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EFFECT OF E-AUDIT, AI, AND BIG DATA ANALYTICS ON AUDIT QUALITY: EMPIRICAL STUDY AT BPK RI

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Abstract: This study investigates the empirical effects of e-audit, Artificial Intelligence (AI)-based audit technology, and Big Data Analytics (BDA) on financial audit quality within the Audit Board of the Republic of Indonesia (BPK RI). Primary data were collected through structured questionnaires distributed to BPK RI auditors. Respondents were selected using a simple random sampling based on the Slovin formula with a ten-percent margin of error. The collected data were analyzed quantitatively using IBM SPSS version 25, including descriptive statistics, data quality testing, classical assumption testing, multiple linear regression, and hypothesis testing. The findings indicate that e-audit and Big Data Analytics (BDA) have a positive and statistically significant effect on audit quality. In contrast, Artificial Intelligence (AI)-based audit technology does not have a statistically significant influence on audit quality.

Keywords: *e-Audit, Artificial Intelligence (AI)-Based Audit Technology, Big Data Analytics, Audit Quality*

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1. Introduction

Government financial reports in Indonesia constitute a fundamental instrument for promoting public accountability and fiscal transparency. The quality of such reports reflects the government's commitment to managing state resources responsibly and in conformity with prevailing regulatory frameworks (Government Regulation No. 71 of 2010). However, a significant paradox persists in Indonesia's public sector auditing environment. Despite a consistent rise in the number of government entities awarded an unqualified audit opinion (WTP), corruption cases implicating those same entities have persisted without abatement. This disconnect suggests that a favorable audit opinion does not inherently guarantee sound financial governance. Data from Indonesia Corruption Watch (2024) recorded 364 corruption cases throughout that year, with the overwhelming majority involving the misappropriation of public funds. Compounding this concern, BPK RI (2024) reported that between 2017 and 2024, a total of 29 investigative audit reports identified potential state losses amounting to IDR 32.90 trillion, while 437 state loss calculation reports totaling IDR 61.19 trillion were forwarded to law enforcement authorities. Collectively, these figures expose a profound gap between audit opinions rendered and the actual state of public financial accountability, underscoring the imperative to fundamentally strengthen audit quality.

The urgency of this challenge is further amplified by the exponential growth of financial data in the digital era. The International Data Corporation (IDC) projects that global data volumes will surge from 33 zettabytes in 2018 to approximately 175 zettabytes by 2025, with roughly 80% comprising unstructured data. Under these conditions, conventional audit methodologies, including sample-based examination and manual document review, are demonstrably inadequate for achieving comprehensive and accurate audit coverage. In response to these challenges, BPK RI has adopted several digital audit technologies. First, e-audit integrates the e-BPK and e-auditee systems, allowing auditors to access financial data in real time (Akmalia & Ariani, 2022; Hakim et al., 2023). Second, Artificial Intelligence (AI)-based audit technology assists auditors in detecting anomalies, identifying irregular transaction patterns, and recognizing potential fraud more effectively (Al-Ateeq et al., 2022; Huang & Liu, 2024). Third, Big Data Analytics (BDA), implemented through the BIDICS platform, enables auditors to collect, process, and analyze large-scale financial data, supporting more comprehensive and evidence-based audit examinations (BPK RI, 2021; Saud et al., 2025).

Despite the increasing adoption of these technologies, several research gaps remain. Previous studies on e-audit at BPK RI were limited to specific work units and relatively small samples, thereby restricting the generalizability of their findings (Hakim et al., 2023). In addition, empirical research examining the effect of Artificial Intelligence (AI)-based audit technology on audit quality within BPK RI remains scarce, as prior studies have primarily focused on private-sector or general auditing contexts (Adeoye et al., 2023; Huang & Liu, 2024). Similarly, studies on Big Data Analytics (BDA) have largely been conducted in broader public sector settings rather than specifically within BPK RI (Putra et al., 2023; Saud et al., 2025). Furthermore, no prior study has comprehensively examined the simultaneous effect of e-audit, Artificial Intelligence (AI)-based audit technology, and Big Data Analytics (BDA) on audit quality within BPK RI. Therefore, this study aims to analyze the effect of these three digital audit technologies on financial audit quality at the Audit Board of the Republic of Indonesia.

