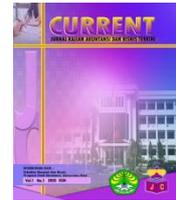




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ARTIFICIAL INTELLIGENCE, BIG DATA, AND AUDIT PROCESS EFFECTIVENESS UNDER UTAUT IN PUBLIC ACCOUNTING FIRMS

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Abstract

Increasingly complex financial transactions require auditors to identify and analyze material misstatements in financial statements accurately and precisely within a reasonable timeframe, making audit process effectiveness a critical issue. This study examines the effects of artificial intelligence, big data analytics technology, and computer-assisted audit techniques on audit process effectiveness using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Data were collected through questionnaires distributed to 70 external auditors working in public accounting firms in South Jakarta and were analyzed using SmartPLS version 4.1. The findings indicate that the use of artificial intelligence and big data analytics technology does not have a significant effect on audit process effectiveness, whereas the use of computer-assisted audit techniques has a significant positive effect. These results provide practical insights for public accounting firms to enhance human resource readiness, organizational support, and technological infrastructure to optimize the use of modern audit technologies and improve audit process effectiveness. From a theoretical perspective, this study extends the application of the UTAUT framework by providing empirical evidence on the role of modern audit technologies in shaping audit process effectiveness within the Indonesian auditing context.

INTRODUCTION

The era of digitalization and globalization has brought significant changes to the business environment, including accounting and auditing practices. Financial transactions have become increasingly complex, rapid, and diverse, thereby heightening the risk of fraud and material misstatements. At the same time, stakeholders demand financial information that is accurate, transparent, and timely. These conditions make audit process effectiveness a critical issue in the auditing profession, requiring auditors to identify and analyze material misstatements in financial statements accurately and within a reasonable timeframe.

Audit process effectiveness is reflected in auditors' ability to plan, execute, and evaluate audit procedures in accordance with professional standards. However, in practice, auditors face numerous challenges, including time constraints, large volumes of data, and increasing transaction complexity. Weaknesses in audit processes are often revealed only after major scandals or corporate failures occur. For example, in the PT Garuda Indonesia case in 2018,



auditors failed to detect unrealized revenue recognition (Andriyana & Trisnaningsih, 2022). Similarly, the SNP Finance case in the same year revealed that a well-known public accounting firm did not identify fictitious receivables (Putri & Zulhaimi, 2023). More recently, the PT Indofarma case in 2024 exposed prolonged practices of window dressing and fictitious transactions that had gone undetected for years (Eko et al., 2025). These cases indicate that conventional audit practices remain limited in detecting material misstatements and fraud, underscoring the need to enhance audit quality through more innovative approaches.

The development of information technology in the Society 5.0 era, driven by the digital economy, has introduced innovations such as artificial intelligence, big data, and other digital technologies that have substantially transformed auditing practices. Auditors are no longer dealing solely with structured data but also with large volumes of complex, real-time data generated by multiple digital systems. Digital technology has therefore become a key factor in enhancing audit quality and effectiveness by expanding audit coverage, improving testing accuracy, and accelerating audit decision-making processes (Bani et al., 2025). Accordingly, the adoption of artificial intelligence, big data analytics technology, and computer-assisted audit techniques (CAATs) has become increasingly important in supporting auditors in managing the complexity of the modern business environment.

Artificial intelligence assists auditors in preparing documentation, analyzing narrative reports, and providing preliminary recommendations related to specific risks. These capabilities enhance work efficiency while improving the accuracy of risk identification and the quality of audit judgment, thereby contributing to overall audit process effectiveness (Binh, 2025). Big data analytics technology enables auditors to perform procedures that are difficult to conduct manually, such as examining entire data populations, which enhances the detection of misstatements and early indications of fraud. Its ability to process large volumes of data quickly and comprehensively allows auditors to obtain stronger and more relevant audit evidence, thereby improving testing precision and audit effectiveness (Suryani et al., 2021). CAATs provide software-based tools that support auditors throughout the audit process, from audit planning to the formulation of conclusions and decision-making. The use of CAATs enhances the reliability and accuracy of audit results by enabling auditors to perform procedures more systematically, efficiently, and accurately, ultimately improving audit process effectiveness (Pramudyastuti et al., 2022).

Despite the recognized benefits of audit technologies, their adoption in Indonesia remains relatively limited. Many public accounting firms continue to rely on basic software, while the use of advanced technologies is constrained by factors such as regulatory compliance, user capability, cost considerations, and system availability (Law & Shen, 2025; Abdelwahed et al., 2025; Awuah et al., 2022). These constraints may reduce the effectiveness of technology utilization in audit practices, highlighting the importance of human resource readiness, organizational support, and clear regulatory frameworks.

Numerous studies have shown that artificial intelligence, big data analytics, and CAATs have the potential to enhance audit process effectiveness (Taunaumang et al., 2025; Kelintinas et al., 2024; Atta et al., 2024). However, prior research has largely emphasized the technical and operational benefits of audit technologies, while relatively limited attention has been given to whether auditors' acceptance and readiness to use these technologies translate into improved audit effectiveness. In practice, successful technology implementation depends not only on system sophistication but also on auditors' perceptions of usefulness, ease of use, and readiness to adopt new technologies (Zhang et al., 2023). Consequently, empirical evidence integrating artificial intelligence, big data analytics, and CAATs within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework in the Indonesian auditing context remains scarce.

From a theoretical perspective, this issue can be explained using the UTAUT

framework, which posits that performance expectancy, effort expectancy, social influence, and facilitating conditions influence individuals' intentions and behaviors related to technology use (Venkatesh et al., 2003). In the auditing context, this framework is relevant for explaining how auditors' acceptance of artificial intelligence, big data analytics technology, and CAATs influences audit process effectiveness. Nevertheless, empirical studies that integrate modern audit technologies with the UTAUT framework to explain audit effectiveness, particularly in Indonesia context, remain limited.

