

How Advanced Audit Technology Capability Influences Audit Quality: The Mediating Role of Audit Process Efficiency

Dr.Khajit Na Kalasindhu

*Assistant Professor of Faculty of Management Sciences and Information Technology,
Nakhon Phanom University*

Received: April 7, 2026

Revised: July 6, 2026

Accepted: July 20, 2026

Pinamporn Malai*

Dr.Kittisak Malai

*Lecturer of Faculty of Management Sciences and Information Technology,
Nakhon Phanom University*

(*Corresponding Author)

ABSTRACT

In the digital era, advanced technologies have played an increasingly important role in auditing by enhancing efficiency and supporting the reliability of financial information. However, prior research has largely emphasized the direct effects of technology on audit quality, with limited attention to the underlying processes. This study examines the effect of advanced audit technology capability on audit quality, with audit process efficiency as a mediating mechanism. Data were collected from 310 certified public accountants (CPAs) in Thailand and analyzed using covariance-based structural equation modeling (CB-SEM). The results indicate that advanced audit technology capability significantly improves audit process efficiency, which in turn enhances audit quality. Furthermore, some technologies influence audit quality only indirectly through audit process efficiency, while others exhibit both direct and indirect effects, highlighting the heterogeneous roles of different technologies. This study contributes by providing a process-based explanation of how technological capability is translated into audit outcomes. The findings offer both theoretical insights and practical guidance for audit firms in effectively integrating advanced technologies into audit processes to improve audit quality.

Keywords: Advanced Audit Technology Capability, Audit Process Efficiency, Audit Quality

การศึกษาผลกระทบของความสามารถด้านเทคโนโลยี การสอบบัญชีขั้นสูงที่มีต่อคุณภาพการสอบบัญชี ผ่านประสิทธิภาพกระบวนการสอบบัญชี

ดร.ขจิต ฑ กาฬสินธุ์

ผู้ช่วยศาสตราจารย์ประจำคณะวิทยาการจัดการและเทคโนโลยีสารสนเทศ
มหาวิทยาลัยนครพนม

วันที่ได้รับต้นฉบับบทความ : 7 เมษายน 2569

วันที่แก้ไขปรับปรุงบทความ : 6 กรกฎาคม 2569

วันที่ตอบรับตีพิมพ์บทความ : 20 กรกฎาคม 2569

ปิ่นอัมภรณ์ มะลัย*

ดร.กิตติศักดิ์ มะลัย

อาจารย์ประจำคณะวิทยาการจัดการและเทคโนโลยีสารสนเทศ

มหาวิทยาลัยนครพนม

(*ผู้ประสานงานหลัก)

บทคัดย่อ

ในยุคดิจิทัล เทคโนโลยีขั้นสูงมีบทบาทสำคัญมากขึ้นในงานสอบบัญชี โดยช่วยเพิ่มประสิทธิภาพและสนับสนุนความน่าเชื่อถือของข้อมูลทางการเงิน อย่างไรก็ตาม งานวิจัยที่ผ่านมาให้ความสำคัญกับผลกระทบทางตรงของเทคโนโลยีต่อคุณภาพการสอบบัญชีเป็นหลัก โดยยังให้ความสนใจต่อกระบวนการพื้นฐานที่อยู่เบื้องหลังค่อนข้างจำกัด การศึกษานี้มีวัตถุประสงค์เพื่อศึกษาผลกระทบของความสามารถด้านเทคโนโลยีการสอบบัญชีขั้นสูงที่มีต่อคุณภาพการสอบบัญชี โดยพิจารณาประสิทธิภาพกระบวนการสอบบัญชีเป็นตัวแปรสื่อกลาง ข้อมูลถูกเก็บรวบรวมจากผู้สอบบัญชีรับอนุญาต (CPAs) ในประเทศไทย จำนวน 310 คน และวิเคราะห์ด้วยแบบจำลองสมการโครงสร้างแบบอิงความแปรปรวนร่วม (CB-SEM) ผลการวิจัยพบว่า ความสามารถด้านเทคโนโลยีการสอบบัญชีขั้นสูงมีอิทธิพลเชิงบวกต่อประสิทธิภาพกระบวนการสอบบัญชี ซึ่งส่งผลให้คุณภาพการสอบบัญชีเพิ่มขึ้น นอกจากนี้ เทคโนโลยีบางประเภทส่งผลต่อคุณภาพการสอบบัญชีทางอ้อมผ่านประสิทธิภาพกระบวนการสอบบัญชีเท่านั้น ในขณะที่บางประเภทมีทั้งอิทธิพลทางตรงและทางอ้อม สะท้อนให้เห็นถึงบทบาทที่แตกต่างกันของเทคโนโลยีแต่ละประเภท การศึกษานี้มีส่วนช่วยในการอธิบายเชิงกระบวนการว่าความสามารถทางเทคโนโลยีถูกถ่ายทอดไปสู่ผลลัพธ์ด้านการสอบบัญชีได้อย่างไร และให้ทั้งข้อค้นพบเชิงทฤษฎีและแนวทางเชิงปฏิบัติสำหรับสำนักงานสอบบัญชีในการบูรณาการเทคโนโลยีขั้นสูงเข้าสู่กระบวนการสอบบัญชีอย่างมีประสิทธิภาพ เพื่อยกระดับคุณภาพการสอบบัญชี