2. Literature Review

Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT)

The Technology Acceptance Model (TAM), introduced by Davis (1989), provides a foundational framework for explaining individual decisions to adopt information technology, centered on two core constructs: perceived usefulness, the degree to which technology is believed to enhance job performance; perceived ease of use, the degree to which its operation is perceived to require minimal effort. Building upon TAM, Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), identifies four principal determinants of technology acceptance: performance expectancy, effort expectancy, social influence, and facilitating conditions, all of which have been empirically validated as significant predictors of technology adoption in professional settings, including auditing (Saud et al., 2025; Sofyani et al., 2025).

In the context of this study, both frameworks provide the theoretical basis for understanding how BPK RI auditors evaluate and adopt e-audit, Artificial Intelligence (AI)-based audit technology, and Big Data Analytics (BDA). TAM explains the role of perceived usefulness and ease of use in driving individual adoption decisions, while UTAUT extends this by incorporating organizational support, peer influence, and institutional infrastructure, factors particularly relevant within a large, hierarchically structured government audit institution. When auditors perceive these technologies as beneficial, manageable, socially endorsed, and institutionally supported, meaningful adoption is more likely to occur, ultimately contributing to improvements in financial audit quality.

Conceptual Framework of Research

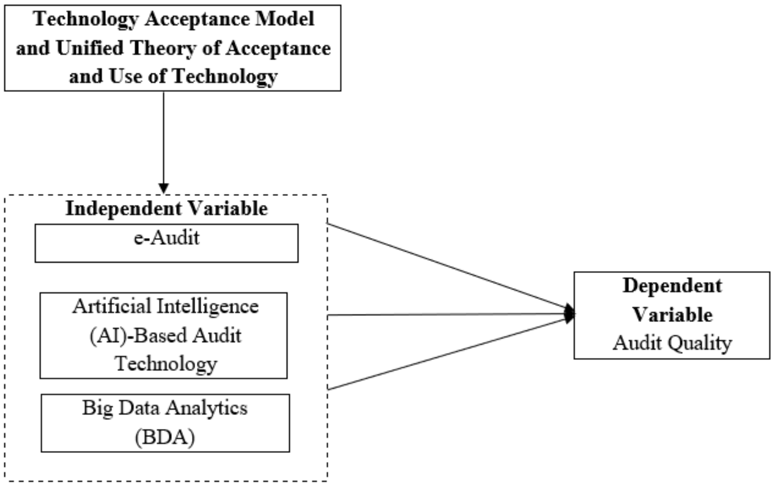
TAM and UTAUT serve as the theoretical foundations for understanding how BPK RI auditors accept and utilize digital audit technologies to enhance financial audit quality. The adoption of e-audit, Artificial Intelligence (AI)-based audit technology, and Big Data Analytics (BDA) has become increasingly critical as a strategic response to the growing volume and complexity of government financial data in the digital era.

E-audit is implemented through a link-and-match integration between the e-BPK system and the e-auditee system, connecting the BPK server directly to auditee servers and enabling auditors to access and analyze financial data in real time, unrestricted by geographical limitations (Akmalia & Ariani, 2022; Hakim et al., 2023). This technology offers considerable advantages, including greater efficiency in audit evidence collection, accelerated risk identification, and expanded audit coverage. Consistent with TAM, auditors who perceive e-audit as useful and easy to operate are more likely to adopt it effectively, thereby contributing positively to audit quality.