Accordingly, this study contributes theoretically by extending the application of the UTAUT model in the auditing context, particularly in explaining the relationship between the acceptance of modern audit technologies and audit process effectiveness. Empirically, this study provides evidence on the influence of artificial intelligence, big data analytics technology, and CAATs on audit process effectiveness in public accounting firms in South Jakarta, a context that has received limited attention in prior research.

Based on this discussion, the objective of this study is to analyze the influence of artificial intelligence, big data analytics technology, and computer-assisted audit techniques on audit process effectiveness by considering factors related to auditors' acceptance and use of technology. The findings are expected to provide practical insights for public accounting firms in formulating audit technology implementation strategies, as well as serve as a reference for regulators and academics in developing policies and future research on technology-based auditing.

HYPOTHESIS DEVELOPMENT

Artificial Intelligence and Effectiveness of The Audit Process

Artificial intelligence (AI) is a branch of computer science that applies machine learning and deep learning techniques to automatically analyze data, recognize patterns, and detect anomalies by simulating human cognitive processes with greater speed and analytical capacity (Syahronny & Dewayanto, 2024; Safitri & Ratnawati, 2025). In the auditing context, AI enables the automation of routine tasks such as document review, transaction testing, risk assessment, and financial statement analysis in high-risk areas, thereby supporting auditors in making faster and more accurate decisions (Silaen & Dewayanto, 2024).

From a theoretical perspective, Binh (2025) argues that AI enhances audit effectiveness by expanding audit coverage, enabling continuous auditing, and improving anomaly detection. Adalakun et al. (2024) further emphasize that AI assists auditors in identifying complex fraud patterns and material misstatements that are difficult to detect using traditional audit techniques. By reducing reliance on manual procedures and improving analytical precision, AI contributes to greater timeliness, accuracy, and completeness of audit evidence, which are key dimensions of audit process effectiveness.

The relationship between AI and audit process effectiveness can also be explained through the UTAUT. Within this framework, performance expectancy reflects auditors' beliefs that AI can enhance audit performance and quality, while effort expectancy represents perceptions regarding the ease of using AI through automated and natural language-based features. Social influence refers to encouragement from the professional environment, regulators, and public accounting firms to adopt advanced technologies. Facilitating conditions denote organizational support in the form of adequate training, infrastructure, and policies to ensure the effective use of AI (Venkatesh et al., 2003). These factors shape auditors' acceptance of AI, which in turn influences audit process effectiveness.

Empirical studies by Pérez-Calderón et al. (2025), Hidayat et al. (2024), Taunamang et al. (2025) demonstrate that AI adoption has a positive effect on audit process effectiveness. These findings suggest that auditors who successfully adopt and utilize AI are better equipped to identify risks, detect anomalies, and enhance the quality of professional judgment.



Accordingly, the following hypothesis is proposed:

H₁: The Use of Artificial Intelligence Influences Audit Process Effectiveness.

Big Data Analytics Technology and Effectiveness of the Audit Process

Big data analytics is a technology used to process and analyze large volumes of data, both structured and unstructured, to generate relevant information and insights. This technology encompasses techniques such as data mining, machine learning, and predictive analytics to support decision-making (Suryani et al., 2021). In the auditing context, big data analytics technology enables auditors to examine entire data populations, identify unusual transaction patterns, and detect misstatements that are difficult to uncover through traditional sampling-based approaches.

According to Khaerunnisa et al. (2025), big data analytics technology enhances audit effectiveness by strengthening auditors' ability to identify risk patterns and relationships across financial and non-financial data. Dako et al. (2020) also state that big data analytics technology allows auditors to shift from periodic audits toward more continuous and comprehensive audit practices, thereby improving the relevance and reliability of audit outcomes. Through real-time analysis and broader data coverage, big data analytics technology strengthens the quality of audit evidence and supports more accurate audit conclusions.

From a causal perspective, big data analytics technology improves audit effectiveness by enhancing auditor's analytical capabilities, increasing information transparency, and strengthening the quality of risk assessment. When auditors perceive big data analytics technology as useful and easy to use, they are more likely to integrate it into audit procedures (Al-Ateeq et al., 2022). This integration leads to more precise testing, earlier detection of irregularities, and more informed audit judgments, which ultimately improve the overall effectiveness of the audit process.

Empirical studies by Nugrahanti et al. (2023), Kelintinas et al. (2024), and Taunaumang et al. (2025) provide evidence that big data analytics technology has a significant effect on audit process effectiveness. Auditors who utilize big data analytics technology are proven to be better able to handle data complexity and enhance audit quality.

Therefore, the hypothesis is formulated as follows:

H₂: The Use of Big Data Analytics Technology Influences Audit Process Effectiveness.

Computer-Assisted Audit Techniques and the Effectiveness of the Audit Process

Computer-assisted audit techniques (CAATs) are audit techniques that utilize computer technology to assist auditors in performing data testing in accordance with audit procedures, either through tests of controls or substantive testing (Andryani et al., 2021). In Indonesia, the use of CAATs is regulated under the Professional Standards for Public Accountants through PSA No. 59 (SA Section 327), which governs the scope, application, and considerations for using CAATs, including auditor competence and the availability of supporting facilities (Fitrianingsih & Khadijah, 2021).

CAATs enhance audit effectiveness by enabling the efficient testing of large volumes of data, reducing human error, and improving the accuracy of audit procedures (Emily et al., 2025). Pramudyastuti et al. (2022) explain that audit software supports all stages of the audit process, from planning to conclusion, thereby increasing the reliability and precision of audit results. Najmuddin & Pamungkas (2021) also state that the development of technology-based audit systems produces more optimal audit outputs through improved processing speed and analytical capacity.

From a causal perspective, CAATs improve audit effectiveness through increased efficiency, accuracy, and audit coverage. By automating routine procedures, auditors can focus more on professional judgment and high-risk areas. When auditors accept and optimally utilize

CAATs, the audit process becomes more systematic and higher in quality, which directly enhances the overall effectiveness of the audit process (Puteri et al., 2023).