คำสำคัญ: ความสามารถด้านเทคโนโลยีการสอบบัญชีขั้นสูง ประสิทธิภาพกระบวนการสอบบัญชี คุณภาพการสอบบัญชี

INTRODUCTION

In the digital era, technological advancements have significantly reshaped organizational operations, particularly in accounting and financial reporting systems. These systems increasingly rely on digital technologies for data collection, processing, and reporting, enabling organizations to handle large volumes of complex financial information more efficiently (Manita et al., 2020; Pristiwanto et al., 2025). At the same time, stakeholders expect financial information to be accurate, timely, and reliable for decision-making purposes. As a result, concerns regarding the credibility and quality of financial reporting have continued to grow, reinforcing the importance of auditing in enhancing information reliability and stakeholder confidence (Cameran et al., 2022).

In response to these developments, auditing practices have gradually evolved alongside technological progress. While earlier technologies were mainly adopted to improve data storage and processing efficiency, recent developments have introduced more advanced tools, such as data analytics, artificial intelligence, blockchain, and continuous auditing (Milad, 2022; Eulerich et al., 2023; Huang et al., 2022; Sharma & Jarial, 2024). These technologies allow auditors to analyze large datasets, identify unusual patterns, and perform audit procedures in a more systematic manner. As a result, auditors are able to devote less time to routine tasks and more attention to analytical evaluation and professional judgment. In this context, advanced audit technology capability can be understood as the auditor's ability to effectively apply these technologies within audit processes (Gokoglan et al., 2022; Vitali & Giuliani, 2024).

Building on task–technology fit theory (Goodhue & Thompson, 1995), performance is likely to improve when technological functionalities are aligned with task requirements. Auditing tasks are inherently complex, as they involve extensive data processing, risk assessment, and the detection of irregularities. When advanced audit technologies are appropriately applied in ways that match these task characteristics, they can improve audit process efficiency by increasing processing speed, reducing manual errors, and supporting more structured audit procedures. In turn, a more efficient audit process tends to support more thorough audit execution, improve the quality of audit evidence, and facilitate the application of professional judgment. This ultimately increases the likelihood of detecting material misstatements and strengthens the reliability of audit opinions (Ditkaew & Suttipun, 2023; Isa & Subramanian, 2024; Nwadiolor & Obi, 2020; Noordin et al., 2022). In this sense, audit process efficiency can be viewed as an important mechanism through which advanced audit technology capability contributes to audit quality.

Although a growing number of studies have examined the role of technology in auditing, much of the existing literature tends to emphasize the direct relationship between technology adoption

and audit quality (Ditkaew & Suttipun, 2023; Isa & Subramanian, 2024). Comparatively less attention has been given to the underlying processes through which technological capability translates into audit outcomes. In particular, the mediating role of audit process efficiency has not been examined in a systematic manner. In addition, prior research often considers audit technologies separately, rather than reflecting their combined and multidimensional nature, especially in emerging market settings such as Thailand.

To address these issues, this study examines the effect of advanced audit technology capability on audit quality, with audit process efficiency considered as a mediating mechanism. By applying task-technology fit theory in the auditing context, the study seeks to provide a clearer explanation of how technological capabilities are translated into audit outcomes. The findings are expected to contribute to the literature by offering further insight into the role of audit processes in technology-enabled auditing, while also providing empirical evidence from an emerging market context.

Research Objectives

This study aims to examine the effect of advanced audit technology capability on audit quality by incorporating audit process efficiency as a mediating mechanism. Specifically, the objectives are as follows:

1. To investigate the effect of advanced audit technology capability on audit process efficiency.
2. To examine the effect of audit process efficiency on audit quality.
3. To analyze the indirect effect of advanced audit technology capability on audit quality through audit process efficiency.