Artificial Intelligence (AI)-based audit technology further strengthens the audit process by enhancing auditors' capacity to automatically detect transactional anomalies, identify irregularities, and uncover potential fraud that conventional techniques are ill-equipped to reveal (Al-Ateeq et al., 2022; Huang & Liu, 2024). Artificial Intelligence (AI)-based audit technology encompasses various analytical approaches, including Machine Learning (ML), Natural Language Processing (NLP), and Neural Networks, each enabling more accurate and evidence-based audit examinations. From the UTAUT perspective, the adoption of Artificial Intelligence (AI)-based audit technology is shaped by auditors' performance expectancy, effort expectancy, social influence, and the availability of adequate organizational infrastructure and training.

In addition, Big Data Analytics (BDA) plays an integral role in supporting large-scale, data-driven auditing. At BPK RI, Big Data Analytics (BDA) is operationalized through the BIDICS platform, developed under the Decree of the Secretary-General of BPK No. 206/K/X-XIII.2/8/2021, which enables auditors to collect, process, and analyze vast volumes of financial data across ten specialized analytical clusters (BPK RI, 2021). Unlike conventional sample-based approaches, Big Data Analytics (BDA) facilitates full-population data analysis, allowing auditors to detect unusual transaction patterns, identify high-risk areas, and strengthen the evidentiary basis for audit decisions (Saud et al., 2025). Consistent with both TAM and UTAUT, auditors who perceive Big Data Analytics (BDA) as beneficial and operationally feasible are more inclined to adopt it, thereby improving the efficiency, accuracy, and overall quality of audit outcomes.

In light of the above given description, the conceptual framework in this research can be described as follows:



Source: Author's own work (2026)

Relationship between Variables

Effect of e-Audit on Audit Quality

The implementation of e-audit has fundamentally transformed the auditing process at BPK RI by enabling auditors to access, collect, and verify financial data electronically through a link-and-match integration between the e-BPK system and the e-auditee system. This mechanism connects the BPK server directly to auditee servers, allowing auditors to obtain financial data in real time without geographical constraints (Akmalia & Ariani, 2022; Hakim et al., 2023). Grounded in TAM, auditors who perceive e-audit as useful for improving audit performance and easy to operate are more likely to adopt it effectively. The UTAUT framework further posits that performance expectancy, effort expectancy, social influence, and facilitating conditions collectively shape auditors' acceptance of e-audit and positively influence audit outcomes. Prior studies by Hakim et al. (2023), Muhammad Diponegoro & Dzikron (2021), and Wiyantoro et al. (2025) confirm that e-audit exerts a positive and significant effect on audit quality. Based on these findings, the following hypothesis is proposed:
H1: e-Audit has a positive effect on audit quality.

Effect of Artificial Intelligence (AI)-Based Audit Technology on Audit Quality

The Artificial Intelligence (AI)-based audit technology represents one of the most transformative innovations in contemporary auditing practice. By replicating aspects of human intelligence, Artificial Intelligence (AI)-based audit technology enables the automation of complex analytical tasks, large-scale data processing, and the generation of insights that exceed the capacity of conventional audit methods (Huang & Liu, 2024). From the TAM perspective, auditors who perceive Artificial Intelligence (AI)-based audit technology as beneficial and operationally accessible are more inclined to integrate it into their audit procedures. The UTAUT framework further suggests that performance expectancy, effort expectancy, social influence, and facilitating conditions collectively determine the extent to which Artificial Intelligence (AI)-based audit technology is embraced within audit organizations. Prior studies by Adeoye et al. (2023) and Sari & Wahyuda (2025) indicate that Artificial Intelligence (AI)-based audit technology has a positive effect on audit quality. Based on these findings, the following hypothesis is proposed:
H2: Artificial Intelligence (AI)-Based Audit Technology has a positive effect on Audit Quality