Empirical studies by Fitriainingsih & Khadijah (2021), Marei & Iskandar (2019), and Atta et al. (2024) Provide evidence that CAATs have a significant effect on audit process effectiveness.

Therefore, the hypothesis is formulated as follows:

H3: The Use of Computer-Assisted Audit Techniques Influences Audit Process Effectiveness

In summary, this study positions audit process effectiveness as an outcome of auditors' acceptance and use of modern audit technologies. The integration of artificial intelligence, big data analytics, and CAATs within the UTAUT framework emphasizes the roles of performance expectancy, effort expectancy, social influence, and facilitating conditions in shaping audit effectiveness, thereby providing the basis for the empirical analysis conducted in this study.

RESEARCH METHOD

Research Design

This study employed a quantitative research design using a survey approach. Primary data were collected through questionnaires distributed in both printed (hard copy) form and online via Google Forms. The population consisted of external auditors working in public accounting firms located in South Jakarta. This region was selected because it represents a major business center with a high concentration of public accounting firms and relatively strong firm reputations compared to other regions.

Purposive sampling was applied based on the following criteria: (1) external auditors employed in public accounting firms in South Jakarta; (2) auditors who had utilized artificial intelligence and computer-assisted audit techniques (CAATs) in audit engagements, enabling them to provide responses based on actual experience; and (3) with respect to big data analytics technology, given its limited implementation in public accounting firms in South Jakarta, respondents were not required to have direct usage experience and were permitted to provide assessments based on perception.

The determination of sample size was based on the Lemeshow (1997) formula, which is commonly applied in survey research with limited or unknown population size, as follows:

$$n = \frac{Z^2 P(1 - P)}{d^2}$$

The calculation was conducted using a 90% confidence level ($Z = 1.645$), a maximum proportion ($p = 0.5$), and a margin of error ($d = 0.10$). Based on this calculation, the minimum required sample size was 68 respondents, which was rounded up to 70. The use of a 10% margin of error was considered appropriate due to limited access to auditor respondents and the relatively hard-to-reach nature of the population. This level of precision remains acceptable for exploratory and behavioral research and is consistent with the minimum sample size requirements for Partial Least Squares–Structural Equation Modeling (PLS-SEM), namely ten times the largest number of structural paths directed at a dependent construct (Hair et al., 2017). In this study, audit process effectiveness was influenced by three independent variables; therefore, the minimum required sample size was 30, and the final sample of 70 respondents exceeded this threshold.

Data analysis was conducted using SmartPLS version 4.1 with a Partial Least Squares–based Structural Equation Modeling (PLS-SEM) approach. PLS-SEM was selected because the study aimed to predict relationships among constructs, involved a relatively small sample size, and did not require strict assumptions of data normality. This method is particularly suitable for exploratory and theory-extension research in emerging contexts such as technology-based auditing. The analysis comprised two main stages: evaluation of the measurement model (outer



model) to assess construct validity and reliability, and evaluation of the structural model (inner model) to examine relationships among variables and test the proposed hypotheses.

This study has several limitations. First, the relatively small sample size and the geographic focus limited to South Jakarta restrict the generalizability of the findings to auditors across Indonesia. Accordingly, the results should be interpreted as context-specific and may serve as a foundation for future studies that expand geographic coverage and increase the number of respondents to obtain more representative and generalizable findings.

Research Variables and Operational Definitions

The constructs in this study were operationalized into measurable indicators based on established theories and prior empirical studies. All variables were measured using a structured questionnaire employing a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The indicators for Artificial Intelligence, Big Data Analytics Technology, and Computer-Assisted Audit Techniques were adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT) framework and relevant prior studies to ensure content validity.

Table 1.
Operational Variabel

| Variable | Definition | Dimension | Indicator | Code | Source |
|------------------------------------|---|-----------------------------|--|---------|--|
| Artificial Intelligence | The field of computer science that focuses on developing systems capable of performing tasks typically requiring human intelligence, such as reasoning, learning, pattern recognition, and decision-making. | Performance | Efficiency of audit work using AI | AI.1 | Lan (2022); Venkatesh et al. (2003); Sholihah et al. (2023); and Caseba & Dewayanto (2024) |
| | | Expectancy | Ease of use of AI | AI.2 | |
| | | Effort | Support from superiors/colleagues for AI | AI.3 | |
| | | Expectancy | Organizational support (AI training/infrastructure) | AI.4 | |
| Big Data Analytics Technology | Big data analytics technology encompasses methods such as data mining, machine learning, and predictive analytics to support decision-making | Perceived Usefulness | Benefits of BDAT in identifying audit risks | BDAT.1 | Nugrahan ti et al. (2023); Venkatesh et al. (2003); and Albawwat & Frijat (2021) |
| | | Perceived Ease of Use | Ease of use of BDAT after training | BDAT.2 | |
| | | Attitude Toward Using | Positive attitudes toward using BDAT | BDAT.3 | |
| | | Behavioral Intention to Use | Intention to use BDAT in the future | BDAT.4 | |
| Computer-Assisted Audit Techniques | Audit activities using computers that assist auditors in conducting data testing based on audit procedures, either through | Performance | CAATs improve error/risk detection | CAATS.1 | Andryani et al. (2021); Venkatesh et al. (2003); Atmaja, (2016) |
| | | Expectancy | Ease of use of CAATs | CAATS.2 | |
| | | Effort | Encouragement from colleagues/superiors to use CAATs | CAATS.3 | |
| | | Expectancy | Organizational | CAATS.4 | |

| Variable | Definition | Dimension | Indicator | Code | Source |
|------------------------------------|--|---|--|-------|--|
| | tests of controls or substantive tests. | Conditions | support (CAAT software/training) | | and Najmuddin & Pamungkas (2021) |
| Effectiveness of the Audit Process | Audit process effectiveness can be defined as the auditor's ability to carry out all audit stages in a timely, accurate, and comprehensive manner while ensuring the accuracy of findings. | Plan and Design an Audit Approach | Ability to develop an audit program according to objectives and time | EAP.1 | Muna & Meutia (2024); Rahmatullah & Purnamasari (2024); Arens et al. (2019), and the SA issued by IAPI in 2021 |
| | | Perform Test of Controls and Substantive Tests of Transactions | Ability to identify risks and test key controls | EAP.2 | |
| | | Perform Substantive Analytical Procedures and Tests of Details of Balance | Obtain reliable audit evidence | EAP.3 | |
| | | Complete the Audit and Issue an Audit Report | Formulate an audit opinion based on sufficient evidence | EAP.4 | |