LITERATURE REVIEW

Task-Technology Fit Theory

Task-technology fit (TTF) theory explains how the alignment between technological capabilities and task requirements influences individual and organizational performance. The theory posits that information systems and technologies are more likely to enhance performance when their functionalities match the demands of the tasks being performed, rather than merely being adopted or available. In this sense, performance outcomes are not determined solely by the presence of technology, but by how well that technology supports task execution. TTF emphasizes that different tasks require different technological features, and a higher degree of fit leads to improved efficiency, effectiveness, and overall task performance. This perspective has been widely applied in information systems and organizational research to explain how technology contributes to productivity and decision-making outcomes (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998; Dishaw & Strong, 1999).

In the context of auditing, TTF theory provides a useful framework for explaining how advanced audit technology capability contributes to audit outcomes through process-level improvements. Auditing tasks involve complex activities such as large-scale data processing, risk assessment, and anomaly detection, which require technologies capable of handling high data volume and analytical complexity. When advanced audit technologies are effectively aligned with these task requirements, they enhance audit process efficiency by improving processing speed, reducing manual errors, and enabling more structured and systematic audit procedures (Eulerich et al., 2023; Huang et al., 2022; Vitali & Giuliani, 2024). In turn, improved audit process efficiency supports more effective audit execution, enhances the quality of audit evidence, and strengthens professional judgment, ultimately leading to higher audit quality (Ditkaew & Suttipun, 2023; Isa & Subramanian, 2024). Accordingly, TTF theory suggests that advanced audit technology capability does not influence audit quality solely through direct effects, but operates through audit process efficiency as a key underlying mechanism.

Advanced Audit Technology Capability

Advanced audit technology capability refers to the auditor's perceived capability to effectively apply advanced auditing tools and techniques to support audit performance (Sayal et al., 2025). In this study, the construct reflects auditors' assessments of their capability to utilize advanced audit technologies rather than the actual implementation level of such technologies within audit firms. In modern auditing, this capability is typically viewed as a multidimensional construct encompassing four key components: data analytics, artificial intelligence, blockchain technology, and continuous auditing. These technologies enable auditors to process large volumes of data, automate complex and repetitive tasks, enhance data reliability, and facilitate real-time monitoring, thereby improving the efficiency and scope of audit processes (Milad, 2022; Sewpersadh, 2025). As auditing increasingly moves from traditional, sample-based approaches toward data-driven and technology-enabled practices, the integration of these capabilities becomes critical in strengthening audit process efficiency and, ultimately, enhancing audit quality. Together, these dimensions represent the major technological functionalities required in modern auditing environments and collectively capture auditors' capability to effectively utilize advanced technologies throughout the audit process (Manita et al., 2020; Eulerich et al., 2023; Vitali & Giuliani, 2024; Sewpersadh, 2025).

Data analytics enables auditors to analyze entire datasets rather than relying on sampling, thereby improving audit coverage and anomaly detection. By supporting real-time monitoring and predictive analysis, it enhances audit process efficiency through faster processing and more accurate identification of high-risk areas (Ditkaew & Suttipun, 2023; Sari, 2024). This, in turn, improves the reliability of audit

evidence and increases the likelihood of detecting material misstatements, contributing to higher audit quality (Nwadior & Obi, 2020; Isa & Subramanian, 2024). According to task–technology fit theory, data analytics aligns closely with audit tasks involving large-scale data processing, risk assessment, and anomaly detection. This alignment enables auditors to perform audit procedures more efficiently and effectively, thereby improving audit process efficiency and enhancing audit quality (Abdelwahed et al., 2025; Celestin, 2020; Sari, 2024).

Artificial intelligence improves auditing by automating complex and repetitive tasks, including risk assessment and anomaly detection. Its ability to process large volumes of data and learn from patterns reduces manual effort and human error, thereby enhancing audit process efficiency (Binh, 2025; Huang et al., 2022). In addition, AI enables more precise risk identification and supports more effective audit procedures, leading to improved audit quality (Kokina et al., 2025; Yin, 2023; Qatawneh, 2024). From a task–technology fit perspective, artificial intelligence is particularly suited to complex audit tasks such as pattern recognition, risk identification, and anomaly detection. As a result, AI can improve the efficiency of audit processes and support higher-quality audit outcomes (Nugraha, 2024; Rahman et al., 2024; Shazly et al., 2024).