Effect of Big Data Analytics (BDA) on Audit Quality

Big Data Analytics **(**BDA) refers to the process of collecting, processing, and analyzing data characterized by extremely large volume, high velocity, and wide variety (Hamdam et al., 2022). At BPK RI, Big Data Analytics **(**BDA) is operationalized through the BIDICS platform, developed under the Decree of the Secretary-General of BPK No. 206/K/X-XIII.2/8/2021, encompassing ten analytical data clusters covering areas including central government, regional government, national development, and social assistance (BPK RI, 2021). Consistent with TAM, auditors who perceive Big Data Analytics **(**BDA) as beneficial for enhancing audit efficiency and risk analysis accuracy are more likely to adopt this technology in practice. The UTAUT framework further emphasizes that performance expectancy, effort expectancy, social influence, and facilitating conditions collectively influence auditors' decisions to adopt Big Data Analytics **(**BDA). Prior studies by Putra et al. (2023), Saud et al. (2025), and Sofyani et al. (2025) demonstrate that Big Data Analytics **(**BDA) exerts a positive and significant effect on audit quality. Based on these findings, the following hypothesis is proposed:
H3: Big Data Analytics (BDA) has a positive effect on Audit Quality

3. Research Method

This study employs a quantitative approach with a survey method to examine the effects of e-audit, Artificial Intelligence (AI)-based audit technology, and Big Data Analytics (BDA) on financial audit quality at BPK RI. The study population comprised all auditors at BPK RI, and the sample was determined using simple random sampling based on the Slovin formula as adopted by Sugiyono (2021), with a 10% margin of error, as follows:

$$n = \frac{N}{1 + Ne^2}$$

Information:
n = number of samples
N = total population
e = margin of error tolerance, set at 10% (0,1), chosen in consideration of time constraints and limited data accessibility.
The Slovin formula was used to determine the minimum number of samples needed for this investigation.

$$n = \frac{9.913}{1 + 9.913\ (0{,}1)^2}$$

= 99 respondent

Applying this formula yielded a minimum sample of 99 respondents; however, 102 completed questionnaires were ultimately retrieved and used in the analysis.
Data were collected through a structured questionnaire distributed via Google Forms, with all items measured using a five-point Likert scale (where 1 indicates "strongly disagree" and 5 signifies "strongly agree"). The study designates audit quality as the dependent variable, while e-audit, Artificial Intelligence (AI)-based audit technology, and Big Data Analytics (BDA) constitute the three independent variables. Each variable was operationalized through a set of statement items reflecting its respective theoretical dimensions.

Data Analysis

Data analysis was conducted using IBM SPSS version 25 through a sequential multi-stage procedure. The first stage involved descriptive statistical analysis to examine the central tendency and dispersion of each variable, including mean, standard deviation, minimum, and maximum values. The second stage assessed data quality through validity and reliability testing. Validity was evaluated using Pearson correlation with a significance threshold of $p < 0.05$, while reliability was measured using Cronbach's Alpha, with an accepted minimum coefficient of $\alpha > 0.70$ (Sugiyono, 2021). The third stage involved classical assumption testing to verify the appropriateness of the regression model, comprising the Kolmogorov-Smirnov normality test, the Variance Inflation Factor (VIF)-based multicollinearity test with a tolerance value > 0.10 and VIF < 10, and the heteroscedasticity test with a significance threshold of $p > 0.05$. The fourth and final stage applied multiple linear regression analysis to assess the direction and magnitude of the effect of each independent variable on dependent variable. Hypothesis testing was subsequently performed through three complementary procedures: the coefficient of determination (R^2) to measure the proportion of variance in audit quality explained by the independent variables, the simultaneous F-test to assess the collective significance of the model, and the partial t-test to evaluate the individual significance of each predictor, with a significance threshold of $p < 0.05$ (Sugiyono, 2021).

4. Results and Discussion

4.1. Result

Each variable was measured through a series of structured statement items. The e-audit variable was operationalized through statements reflecting the utilization of the e-BPK system and its contribution to audit effectiveness and precision. The Artificial Intelligence (AI)-based audit technology variable was measured via statements addressing the application of AI approaches in supporting audit procedures. The Big Data Analytics (BDA) variable was assessed through statements pertaining to the use of the BIDICS platform in processing and analyzing large-scale government financial data. Audit quality, as the dependent variable, was measured through statements evaluating the accuracy of audit findings, the reliability of recommendations, and the overall effectiveness of the audit process.