RESEARCH RESULTS AND DISCUSSION

Data were collected through questionnaires distributed to external auditors in the South Jakarta area, resulting in 70 usable responses out of 80 questionnaires distributed. The general profile of the respondents is presented as follows:

Table 2.
Characteristics of Respondents

| Description | Total | Percentage |
|----------------------------|-------|------------|
| Gender: | | |
| Male | 29 | 41,4% |
| Female | 41 | 58,6% |
| Age: | | |
| 20-30 Years | 58 | 82,9% |
| 31-40 Years | 10 | 14,3% |
| 41-50 Years | 2 | 2,9% |
| >50 Years | 0 | 0% |
| Highest Education Level: | | |
| D3 | 1 | 1,4% |
| S1 | 64 | 91,4% |
| S2 | 5 | 7,1% |
| S3 | 0 | 0% |
| Position: | | |
| Junior Auditor | 50 | 71,4% |
| Senior Auditor | 14 | 20% |
| Supervisor | 3 | 4,3% |
| Manager | 3 | 4,3% |
| Partner | 0 | 0% |
| Length of Work Experience: | | |
| < 1 Years | 42 | 60% |



| Description | Total | Percentage |
|-------------------------------------|-------|------------|
| 1-5 Years | 17 | 24,3% |
| 5-10 Years | 7 | 10% |
| > 10 Years | 4 | 5,7% |
| Experience in Using the Technology: | | |
| Yes | 70 | 100% |
| No | 0 | 0% |

The SEM analysis was conducted through two main stages, namely evaluation of the measurement model (outer model) and evaluation of the structural model (inner model). The measurement model evaluation aims to assess the quality of the research data, which consists of two types of testing: validity testing (convergent and discriminant validity) and reliability testing (Herianti, 2020).

Convergent Validity

Convergent validity assesses the extent to which indicators within a construct are highly correlated. An indicator is considered valid when it has a loading factor greater than 0.70 and an Average Variance Extracted (AVE) value exceeding 0.50.

Table 3.

Outer Loading Results

| Variable Item | Outer Loading | Information |
|---------------|---------------|-------------|
| AI.1 | 0.908 > 0.70 | VALID |
| AI.2 | 0.826 > 0.70 | VALID |
| AI.3 | 0.952 > 0.70 | VALID |
| AI.4 | 0.790 > 0.70 | VALID |
| BDAT.1 | 0.879 > 0.70 | VALID |
| BDAT.2 | 0.806 > 0.70 | VALID |
| BDAT.3 | 0.863 > 0.70 | VALID |
| BDAT.4 | 0.744 > 0.70 | VALID |
| CAATS.1 | 0.824 > 0.70 | VALID |
| CAATS.2 | 0.876 > 0.70 | VALID |
| CAATS.3 | 0.867 > 0.70 | VALID |
| CAATS.4 | 0.727 > 0.70 | VALID |
| EAP.1 | 0.948 > 0.70 | VALID |
| EAP.2 | 0.931 > 0.70 | VALID |
| EAP.3 | 0.914 > 0.70 | VALID |
| EAP.4 | 0.951 > 0.70 | VALID |

Source: SmartPLS Data Processing, 2025.

The convergent validity results indicate that all indicators for each construct exhibit outer loading values of ≥ 0.70 and are therefore considered valid. Although some studies accept loading factors above 0.50 in exploratory research, this study adopts a more stringent threshold of 0.70, as recommended by Hair et al., (2017), to ensure stronger convergent validity and measurement reliability. Consequently, all indicators are deemed to adequately represent their respective constructs.

Table 4.

Average Variance Extracted Results

| Variable | Average Variance Extracted (AVE) |
|----------|----------------------------------|
| EAP | 0.876 |
| CAATS | 0.682 |
| BDAT | 0.680 |
| AI | 0.759 |

Source: SmartPLS Data Processing, 2025.

The Average Variance Extracted (AVE) results indicate that all constructs have AVE

values exceeding 0.50. According to Herianti (2020), an AVE value of at least 0.50 suggests that a construct explains more than 50% of the variance of its indicators. Accordingly, the indicators in this study demonstrate strong convergent validity and are appropriate for measurement purposes.

Discriminant Validity

Discriminant validity was assessed to confirm that each construct is empirically distinct from others in the model. Following PLS-SEM guidelines, the Fornell–Larcker criterion and/or HTMT ratio were applied. The results are presented in Table 5.

Table 5.

Result of Discriminant Validity

| | EAP | CAATS | BDAT | AI |
|----------------|------------|--------------|-------------|-----------|
| EAP.1 | 0.948 | 0.461 | 0.322 | 0.263 |
| EAP.2 | 0.931 | 0.421 | 0.214 | 0.162 |
| EAP.3 | 0.914 | 0.410 | 0.293 | 0.195 |
| EAP.4 | 0.951 | 0.416 | 0.248 | 0.198 |
| CAATS.1 | 0.396 | 0.824 | 0.708 | 0.630 |
| CAATS.2 | 0.332 | 0.876 | 0.535 | 0.448 |
| CAATS.3 | 0.373 | 0.867 | 0.550 | 0.471 |
| CAATS.4 | 0.392 | 0.727 | 0.445 | 0.415 |
| BDAT.1 | 0.304 | 0.595 | 0.879 | 0.562 |
| BDAT.2 | 0.254 | 0.648 | 0.806 | 0.682 |
| BDAT.3 | 0.165 | 0.510 | 0.863 | 0.532 |
| BDAT.4 | 0.173 | 0.452 | 0.744 | 0.524 |
| AI.1 | 0.184 | 0.548 | 0.648 | 0.908 |
| AI.2 | 0.118 | 0.397 | 0.620 | 0.826 |
| AI.3 | 0.271 | 0.616 | 0.656 | 0.952 |
| AI.4 | 0.054 | 0.462 | 0.507 | 0.790 |

Source: SmartPLS Data Processing, 2025.