Blockchain technology provides a secure and immutable record of transactions, allowing auditors to verify data directly from the source. This reduces reliance on third-party confirmations and simplifies audit trails, thereby improving audit process efficiency. At the same time, enhanced data integrity supports the collection of reliable audit evidence, strengthening the credibility of audit findings and contributing to higher audit quality (Arianpoor & Borhani, 2025; Gokoglan et al., 2022; Qader & Cek, 2024; Ziemba et al., 2025). Task–technology fit theory suggests that blockchain technology is highly compatible with audit tasks requiring transaction verification, audit trail validation, and evidence reliability. This fit facilitates more efficient audit procedures and strengthens audit quality through improved data integrity and transparency (Anis, 2023; Bellucci et al., 2022; Bonsón & Bednárová, 2019; Bonyuet, 2020).

Continuous auditing enables real-time monitoring of transactions, allowing auditors to identify risks and anomalies as they occur. This reduces delays in issue detection and enhances audit process efficiency. Moreover, timely and relevant audit evidence supports more proactive audit practices and improves audit quality (Alles et al., 2006; Meiryani et al., 2021; Rikhardsson et al., 2019; Wang, W., & Vasarhelyi, 2024). According to task–technology fit theory, continuous auditing fits audit tasks that require real-time monitoring and continuous risk assessment. This compatibility enables auditors to respond more promptly to emerging issues, thereby improving audit process efficiency and supporting audit quality (Almasoudi & Al-Refiay, 2023; Lee et al., 2014; Rezaee et al., 2002).

Advanced audit technologies enhance audit process efficiency by improving data processing, reducing errors, and supporting more systematic audit procedures. As efficiency increases, auditors are better able to obtain reliable evidence and perform audit tasks more effectively, which in turn leads to higher audit quality. Accordingly, advanced audit technology capability is expected to influence audit quality through audit process efficiency.

Audit Process Efficiency

Audit process efficiency refers to the extent to which audit activities are performed in a timely, systematic, and resource-effective manner while maintaining the appropriateness of audit procedures. It reflects how well key audit stages—such as planning, risk assessment, and evidence collection—are executed in a structured and coordinated way, rather than simply emphasizing speed or cost reduction (Friska & Agustia, 2025; Sulaiman et al., 2018). Importantly, audit process efficiency also involves the effective allocation of audit resources, including time, personnel, and technological tools, to ensure that audit objectives are achieved without compromising audit standards. In this sense, efficiency is not solely about doing tasks faster, but about performing audit procedures in a way that enhances both consistency and reliability across different audit engagements.

In complex audit environments, efficient processes enable auditors to handle large volumes of data, conduct more comprehensive risk assessments, and obtain sufficient and appropriate audit evidence. As audit procedures become more systematic and consistent, auditors are better able to detect material misstatements and reduce the likelihood of oversight. Moreover, improved efficiency allows auditors to devote greater attention to analytical evaluation and professional judgment, rather than routine or repetitive tasks. Thus, audit process efficiency plays a critical role in shaping how audit activities are conducted and serves as an important driver of audit quality (Sayal et al., 2025; Xiao et al., 2020). Although audit process efficiency and audit quality are closely related, audit process efficiency focuses on the effectiveness of audit procedures, whereas audit quality reflects the reliability and credibility of audit outcomes.

Audit Quality

Audit quality refers to the extent to which an audit increases the likelihood of detecting and reporting material misstatements in financial statements. It is conceptualized as an outcome of the audit, reflecting the reliability and credibility of audit conclusions provided to stakeholders (Christensen et al., 2016; Akuoko-Sarpong et al., 2024; Rajgopal et al., 2021). In fulfilling their responsibility, auditors provide an independent and professional opinion on whether financial statements are prepared, in

all material respects, in accordance with generally accepted accounting principles, thereby enhancing users' confidence in reported information. High audit quality is reflected in accurate and unbiased audit opinions, clear and understandable communication, comprehensive and reliable risk assessment, and the timely issuance of audit reports (Oraka & Okegbe, 2015). These outcomes collectively enhance the credibility and usefulness of financial reporting for decision-making purposes (Alsughayer, 2021; Noordin et al., 2022).

Research Hypotheses

Hypothesis 1: Advanced audit technology capability, including (a) data analytics, (b) artificial intelligence, (c) blockchain technology, and (d) continuous auditing, have positive effects on audit process efficiency.