Table 1. Descriptive Statistical Analysis

Variable	N	Minimum	Maximum	Mean	Std. Deviation
e-Audit	102	25	55	43,60	6,699
Artificial Intelligence (AI)-Based Audit Technology	102	10	25	19,96	3,076
Big Data Analytics (BDA)	102	14	25	20,34	2,920
Audit Quality	102	31	44	38,80	3,113

Source: Primary Data processed by SPSS 25 Software (2026)

Validity Test result

Table 2. Validity Test

Validity Test for e-Audit			
Statement item	**Pearson Correlation**	**Sig.2 - Tailed**	**Result**
X1.1	.738**	.000	Valid
X1.2	.744**	.000	Valid
X1.3	.801**	.000	Valid
X1.4	.771**	.000	Valid
X1.5	.747**	.000	Valid
X1.6	.730**	.000	Valid
X1.7	.757**	.000	Valid
X1.8	.769**	.000	Valid

X1.9	.776**	.000	Valid
X1.10	.730**	.000	Valid
X1.11	.686**	.000	Valid
Validity Test for Artificial Intelligence (AI)-Based Audit Technology			
Statement Item	**Pearson Correlation**	**Sig. 2 - Tailed**	**Result**
X2.1	.843**	.000	Valid
X2.2	.842**	.000	Valid
X2.3	.855**	.000	Valid
X2.4	.754**	.000	Valid
X2.5	.850**	.000	Valid
Validity Test for Big Data Analytics (BDA)			
Statement Item	**Pearson Correlation**	**Sig. 2 - Tailed**	**Result**
X3.1	.787**	.000	Valid
X3.2	.732**	.000	Valid
X3.3	.820**	.000	Valid
X3.4	.704**	.000	Valid
X3.5	.832**	.000	Valid
Validity Test for Audit Quality			
Statement Item	**Pearson Correlation**	**Sig.2 - Tailed**	**Result**
Y.1	.810**	.000	Valid
Y.2	.741**	.000	Valid
Y.3	.772**	.000	Valid
Y.4	.761**	.000	Valid
Y.5	.588**	.000	Valid
Y.6	.735**	.000	Valid
Y.7	.678**	.000	Valid
Y.8	.643**	.000	Valid
Y.9	.731**	.000	Valid

Source: Primary Data processed by SPSS 25 Software (2026)

Based on the validity test results, all statement items across the e-audit, AI-based audit technology, BDA, and audit quality variables produced positive and valid outcomes. This is indicated by a significance value of less than 0.05, confirming that all statement items met the validity criteria and are suitable for further analysis.

Reliability Test Result

Table 3. Reliability Test Result

Variable	Cronbach's Alpha	N of Items
e-Audit	0,920	11
Artificial Intelligence (AI)-Based Audit Technology	0,886	5
Big Data Analytics (BDA)	0,829	5
Audit Quality	0,912	9

Source: Primary Data processed by SPSS 25 Software (2026)

All variables returned Cronbach's Alpha values exceeding the minimum threshold of 0.70, confirming the internal consistency and reliability of all measurement instruments employed in this study.

Classical Assumption test Result

Normality Test

Table 4. Normality Test

One-Sample Kolmogorov-Smirnov Test			
			Unstandardized Residual
N			102
Normal Parameters[a,b]	Mean		.0000000
	Std. Deviation		1.07472917
Most Extreme Differences	Absolute		.095
	Positive		.095
	Negative		-.083
Test Statistic			.095
Asymp. Sig. (2-tailed)[c]			.023[c]
Monte Carlo Sig. (2-tailed)[d]	Sig.		**.290[d]**
	99% Confidence Interval	Lower Bound	.278
		Upper Bound	.302

Source: Primary Data processed by SPSS 25 Software (2026)

The normality test was conducted utilizing the Kolmogorov-Smirnov test. The results showed an Monte Carlo Sig. (2-tailed) value of greater than 0.05, indicating that the data in this study are normally distributed and meet the normality assumption required for further regression analysis.