Discriminant validity, assessed using cross-loading values, indicates that each indicator loads more highly on its respective construct than on other constructs. This result demonstrates that the constructs are conceptually distinct and do not overlap, thereby confirming adequate discriminant validity (Herianti, 2020).

Reliability Test

Reliability was assessed by evaluating internal consistency using Cronbach’s Alpha, with values of at least 0.70, and composite reliability, with values of ≥ 0.70 , indicating that the indicators reliably measure their respective constructs.

Table 6.

Reliability Test Results

| | Cronbach's Alpha | Composite Reliability | Information |
|--------------|-------------------------|------------------------------|--------------------|
| AI | 0.899 | 1.098 | Reliable |
| BDAT | 0.847 | 0.892 | Reliable |
| CAATS | 0.842 | 0.841 | Reliable |
| EAP | 0.953 | 0.955 | Reliable |

Source: SmartPLS Data Processing, 2025.

The reliability test results indicate that all constructs have Cronbach’s Alpha and Composite Reliability values exceeding 0.70. Hair et al. (2017) Note that Composite Reliability values of 0.70 or higher reflect good internal consistency. Accordingly, the research instrument is considered reliable and consistent in measuring the constructs under investigation.



Coefficient of Determination (R²) Results

The R-square value of 0.213 indicates that Artificial Intelligence, Big Data Analytics Technology, and Computer-Assisted Audit Techniques collectively explain 21.3% of the variance in audit process effectiveness, while the remaining 78.7% is attributable to other factors not included in the research model. According to Ghozali (2021), R-square values of 0.19, 0.33, and 0.67 are categorized as weak, moderate, and strong, respectively. Accordingly, the model’s predictive power can be classified as weak to moderate, which is reasonable given that audit process effectiveness is influenced by multiple factors, such as auditor competence, time pressure, professional ethics, and client complexity.

Table 7.

Path Coefficient

| Variabel | EAP |
|----------|--------|
| AI | -0.087 |
| BDAT | 0.003 |
| CAATS | 0.507 |

Source: SmartPLS Data Processing, 2025

Table 7 presents the path coefficient results for the relationships between Artificial Intelligence and Audit Process Effectiveness (−0.087), Big Data Analytics Technology and Audit Process Effectiveness (0.003), and Computer-Assisted Audit Techniques and Audit Process Effectiveness (0.507). A positive coefficient indicates a direct relationship between variables, whereas a negative coefficient reflects an inverse relationship (Hair et al., 2017). However, the strength and statistical significance of these relationships are determined by the T-statistics and p-values, which indicate whether the effects are meaningful in explaining variations in audit process effectiveness.

Table 8.

Hypothesis Test

| | Original Sample (O) | Standard Deviation | T Statistic | P Value |
|--------------|---------------------|--------------------|-------------|---------|
| AI -> EAP | -0.087 | 0.193 | 0.452 | 0.651 |
| BDAT -> EAP | 0.003 | 0.175 | 0.017 | 0.987 |
| CAATS -> EAP | 0.507 | 0.159 | 3.193 | 0.001 |

Source: SmartPLS Data Processing, 2025.

As presented in Table 8, the hypothesis testing results indicate that artificial intelligence does not have a significant effect on audit process effectiveness, as reflected by a t-statistic of 0.452, which is below the critical value of 1.67, and a p-value of 0.651, exceeding the 0.10 significance level. Thus, H1 is rejected. Similarly, big data analytics technology does not show a significant influence on audit process effectiveness, with a t-statistic of 0.017 and a p-value of 0.987, both failing to meet the required significance threshold. Accordingly, H2 is rejected. In contrast, computer-assisted audit techniques demonstrate a significant positive effect on audit process effectiveness, as indicated by a t-statistic of 3.193, which surpasses the critical value, and a p-value of 0.001, well below the 0.10 significance level. Therefore, H3 is accepted.

Discussion

Artificial Intelligence Does Not Significantly Affect Audit Process Effectiveness

The statistical test results indicate that artificial intelligence does not have a significant effect on audit process effectiveness (t-statistic = 0.452; p-value = 0.651). From a descriptive perspective, most respondents remain at an early stage of familiarization with and utilization of artificial intelligence in audit assignments. Many auditors do not yet routinely use AI-based applications in their audit activities, resulting in limited realization of the practical benefits of this technology.

From a theoretical perspective, these findings suggest that the four core constructs of the UTAUT have not been optimally fulfilled. In terms of performance expectancy, auditors have not yet perceived substantial improvements in efficiency, accuracy, or audit quality arising from artificial intelligence adoption. With respect to effort expectancy, artificial intelligence is perceived as complex and difficult to use due to limited training opportunities and insufficient hands-on experience. Social influence also remains weak, as encouragement from supervisors, colleagues, and professional regulations to adopt artificial intelligence in audit practices is still minimal. Furthermore, inadequate facilitating conditions—such as limited infrastructure, supporting systems, and internal organizational policies—hinder the effective implementation of artificial intelligence within public accounting firms.

These findings are consistent with Law & Shen (2025) and Awuah et al. (2022), who emphasize that the primary barriers to artificial intelligence adoption in auditing stem from insufficient human resource readiness and organizational support rather than from technological limitations. However, the results contradict those of Pérez-Calderón et al. (2025), Hidayat et al. (2024), Taunaumang et al. (2025), who report a positive effect of artificial intelligence on audit effectiveness. This discrepancy can be theoretically explained by differences in technological maturity, organizational readiness, and the extent of artificial intelligence implementation across regions. Therefore, the effective use of artificial intelligence to enhance audit process effectiveness largely depends on auditors' readiness and strong organizational support.

