful magnitude. The unstandardised coefficient indicates that each one-unit increase in AI Intensity on the five-point Likert scale is associated with a predicted 0.485-unit increase in Audit Quality, holding all else constant. The standardised coefficient ß = 0.499 indicates that a one-standard-deviation increase in AI Intensity (0.713 units) is associated with a 0.499-standard-deviation increase in Audit Quality (0.345 units), confirming a moderate-to-strong effect size consistent with Cohen's (1988) benchmarks for social science research. The t-statistic of 3.104 is well above the critical value of 2.045 for α = 0.05, two-tailed, with df = 29. These results collectively confirm that H1 = AI intensity has a positive and significant effect on audit quality among accounting interns is empirically supported at the conventional significance level.

Discussion

The empirical support for H1 (ß = 0.499, p = 0.004) demands a theoretically grounded explanation of the mechanisms through which AI intensity translates into quality improvements in the audit internship context. The following discussion constructs a multi-layered interpretation that progresses from theoretical mechanism, through empirical corroboration, to boundary conditions and critical limitations.

From a TAM perspective, the positive AI intensity–audit quality relationship is expected because interns who perceive AI tools as useful (PU) and accessible (PEOU) will deploy them more intensively covering larger transaction samples, flagging a broader array of anomalies, and generating more complete evidentiary documentation within a given engagement timeline. This expanded evidence base directly improves the probability of misstatement detection, the definitional core of audit quality per DeAngelo (1981). The moderate mean AI intensity score of 3.23 in this sample suggests that the sample is operating in the positive, upward-sloping segment of the AI intensity–quality function a region where each additional unit of AI deployment produces net quality gains because the detection benefits of AI outweigh the cognitive disengagement costs of partial automation. Fedyk et al. (2022) document precisely this pattern in their large-sample archival analysis: AI-assisted engagements exhibit superior material misstatement detection rates relative to matched non-AI engagements, with the performance gap widening as AI integration depth increases up to an unspecified saturation threshold.

From an Agency Theory perspective, AI intensity enhances the intern's effective monitoring capability by shifting evidence-gathering from probabilistic sampling with its associated sampling risk toward population-based analytical procedures. This methodological transition has a direct, structural effect on audit quality: when AI tools process 100% of a transaction population rather than a selected sample, the probability of failing to detect a material misstatement embedded in the non-sampled portion drops to zero eliminating one of the most consequential sources of Type II error (false negative) in conventional auditing (Cao et al., 2015). For interns, whose limited experience might otherwise necessitate conservative sampling strategies, AI-enabled population testing provides a quality equaliser that partially compensates for experiential deficits. The

Agency Theory prediction that AI intensity is positively associated with audit quality is thus confirmed not only statistically but also through the theoretical mechanism it describes.

The moderate explanatory power of the model ($R^2 = 0.249$) while statistically significant simultaneously warrants a candid acknowledgement of the substantial audit quality variance that AI Intensity alone does not explain (75.1%). This residual variance is theoretically attributable to a constellation of factors absent from the present model: individual auditor cognitive ability and professional scepticism disposition (Brown-Liburd et al., 2015); supervisor quality and the richness of real-time feedback provided during engagements (Earley, 2015); organisational audit culture and the degree to which KAP leadership actively promotes critical interrogation of AI outputs; client complexity and inherent risk profile; and time pressure and workload intensity, both of which are known to attenuate audit judgement quality independent of AI adoption (MacKenzie et al., 2024). Future research incorporating these variables within a multiple regression or structural equation modelling framework would substantially improve explanatory coverage and yield more precise estimates of AI intensity's unique contribution.

Perhaps the most theoretically significant finding to emerge from the discussion is the critical boundary condition implied by the study's results: while AI intensity enhances audit quality at the moderate levels observed in this sample, the positive relationship is not infinite or unconditional. Brown-Liburd et al. (2015) demonstrate experimentally that as AI output volume and complexity increase, auditors' capacity for independent critical interrogation diminishes a phenomenon they term 'automation complacency.' MacKenzie et al. (2024) find that this complacency effect is strongest in conditions of high task complexity and high AI output confidence, precisely the conditions in which automation failures are most consequential. For accounting interns, who lack the experiential baselines needed to identify plausible AI failure modes, this risk is structurally elevated. Item Y4 in the study's instrument 'I consciously maintain professional scepticism and critically evaluate AI-generated outputs rather than accepting them without independent verification' directly captures this behavioural disposition, and its inclusion in the Audit Quality construct reflects the study's conceptualisation of quality as encompassing not merely technical accuracy but also the cognitive engagement underlying that accuracy. This conceptualisation is consistent with the International Standards on Auditing (ISA 200), which identifies professional scepticism as an attitudinal requirement rather than a procedural one irreducible to any automated workflow.

Compared with prior studies that examine AI and audit quality at the firm level or using experienced auditor samples (Fedyk et al., 2022; Vale, 2023), this study's contribution lies in its micro-level, individual-intern perspective. This unit of analysis is arguably more important for long-term profession-wide quality outcomes than firm-level aggregate measures: the norms, habits, and cognitive frameworks that interns develop during their initial AI-augmented engagements are likely to persist, calcify, and propagate as they advance to senior and managerial audit roles (Earley, 2015). A generation of auditors whose professional identity was formed in AI-intensive environments but without deliberate scepticism training represents a qualitatively different systemic risk than current aggregate quality metrics would suggest — a risk that the profession's governance infrastructure has not yet fully operationalised.

CONCLUSION

This study examined the effect of artificial intelligence intensity on audit quality among 31 accounting interns at registered public accounting firms (KAP) in Indonesia. The principal empirical finding is unambiguous: AI intensity exerts a positive and statistically significant effect on audit quality ($B = 0.485$, $\beta = 0.499$, $t = 3.104$, $p = 0.004$, $R^2 = 0.249$, $F = 9.636$, $p = 0.004$). H1 is supported. The descriptive statistics moderate AI intensity ($M = 3.23$, $SD = 0.71$) and moderately high audit quality ($M = 3.65$, $SD = 0.69$) suggest that the Indonesian KAP sector is in a transitional phase of AI adoption. This study acknowledges four material limitations. First, the sample of $n = 31$ is below the conventional minimum recommended for regression studies, limiting statistical power and constraining generalisability. Second, purposive sampling restricts external validity. Third, both constructs are measured through self-report Likert instruments, susceptible to social desirability bias and common method variance. Fourth, the cross-sectional design precludes causal inference.

Theoretically, this study contributes micro-level empirical validation of TAM and Agency Theory predictions in the underexplored context of early-career auditors in a developing ASEAN economy. Practically, the findings carry implications for three stakeholder groups: KAP management (invest in AI infrastructure paired with structured training to critically evaluate AI outputs); accounting educators (incorporate AI ethics and automation-scepticism modules); and professional regulators (develop AI-specific competency standards and quality review protocols evaluating human oversight). Three research directions are recommended. First, longitudinal cohort studies should track how AI exposure during internship influences professional scepticism development over a three-to-five-year horizon. Second, researchers should employ larger, probability-sampled national datasets incorporating firm-level moderators within a multilevel modelling framework. Third, experimental designs using objective audit accuracy measures actual error detection rates, false positive rates rather than perceptual self-assessments would provide causally stronger evidence.

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