Hypothesis 2: Advanced audit technology capability, including (a) data analytics, (b) artificial intelligence, (c) blockchain technology, and (d) continuous auditing, have positive effects on audit quality.

Hypothesis 3: Audit process efficiency has a positive effect on audit quality.

Hypothesis 4: Advanced audit technology capability has a positive indirect effect on audit quality through audit process efficiency.

RESEARCH METHODOLOGY

Population and Sample

The population of this study consists of certified public accountants (CPAs) in Thailand who consented to publicly disclose their contact information with the Federation of Accounting Professions under the Royal Patronage of His Majesty the King. CPAs were selected because they possess direct professional experience in audit planning, evidence evaluation, risk assessment, and audit reporting, making them suitable respondents for evaluating advanced audit technology capability in auditing practice. According to the official registry, a total of 1,205 CPAs were listed as eligible participants (Federation of Accounting Professions, 2025). Data collection was conducted between October 1, 2025 and December 31, 2025. Questionnaires were distributed by postal mail to all eligible CPAs. A follow-up reminder was sent one month after the initial distribution to encourage participation and improve the response rate. A total of 318 questionnaires were returned. However, eight questionnaires were excluded due to incomplete responses. Consequently, 310 valid responses were retained for the final analysis, representing a response rate of 25.73%. This sample size is considered adequate for structural equation modeling (SEM), as a minimum of 200 observations is generally recommended for

reliable model estimation. In addition, the study includes 26 observed indicators, and the obtained sample exceeds the recommended threshold of at least 10 responses per indicator, further supporting the adequacy of the sample size for statistical analysis and hypothesis testing (Hair et al., 2019).

Research Instrument

This study employed a structured questionnaire developed based on the research objectives and conceptual framework. The measurement items were developed from a review of relevant literature and prior studies to ensure consistency with the conceptual definitions of the constructs examined in this study. The instrument comprised four sections. Section 1 collected demographic information of certified public accountants (CPAs) in Thailand using a checklist format. Sections 2–4 were measured using a five-point Likert scale. Specifically, Section 2 assessed advanced audit technology capability with 16 items across four dimensions: data analytics, artificial intelligence, blockchain technology, and continuous auditing. The measurement items assessed respondents' perceived capability in applying advanced audit technologies in auditing practice. Section 3 measured audit process efficiency with 6 items, while Section 4 evaluated audit quality with 6 items.

Common Method Bias

To assess the potential risk of common method bias, Harman's single-factor test was conducted using all measurement items. The results indicated that the first factor accounted for 34.26% of the total variance, which is below the recommended threshold of 50%. Therefore, common method bias was unlikely to be a serious concern in this study.

Data Analysis

Data were analyzed using covariance-based structural equation modeling (CB-SEM) with Mplus software. The analysis was conducted in two stages. First, the measurement model was evaluated to assess reliability and validity, including convergent validity (factor loadings, AVE, and CR) and discriminant validity (Fornell–Larcker criterion). Second, the structural model was examined to test the hypothesized relationships among constructs. In addition, indirect effects were assessed using the bootstrap method with 5,000 resamples to estimate standard errors and significance levels. Model fit was evaluated using multiple goodness-of-fit indices, including χ^2/df , RMSEA, CFI, TLI, and SRMR, based on recommended thresholds. Standardized coefficients were reported for the measurement and structural model analyses.

RESULTS

Descriptive Statistics

Table 1 presents the descriptive statistics of the study constructs. Overall, respondents report relatively high levels of agreement across all constructs, with mean scores ranging from 3.806 to 3.910. For Data analytics (DA), the overall mean is 3.806 (S.D. = 0.789), with DA4 receiving the highest mean score (4.042) and DA2 the lowest (3.581). Artificial intelligence (AI) has an overall mean of 3.835 (S.D. = 0.807), with AI4 reporting the highest mean (4.061) and AI1 the lowest (3.619). Blockchain technology (BC) records a mean of 3.810 (S.D. = 0.798), where BC4 has the highest mean (4.023) and BC1 the lowest (3.597). Continuous auditing (CA) has an overall mean of 3.855 (S.D. = 0.813), with CA4 obtaining the highest mean (4.081) and CA2 the lowest (3.639). Audit process efficiency (AP) records the highest construct mean (3.910, S.D. = 0.818), with AP6 showing the highest mean (4.142) and AP1 the lowest (3.697). Finally, Audit quality (AQ) has a mean of 3.878 (S.D. = 0.820), with AQ6 receiving the highest mean (4.152) and AQ1 the lowest (3.652).