Multicolinearity Test

Table 5. Multicolinearity Test

Variable	Tolerance	VIF	Result
e-Audit	.434	2.307	No multicollinearity
Artificial Intelligence (AI)-Based Audit Technology	.414	2.417	No multicollinearity
Big Data Analytics (BDA)	.498	2.007	No multicollinearity

Source: Primary Data processed by SPSS 25 Software (2026)

All independent variables had tolerance values larger than 0.1 and Variance Inflation Factor (VIF) values less than 10, according to the multicollinearity test results. These findings verify that all independent variables are appropriate for use in multiple linear regression analysis and do not exhibit indications of multicollinearity.

Heteroscedasticity Test

Table 6. Heteroscedasticity Test

Coefficients[a]						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.933	.460		4.206	.000

	e-Audit	-.013	.014	-.136	-.918	**.361**
	Artificial Intelligence (AI)-Based Audit Technology	.022	.030	.110	.725	**.470**
	Big Data Analytics (BDA)	-.047	.029	-.221	-1.600	**.113**
a. Dependent Variable: ABS_RES						

Source: Primary Data processed by SPSS 25 Software (2026)

The heteroscedasticity test results indicated that this regression model does not suffer from heteroscedasticity problems. Each independent variable's significance value (Sig.), which is more than 0.05, demonstrates this. The significant values for e-Audit, Artificial Intelligence (AI)-Based Audit Technology, and Big Data Analytics (BDA) are 0.361, 0.470, and 0.113, respectively.

Multiple Linear Regression Equation Test

Table 7. Multiple Linear Regression Equation Test

Coefficients[a]							
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	**18.129**	.828		21.887	.000
	e-Audit	**.064**	.025	.138	2.607	.011
	Artificial Intelligence (AI)-Based Audit Technology	**-.080**	.055	-.079	-1.455	.149
	Big Data Analytics (BDA)	**.957**	.053	.897	18.167	.000
a. Dependent Variable: Audit Quality						

Source: Primary Data processed by SPSS 25 Software (2026)

According to the multiple linear regression analysis, the regression equation formed is as follows:

$$\mathbf{Y = 18.129 + 0.064\ X_1 - 0.080\ X_2 + 0.957\ X_3 + e}$$

The regression model above can be interpreted as follows:

1. The constant value of 18.129 indicates that when the e-audit variable (X1), Artificial Intelligence (AI)-based audit technology variable (X2), and Big Data Analytics (BDA) variable (X3) are all equal to zero, the projected Audit Quality (Y) is 18.129.
2. The regression coefficient of e-audit (X1) is 0.064 with a positive direction, indicating that every one-unit increase in the e-audit variable will result in an increase in Audit Quality by 0.064, assuming all other variables remain constant.
3. The regression coefficient of Artificial Intelligence (AI)-based audit technology (X2) is -0.080 with a negative direction, indicating that every one-unit increase in the Artificial Intelligence (AI)-based audit technology variable will result in a decrease in Audit Quality by 0.080, assuming all other variables remain constant.
4. The regression coefficient of Big Data Analytics (BDA) (X3) is 0.957 with a positive direction, indicating that every one-unit increase in the Big Data Analytics (BDA) variable will result in an increase in Audit Quality by 0.957, assuming all other variables remain constant.

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Hypothesis Test

Coefficient of Determination (R^2)

Table 9. Coefficient of Determination (R^2)

	Result
R-squared	0,881

Source: Primary Data processed by SPSS 25 Software (2026)

According to the coefficient of determination, as reflected by the R-Square value, is 0.881 or 88.1%. This indicates that e-audit (X1), Artificial Intelligence (AI)-based audit technology (X2), and Big Data Analytics (BDA) (X3) collectively explain 88.1% of the variance in Audit Quality (Y). The remaining 11.9% is attributed to other factors beyond the scope of this study.