Big Data Analytics Technology Does Not Significantly Affect Audit Process Effectiveness

The statistical test results further indicate that big data analytics technology does not have a significant effect on audit process effectiveness (t-statistic = 0.017; p-value = 0.987). Descriptively, most auditors have not yet implemented big data analytics in audit procedures and continue to rely predominantly on conventional audit techniques. Consequently, the potential benefits of big data analytics have not been reflected in improvements in audit effectiveness.

From a theoretical standpoint, these findings suggest that the core constructs of the Technology Acceptance Model (TAM), as an extension of UTAUT, have not been firmly established. In terms of perceived usefulness, auditors have not fully experienced the benefits of big data analytics in enhancing risk identification, fraud detection, and audit planning. Regarding perceived ease of use, the technology is viewed as complex and requiring advanced technical and data analysis skills that are not yet widely mastered. As a result, auditors' attitudes toward using big data analytics remain largely neutral, leading to a low level of behavioral intention to adopt the technology. Because this study focuses on perceptions and intentions rather than actual usage, the findings primarily reflect auditor readiness rather than the actual level of technology implementation in audit practice.

These results are consistent with Abdelwahed et al. (2025), who argue that the impact of big data analytics on audit process effectiveness remains limited due to insufficient technical competence and inadequate supporting infrastructure. However, the findings differ from Nugrahanti et al. (2023); Kelintinas et al. (2024), and Taunaumang et al. (2025), who document a significant positive effect of big data analytics on audit effectiveness. This discrepancy can be attributed to differences in the level of technology adoption and organizational readiness, as prior studies were conducted in organizations that had actively implemented big data analytics, whereas the auditors in this study generally had not yet utilized the technology. Accordingly, big data analytics is expected to enhance audit process effectiveness only when auditors possess adequate competencies supported by training, clear organizational policies, and strong institutional commitment.



Computer-Assisted Audit Techniques Significantly Affect Audit Process Effectiveness

In contrast to the previous variables, the statistical test results demonstrate that computer-assisted audit techniques (CAATs) have a significant positive effect on audit process effectiveness (t-statistic = 3.193; p-value = 0.001). Descriptive findings indicate that most auditors are already familiar with and routinely use CAATs in audit engagements, particularly for data testing, transaction analysis, and sampling procedures. This high level of utilization explains why CAATs generate tangible improvements in audit effectiveness.

From a theoretical perspective, these results indicate that all four constructs of the UTAUT have been fulfilled. In terms of performance expectancy, auditors perceive CAATs as effective tools for enhancing efficiency, accuracy, and the reliability of audit outcomes. Regarding effort expectancy, CAATs are considered easy to use because they have become an integral part of routine audit practices. Social influence also plays a supportive role, reinforced by encouragement from supervisors, colleagues, and professional standards that promote the use of CAATs. In addition, facilitating conditions are well established through the availability of audit software, training programs, and technical guidelines.

These findings are consistent with Fitrianiingsih & Khadijah (2021), Marei & Iskandar (2019), and Atta et al. (2024), who conclude that CAATs significantly enhance audit process effectiveness. Theoretically, this supports the argument that when a technology is perceived as useful, easy to use, socially supported, and adequately facilitated, auditors are more likely to adopt it, resulting in substantial improvements in audit process effectiveness.

CONCLUSION

This study concludes that artificial intelligence and big data analytics technology do not have a significant effect on audit process effectiveness, whereas computer-assisted audit techniques (CAATs) have a significant positive effect on audit process effectiveness. Accordingly, hypotheses H1 and H2 are rejected, while H3 is accepted. These findings indicate that, among the three technologies examined, only CAATs are empirically proven to enhance audit process effectiveness among external auditors in public accounting firms located in South Jakarta.

From a theoretical perspective, this study contributes to the development of the Unified Theory of Acceptance and Use of Technology (UTAUT) by demonstrating that the adoption of modern audit technologies does not automatically lead to improvements in audit process effectiveness. The non-significant effects of artificial intelligence and big data analytics indicate that performance expectancy and effort expectancy alone are insufficient to generate tangible performance outcomes in the absence of adequate user readiness, facilitating conditions, and a sufficient level of practical implementation. In contrast, the significant effect of computer-assisted audit techniques (CAATs) suggests that technologies that are well integrated into routine audit practices and supported by established procedures are more likely to produce measurable improvements in audit effectiveness. Overall, these findings extend the UTAUT framework by highlighting the critical role of professional context and implementation maturity in explaining the relationship between technology acceptance and performance outcomes in auditing.

From a practical perspective, the findings suggest that public accounting firms should maintain and further optimize the use of computer-assisted audit techniques (CAATs), as they have been empirically shown to enhance audit efficiency, accuracy, and reliability. In addition, firms are encouraged to strengthen auditor readiness for the adoption of artificial intelligence and big data analytics by improving digital literacy, implementing continuous and structured training programs, and providing adequate infrastructure as well as clear internal policies to support the effective integration of these technologies into audit procedures.

This study has several limitations. First, the sample is confined to external auditors

working in public accounting firms located in South Jakarta, which limits the generalizability of the findings to the broader population of auditors in Indonesia. Second, the analysis focuses on three audit technologies—artificial intelligence, big data analytics, and computer-assisted audit techniques (CAATs)—while other factors that may influence audit process effectiveness were not examined comprehensively. Accordingly, future research is encouraged to broaden the geographical coverage and increase the number of respondents, as well as to incorporate additional variables such as auditor competence, professional skepticism, organizational culture, and time pressure. Moreover, subsequent studies may examine the actual level of digital technology implementation in audit practices to provide a more comprehensive understanding of the determinants of audit process effectiveness.