Table 1 Descriptive Statistics

Construct	Number of items	Mean	S.D.	Lowest item (Mean)	Highest item (Mean)
DA	4	3.806	0.789	DA2 (3.581)	DA4 (4.042)
AI	4	3.835	0.807	AI1 (3.619)	AI4 (4.061)
BC	4	3.810	0.798	BC1 (3.597)	BC4 (4.023)
CA	4	3.855	0.813	CA2 (3.639)	CA4 (4.081)
AP	6	3.910	0.818	AP1 (3.697)	AP6 (4.142)
AQ	6	3.878	0.820	AQ1 (3.652)	AQ6 (4.152)

Measurement Model Assessment

Convergent validity was assessed using factor loadings, average variance extracted (AVE), and composite reliability (CR). As reported in Table 2, all factor loadings ranged from 0.757 to 0.863, exceeding the recommended threshold of 0.70 (Hair et al., 2019), indicating satisfactory indicator reliability. In addition, the AVE values ranged from 0.641 to 0.697, which are above the minimum acceptable level of 0.50 (Fornell & Larcker, 1981), suggesting that the constructs adequately capture the variance of their indicators.

Furthermore, composite reliability (CR) values ranged from 0.877 to 0.924, exceeding the recommended threshold of 0.70 (Hair et al., 2019), indicating that all constructs exhibit a high level of internal consistency reliability at the construct level. In addition, Cronbach's alpha coefficients ranged from 0.872 to 0.918, also above the acceptable threshold of 0.70 (Cronbach, 1951; Hair et al., 2019), further supporting the internal consistency of the measurement scales. Accordingly, these results confirm that the measurement model demonstrates adequate convergent validity and reliability (see Table 2).

Table 2 Construct Validity and Internal Consistency Reliability

Construct	Factor Loadings	AVE	CR	Cronbach's α
DA	0.773–0.837	0.641	0.877	0.873
AI	0.757–0.854	0.654	0.883	0.872
BC	0.821–0.863	0.697	0.902	0.888
CA	0.770–0.840	0.663	0.887	0.879
AP	0.760–0.852	0.653	0.919	0.915
AQ	0.801–0.860	0.671	0.924	0.918

Table 3 Results of Discriminant Validity Assessment Using the Fornell–Larcker Criterion

Construct	DA	AI	BC	CA	AP	AQ
DA	0.801					
AI	0.301	0.809				
BC	0.318	0.301	0.835			
CA	0.129	0.211	0.247	0.814		
AP	0.285	0.382	0.311	0.172	0.808	
AQ	0.247	0.281	0.338	0.190	0.648	0.819

Discriminant validity was evaluated using the Fornell–Larcker criterion. As shown in Table 3, the square root of the AVE for each construct (ranging from 0.801 to 0.835) is greater than the corresponding inter-construct correlations. This indicates that each construct is empirically distinct and captures phenomena not represented by other constructs. In addition, the relatively low correlations among

constructs further support the absence of redundancy across latent variables. Therefore, discriminant validity is established, and no multicollinearity issues are detected among the constructs (Fornell & Larcker, 1981) (see Table 3)

Model Fit Assessment

The overall model fit was evaluated using multiple goodness-of-fit indices, including chi-square (χ^2), the ratio of chi-square to degrees of freedom (χ^2/df), the root mean square error of approximation (RMSEA), the comparative fit index (CFI), the Tucker–Lewis index (TLI), and the standardized root mean square residual (SRMR). The results, as presented in Table 4, indicate that the model demonstrates an excellent fit to the data (Hair et al., 2019). These indices provide a comprehensive and robust assessment of model fit.

Specifically, the chi-square value was 365.257 with 332 degrees of freedom and was not statistically significant ($p = 0.101$), suggesting that the model is consistent with the observed data. The χ^2/df value was 1.101, which is below the recommended threshold of 3.00, indicating a good model fit. In addition, the RMSEA value was 0.018, which is well below the acceptable level of 0.05, reflecting a close fit. These results indicate minimal discrepancy between the hypothesized model and the empirical data. Moreover, the narrow confidence interval of RMSEA further supports the stability of the model fit.

Furthermore, the incremental fit indices also demonstrated excellent values, with CFI = 0.994 and TLI = 0.993, both exceeding the recommended threshold of 0.95. The SRMR value was 0.037, which is below the acceptable cutoff of 0.08, indicating a good fit between the observed and predicted covariance matrices. Overall, these results confirm that the proposed structural model fits the empirical data well and is appropriate for subsequent hypothesis testing. The consistent fit indices support the adequacy of the model.