Simultaneously Test (F Test)

Table 10. Simultaneously Test (F Test)

	Result
F-statistic	241.453
Significance Value	0,000

Source: Primary Data processed by SPSS 25 Software (2026)

According to the F-test results show a significance value of 0.000, which is less than 0.05, and an F-statistic of 241.453 > 2,670, which exceeds the F-table value. These results indicate that e-audit (X1), Artificial Intelligence (AI)-based audit technology (X2), and Big Data Analytics (BDA) (X3) simultaneously exert a positive and significant influence on Audit Quality (Y). Therefore, the conclusion is three independent variables collectively and meaningfully affect financial audit quality at the Audit Board of the Republic of Indonesia.

Partial Correlation Test (t-Test)

Table 11. Partial Correlation Test (t-Test)

Variable	T-Statistic	Sig.	Result
e-Audit	2.607	0,011	Hypothesis accepted
Artificial Intelligence (AI)-Based Audit Technology	-1.455	0,149	Hypothesis rejected
Big Data Analytics (BDA)	18.167	0,000	Hypothesis accepted
a. Dependent Variable: Audit Quality			

Source: Primary Data processed by SPSS 25 Software (2026)

According to the partial t-test, the e-audit variable (X1) obtained a t-statistic of 2.607, which exceeds the t-table value of 1.985, with a significance value of 0.011 < 0.05, indicating that e-audit has a significant positive impact on audit quality and thus H1 is accepted. The Artificial Intelligence (AI)-based audit technology variable (X2) obtained a t-statistic of -1.455, which is below the t-table value of 1.985, with a significance value of 0.149 > 0.05, indicating that AI-based audit technology does not have a significant effect on audit quality and thus H2 is rejected. The Big Data Analytics variable (X3) obtained a t-statistic of 18.167, which exceeds the t-table value of 1.985, with a significance value of 0.000 < 0.05, indicating that Big Data Analytics has a significant positive impact on audit quality and thus H3 is accepted.

4.2. Discussion

Effect of e-Audit on Audit Quality

The acceptance of H1 ($t = 2.607$, $p = 0.011$) confirms that e-audit positively and significantly affects financial audit quality at BPK RI. These results are consistent with the findings of Hakim et al. (2023), who demonstrated that e-audit positively influences audit quality among auditors at BPK RI's central office, concluding that the more optimal the implementation of e-audit, the greater the improvement in audit quality. This finding is further supported by Wiyantoro et al. (2025), who confirmed that higher digital competence among auditors in utilizing e-audit contributes significantly to improved audit quality. From the perspective of the Technology Acceptance Model (TAM), the use of e-audit at BPK RI is influenced by auditors' perceived usefulness and perceived ease of use. When auditors believe that e-audit simplifies the examination process and enhances efficiency, they tend to use it more optimally, which in turn leads to improvements in audit quality. Furthermore, from the UTAUT perspective, the effectiveness of e-audit adoption is determined by performance expectancy, effort expectancy, social influence, and facilitating conditions. The fulfillment of these factors at BPK RI drives optimal e-audit utilization and ultimately enhances audit quality.

Effect of Artificial Intelligence (AI)-Based Audit Technology on Audit Quality

The rejection of H2 ($t = -1.455$, $p = 0.149$) establishes that AI-based audit technology does not significantly affect audit quality at BPK RI, a finding that diverges from Adeoye et al. (2023) and Sari & Wahyuda (2025), both of whom reported positive AI–audit quality associations. This divergence is theoretically explicable: both prior studies were conducted in private-sector or general auditing environments where AI infrastructure is more mature and organizational support more developed, conditions that differ substantially from BPK RI's regulatory and institutional constraints. More critically, the negative coefficient ($\beta = -0.080$) suggests that suboptimal AI deployment may actively introduce inconsistencies into the audit process, likely by eroding professional judgment rather than augmenting it. Wijaya et al. (2025) identified auditor resistance, perceived complexity, and insufficient training as the dominant barriers to AI adoption across emerging economy contexts. Sari & Putri (2024) and Adeoye et al. (2023) similarly emphasized that AI's effectiveness is conditional upon auditor competence and organizational readiness, prerequisites that the present findings suggest remain insufficiently established within BPK RI. Collectively, the insignificant effect of AI-based audit technology reflects not a fundamental limitation of the technology itself, but the current stage of BPK RI's institutional unpreparedness for its effective deployment.