REFERENCES

- Abdelwahed, A. S., Abu-Musa, A. A., Badawy, H. A., & Moubarak, H. (2025). Unleashing the beast: the impact of big data and data analytics on the auditing profession—Evidence from a developing country. *Future Business Journal*, 11(1). <https://doi.org/10.1186/s43093-024-00420-7>
- Adelakun, B. O., Antwi, B. O., Fatogun, D. T., & Olaiya, O. P. (2024). *Enhancing audit accuracy : The role of AI in detecting financial anomalies and fraud*. 6(6), 1049–1068. <https://doi.org/10.51594/farj.v6i6.1235>
- Al-Ateeq, B., Sawan, N., Al-Hajaya, K., Altarawneh, M., & Al-Makhadmeh, A. (2022). Big Data Analytics in Auditing and the Consequences for Audit Quality: a Study Using the Technology Acceptance Model (Tam). *Corporate Governance and Organizational Behavior Review*, 6(1), 64–78. <https://doi.org/10.22495/cgobrv6i1p5>
- Albawwat, I., & Frijat, Y. Al. (2021). An analysis of auditors' perceptions towards artificial intelligence and its contribution to audit quality. *Accounting*, 7(4), 755–762. <https://doi.org/10.5267/j.ac.2021.2.009>
- Andriyana, H., & Trisnarningsih, S. (2022). *Analisis Pelanggaran Etika Dan Kode Etik Profesi Akuntan Di Era Persaingan Yang Kompetitif (Studi Kasus Pt. Garuda Indonesia (Persero), Tbk.)*. 16(6), 2304–2318.
- Andryani, Dani, A. R., Gubinata, B. T., & Purnamasari, F. (2021). Teknik Audit di Era Digital: Computer Assisted Audit Techniques (Studi Kajian Teoritis). *Prosiding National Seminar on Accounting, Finance, and Economics (NSAFE)*, 1(2), 99–106.
- Arens, A. A., Elder, R. J., Beasley, M. S., & Hogan, C. E. (2019). Auditing & Assurance Services Pendekatan Terintegrasi. In *Pearson Education Limited*.
- Atmaja, D. (2016). Kompetensi dan Profesionalisme ke Kemampuan Auditor. *Media Riset Akuntansi, Auditing, Dan Informasi*, 16(1), 53–68.
- Atta, A. A. B., Baniata, H. M., Othman, O. H., A., A. B. J., Abughaush, S. W., Abdallah, A. N., & Ahmad, A. Y. B. (2024). *The impact of computer assisted auditing techniques in the audit process: an assessment of performance and effort expectancy*. 8, 977–988. <https://doi.org/10.5267/j.ijdns.2023.12.009>
- Awuah, B., Onumah, J. M., & Duho, K. C. T. (2022). Determinants of adoption of computer-assisted audit tools and techniques among internal audit units in Ghana. *Electronic Journal of Information Systems in Developing Countries*, 88(2), 1–20. <https://doi.org/10.1002/isd2.12203>
- Bani, P., Siregar, N., Subiyanto, B., & Awaludin, D. T. (2025). *Digital Transformation in the Audit Process : A Systematic Review of Innovation , Challenges , and its Impact on Audit Quality*. 05(03), 3454–3471.
- Binh, N. T. T. (2025). Transforming Auditing in the AI Era: A Comprehensive Review. *Information (Switzerland)*, 16(5), 1–17. <https://doi.org/10.3390/info16050400>
- Caseba, F. L., & Dewayanto, T. (2024). Penerapan Artificial Intelligence, Big Data, Dan



- Blockchain Dalam Fintech Payment Terhadap Risiko Penipuan Komputer (Computer Fraud Risk): a Systematic Literature Review. *Diponegoro Journal of Accounting*, 1–15.
- Dako, O. F., Onalaja, T. A., Nwachukwu, P. S., & Bankole, F. A. (2020). *Big data analytics improving audit quality , providing deeper financial insights , and strengthening compliance reliability*. 64–80.
- Eko, N. A. T., S. Rifaldi, A., Fadhillah, J., & Ratuliu. (2025). *Analisis Peran Audit Siklus Penjualan Dan Pengihan Dalam Mengidentifikasi Risiko Kecurangan (Frud): Studi Kasus Pada Pt Indofarma Tbk. 11*.
- Emily, L. C., Sujanto, K. A., & Angelus, M. (2025). *Exploring the impact of CAATs adoption on audit quality: A TOE framework approach*. 9(11), 320–333. <https://doi.org/10.55214/2576-8484.v9i11.10872>
- Fitrianiingsih, S. K., & Khadijah, T. A. Z. (2021). Implementasi Teknik Audit Berbantuan Komputer di Era Digital. *Prosiding National Seminar on Accounting, Finance, and Economics (NSAFE)*, 1(2), 221–227.
- Ghozali, P. H. I. (2021). *Aplikasi Analisis Multivariate Dengan Program Ibm Spss 26*.
- Hair, J. F., Hult, G. T. M., & Ringle, C. M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*.
- Herianti, E. (2020). Modul pelatihan penelitian kuantitatif dengan aplikasi SMARTPLS. *Jurnal Ilmu Pendidikan*, 7(2), 809–820.
- Hidayat, I., Antong, & Rahmawati. (2024). The Role of Artificial Intelligence (AI) in Improving Audit Efficiency and Effectiveness. *Proceedings Series on Proceedings of Multidisciplinary Sciences*, 1(1), 1195–1202.
- Kelintinas, I., Dian, A., Safitri, C., & Kuntadi, C. (2024). Pengaruh Penerapan Teknologi Big Data, Independensi Auditor, Dan Kualitas Pelaporan Keuangan Terhadap Efektifitas Proses Audit. *Jma*, 2(6), 3031–5220.
- Khaerunnisa, A., Karfina, L., & Amiruddin, A. R. (2025). *Atestasi : Jurnal Ilmiah Akuntansi Integrasi Big Data dalam Penilaian Risiko : Tantangan dan Peluang bagi Akuntan Modern*. 8(2), 102–114.
- Lan, Z. (2022). From Animals to Artificial Intelligence: Non-Human Beings’ Intellectual Property Protection by “Judicial Capacity for Copyrights.” *Beijing Law Review*, 13(04), 697–714. <https://doi.org/10.4236/blr.2022.134045>
- Law, K. K. F., & Shen, M. (2025). How Does Artificial Intelligence Shape Audit Firms? *Management Science*, 71(5), 3641–3666. <https://doi.org/10.1287/mnsc.2022.04040>
- Marei, D. A., & Iskandar, P. E. (2019). The impact of Computer Assisted Auditing Techniques (CAATs) on development of audit process: an assessment of Performance Expectancy of by the auditors. *International Journal of Management and Commerce Innovations*, 7(2), 1199–1205. www.researchpublish.com
- Muna, K., & Meutia, T. (2024). Efektivitas Pelaksanaan Audit Investigatif Dalam Mendeteksi Kecurangan Ditinjau Dari Independensi Dan Penerapan Teknik Audit Berbantuan Komputer (TABK). *Jurnal Riset Akuntansi*, 2(2), 250–260. <https://doi.org/10.54066/jura-itb.v2i2.1786>
- Najmuddin, A. B., & Pamungkas, I. D. (2021). Pengaruh independensi, pengalaman, penerapan akuntansi forensik dan teknik audit berbantuan komputer (TABK) terhadap efektivitas pelaksanaan audit investigatif dalam mendeteksi kecurangan (Studi kasus pada BPKP Jawa Tengah). *Proceeding SENDIU*, 220–228.
- Nugrahanti, T. P., Sudarmanto, E., Bakri, A. A., Susanto, E., & Male, S. R. (2023). Pengaruh Penerapan Teknologi Big Data, Independensi Auditor, dan Kualitas Pelaporan Keuangan terhadap Efektivitas Proses Audit. *Sanskara Akuntansi Dan Keuangan*, 2(01), 47–54. <https://doi.org/10.58812/sak.v2i01.249>
- Pérez-Calderón, E., Alrahamneh, S. A., & Milanés Montero, P. (2025). Impact of artificial