Table 4 Results of Model Fit Analysis

χ^2 (df, p)	χ^2/df (< 3)	RMSEA (< 0.050)	CFI (≥ 0.950)	TLI (≥ 0.950)	SRMR (≤ 0.080)
365.257 (332, $p = 0.101$)	1.101	0.018	0.994	0.993	0.037

Hypothesis Testing

Table 5 presents the results of the causal structural equation model analysis using the CB-SEM approach. The findings revealed that advanced audit technology capability dimensions exerted positive effects on audit process efficiency. Specifically, data analytics had a positive and significant effect on audit process efficiency ($\beta = 0.161$, $p < .01$). Artificial intelligence was found to be the strongest predictor, exerting the highest positive effect ($\beta = 0.336$, $p < .01$). Blockchain technology also showed a positive and significant effect ($\beta = 0.251$, $p < .01$). In addition, continuous auditing had a positive but marginally significant effect ($\beta = 0.103$, $p < .10$). Therefore, Hypothesis 1a–1d was supported.

Regarding the direct effects on audit quality, the results indicated that data analytics ($\beta = 0.187$, $p < .01$) and blockchain technology ($\beta = 0.257$, $p < .01$) had significant positive effects on audit quality. Thus, Hypothesis 2a and 2c was supported. However, artificial intelligence ($\beta = 0.001$, $p > .10$) and continuous auditing ($\beta = 0.081$, $p > .10$) did not exhibit significant effects. Therefore, Hypothesis 2b and 2d was not supported. In addition, audit process efficiency was found to have a positive and significant effect on audit quality ($\beta = 0.371$, $p < .01$), supporting Hypothesis 3.

Furthermore, the mediation analysis revealed that advanced audit technology capability exerted indirect effects on audit quality through audit process efficiency. Specifically, data analytics ($\beta = 0.060$, $p < .05$), artificial intelligence ($\beta = 0.125$, $p < .01$), and blockchain technology ($\beta = 0.093$, $p < .01$) demonstrated significant indirect effects. Continuous auditing also showed a marginally significant indirect effect ($\beta = 0.038$, $p < .10$). These results confirm that audit process efficiency serves as a mediating mechanism. Therefore, Hypothesis 4 was supported.

Table 5 Results of the Structural Equation Model Analysis

Path	DE	IE via AP	TE
DA → AP	0.161 (0.058)***	–	–
AI → AP	0.336 (0.056)***	–	–
BC → AP	0.251 (0.057)***	–	–
CA → AP	0.103 (0.055)*	–	–
DA → AP → AQ	0.187 (0.054)***	0.060 (0.025)**	0.247 (0.059)***
AI → AP → AQ	0.001 (0.059)	0.125 (0.030)***	0.126 (0.063)**
BC → AP → AQ	0.257 (0.056)***	0.093 (0.026)***	0.350 (0.067)***
CA → AP → AQ	0.081 (0.052)	0.038 (0.024)*	0.119 (0.054)*
AP → AQ	0.371 (0.060)***	–	–

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, a standardized coefficients and standard errors (S.E.) in parentheses.

Note: DA = Data Analytics; AI = Artificial Intelligence; BC = Blockchain Technology; CA = Continuous Auditing; AP = Audit Process Efficiency; AQ = Audit Quality; DE = Direct Effect; IE = Indirect Effect; TE = Total Effect.