Effect of Big Data Analytics (BDA) on Audit Quality

The acceptance of H3 ($t = 18.167$, $p = 0.000$) confirms that Big Data Analytics exerts a positive and significant effect on financial audit quality at BPK RI, with a dominant regression coefficient of $\beta = 0.957$, markedly exceeding those of e-audit ($\beta = 0.064$) and AI-based technology ($\beta = -0.080$), indicating that more effective BDA utilization through the BIDICS platform is directly associated with higher audit quality outcomes. These findings are consistent with Putra et al. (2023), who confirmed a positive BDA and audit quality relationship in Indonesian government institutions, and Saud et al. (2025), who demonstrated that UTAUT positively drive BDA adoption and audit quality in Indonesia's public sector. However, neither study was situated specifically within BPK RI, a contextual gap this study directly addresses. The substantially stronger effect observed here is attributable to BPK RI's BIDICS platform which provides the institutional infrastructure for full-population financial data analysis that broader public sector studies lack, a finding further corroborated by Sofyani et al. (2025) and Abdelwahed et al. (2025), both of whom confirmed BDA's significant positive effects on audit process quality and auditor competence across multiple audit contexts. From the TAM perspective, auditors who perceive BDA as beneficial and operationally accessible adopt it more effectively; from the UTAUT perspective, BIDICS' institutionalization fulfills all four adoption determinants simultaneously, lowering perceived operational barriers while elevating performance expectancy.

5. Conclusion

This investigation attempts aims to examine the effects of e-audit, AI-based audit technology, and BDA on financial audit quality at the Audit BPK RI. Questionnaires were used to gather data from 102 auditors who participated as respondents, and IBM SPSS version 25 was utilized for multiple linear regression analysis. Several findings regarding the relationship between the variables under investigation were drawn from this study.

1. E-audit improves financial audit quality at BPK RI. In other words, the quality of audits produced by BPK RI auditors will increase in tandem with the effectiveness of e-audit implementation through the e-BPK system.
2. Artificial Intelligence (AI)-based audit technology does not significantly improve financial audit quality at BPK RI. In other words, the application of AI-based audit technology has not been statistically proven to enhance audit quality, as its adoption remains suboptimal due to varying auditor perceptions, limited digital competence, and insufficient organizational support.
3. Big Data Analytics (BDA) improves financial audit quality at BPK RI. In other words, the more effectively Big Data Analytics is utilized through the BIDICS platform in the audit process, the greater the audit quality that BPK RI auditors produce.

Research Limitation

This investigation has several limitations that should be considered in future study. The questionnaire distribution took a considerable amount of time due to the concurrent examination duties of BPK RI auditors, which may have affected the consistency and depth of responses. The varying levels of understanding and experience among respondents may also have influenced the consistency of their assessments, possibly impacting the analysis's accuracy. Lastly, although the coefficient of determination shows that the three independent variables account for 88.1% of the variance in audit quality, other elements outside the purview of this investigation are responsible for the remaining 11.9%.

Suggestion

Considering the limitations of this study, future researchers are urged to use different techniques for gathering data, such structured interviews, in order to get more thorough results that more accurately reflect real-world settings. Moreover, it is recommended that subsequent studies consider incorporating supplementary variables including Auditor Digital Competence, Management Support, and Organizational Readiness, which may potentially exert a considerable influence on audit quality in the public sector. Future study is also expected to investigate more deeply the factors that hinder the adoption of AI-based audit technology at BPK RI, given that this variable was found to have no significant impact on audit quality in the present investigation.

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