- intelligence on auditing: an evaluation from the profession in Jordan. *Discover Sustainability*, 6(1). <https://doi.org/10.1007/s43621-025-01058-3>
- Pramudyastuti, O. L., Utpala, R., Pradana, S. K., & Wahyuningtiyas, T. N. (2022). Persepsi Auditor Eksternal Terhadap Digitalisasi Audit Melalui Teknik Audit Berbantuan Komputer. *Jurnal Maneksi*, 11(2), 448–455.
- Puteri, A. D., Utomo, P. E. P., & Arsa, D. (2023). Evaluasi Penerimaan Teknologi Metaverse Pendekatan Teori Utaut (Studi Kasus : Pojok Statistik Virtual). *Journal of Information System, Graphics, Hospitality and Technology*, 5(2), 86–94. <https://doi.org/10.37823/insight.v5i2.319>
- Putri, A. A., & Zulhaimi, H. (2023). Pengaruh Tipe Kepribadian Auditor dan Pengetahuan Teknologi Informasi terhadap Pendeteksian Fraud (Studi pada Kantor Akuntan Publik di Kota Bandung). 11(3), 595–604.
- Rahmatullah, R., & Purnamasari, P. (2024). Pengaruh Efektivitas Penggunaan E-Audit dan Pengalaman Auditor terhadap Pendeteksian Kecurangan. *Bandung Conference Series: Accountancy*, 4(1), 554–559. <https://doi.org/10.29313/bcsa.v4i1.12116>
- Safitri, E. D., & Ratnawati, T. (2025). *Jurnal Inovasi Akuntansi Modern Pengaruh Skeptisisme Profesional , Time Bduget Pressure Dan Audit Artificial Intelligence Terhadap Kemampuan Deteksi Fraud Dan Kualitas Audit Judgment Dengan Kepatuhan Terhadap Standar Audit Sebagai Variabel Moderasi Pada A. 07(1).*
- Sholihah, S. N. A., Widyastuti, R. A., & Ratnawati, T. (2023). Peran Artificial Intelligence Untuk Mendeteksi Fraud Dalam Audit: Sebuah Studi Literatur. *Jurnal Riset Ekonomi Dan Akuntansi*, 1(4), 226–238. <https://doi.org/10.54066/jrea-itb.v1i4.991>
- Silaen, R. P., & Dewayanto, T. (2024). Penggunaan Berbagai Artificial Intelligence Pada Proses Audit-a Systematic Literature Review. *Diponegoro Journal of Accounting*, 13(2), 1–15. <http://ejournal-s1.undip.ac.id/index.php/accounting>
- Suryani, I. D. R., Kurniawati, E., Wulan, G. A. N., & Dinniah, H. C. (2021). Konseptualisasi Peran Teknologi Informasi Dalam Praktik Audit Untuk Membantu Pengungkapan Fraud Di Indonesia. *El Muhasaba Jurnal Akuntansi*, 12(2), 138–156. <https://doi.org/10.18860/em.v12i2.12070>
- Syahronny, M. R., & Dewayanto, T. (2024). Penerapan Teknologi Artificial Intelligence Dan Blockchain Dalam Mendeteksi Fraud Pada Proses Audit: Systematic Literature Review. *Diponegoro Journal of Accounting*, 13(3), 1–14. <http://ejournal-s1.undip.ac.id/index.php/accounting>
- Taunaumang, H., Lima, R., & Gomez, R. (2025). The Influence of Audit Technology on Audit Efficiency and Effectiveness: Auditor’s Perspective. *Journal Markcount Finance*, 3(1), 38–49. <https://doi.org/10.70177/jmf.v3i1.2139>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Zhang, W., Zeng, X., Liang, H., Xue, Y., & Cao, X. (2023). Understanding how organizational culture affects innovation performance: A management context perspective. *Sustainability (Switzerland)*, 15(8), 1–18.