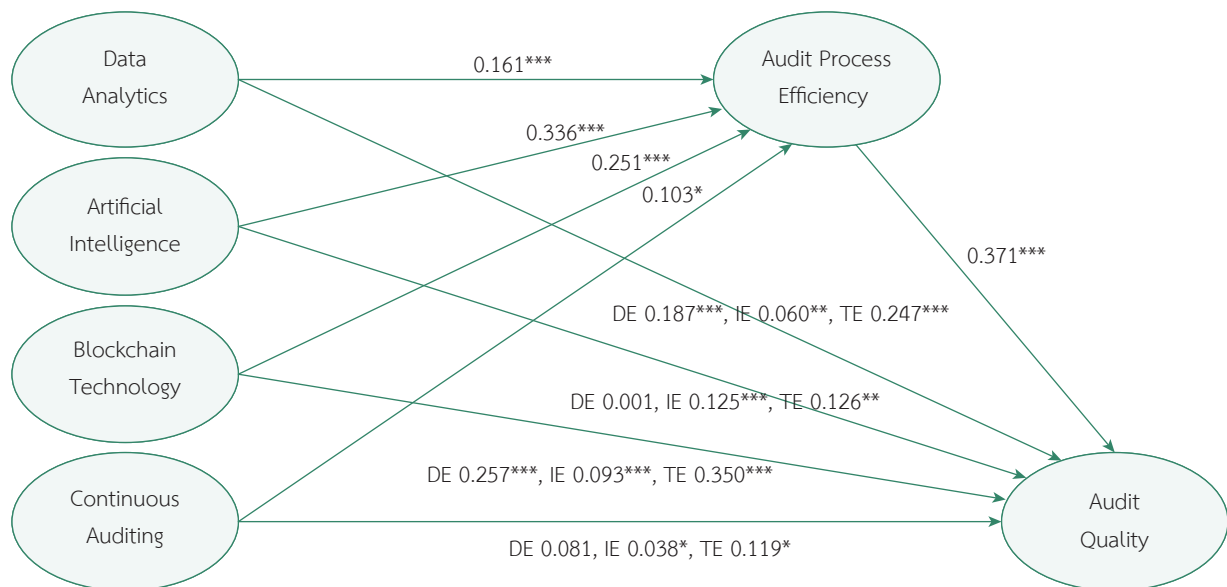


Figure 1 Results of the CB-SEM analysis using Mplus

* Note: DE = Direct Effect; IE = Indirect Effect; TE = Total Effect. * $p < .10$, ** $p < .05$, *** $p < .01$

DISCUSSION

This study aims to examine the effect of advanced audit technology capability on audit quality by incorporating audit process efficiency as a mediating mechanism, thereby addressing a key gap in prior research that has largely focused on direct relationships while overlooking the underlying process through which technological capabilities translate into audit outcomes. The findings reveal that advanced audit technology capability significantly enhances audit process efficiency, which in turn improves audit quality. This result is consistent with the perspective of task-technology fit theory, suggesting that when technological capabilities are aligned with the requirements of audit tasks, performance outcomes are improved. In the auditing context, technologies such as data analytics, artificial intelligence, blockchain, and continuous auditing contribute to more structured, systematic, and data-driven audit processes, ultimately strengthening audit effectiveness and reliability. This finding is in line with prior research indicating that the application of advanced technologies enhances audit performance through improved data processing, risk assessment, and the quality of audit evidence (Ditkaew & Suttipun, 2023; Eulerich et al., 2023; Huang et al., 2022).

The results further provide important insights into the mechanism through which advanced audit technology capability influences audit quality. It was found that certain technologies, particularly artificial intelligence and continuous auditing, do not exert a significant direct effect on audit quality but instead influence audit quality indirectly through audit process efficiency. This suggests that these technologies primarily function as enablers of more efficient and structured audit processes, rather than directly improving audit outcomes. Moreover, audit quality ultimately depends on auditors' professional judgment, evaluation of audit evidence, and decision-making, which may limit the direct contribution of artificial intelligence and continuous auditing to audit quality. This explanation is consistent with prior studies highlighting that artificial intelligence and continuous auditing enhance audit effectiveness through process improvements such as automation, real-time monitoring, and systematic audit procedures (Huang et al., 2022; Meiryani et al., 2021; Rikhardsson et al., 2019). In contrast, data analytics and blockchain technology exhibit both direct and indirect effects, indicating that they not only improve audit processes but also directly enhance the reliability and transparency of audit evidence (Gokoglan et al., 2022; Nwadiakor & Obi, 2020). These findings highlight the critical role of audit process efficiency as a central mechanism linking technological capability to audit outcomes, indicating that improvements in audit processes significantly enhance audit quality.

In summary, This study suggests that audit process efficiency serves as a key mechanism through which advanced audit technology capability is associated with audit quality. The findings suggest that the benefits of advanced audit technologies are realized primarily through process-level improvements

that enable more systematic, consistent, and reliable audit execution. It should be noted that the findings reflect auditors' perceived capability in applying advanced audit technologies rather than the actual level of technology implementation within audit firms. Furthermore, because this study is based on cross-sectional survey data, the findings should be interpreted as indicating associations among the constructs rather than definitive causal relationships. Therefore, the observed relationships should be interpreted as perceived benefits associated with advanced audit technology capability, particularly in contexts where the adoption of advanced technologies may still vary across audit firms. Consequently, organizations and auditors should not only focus on adopting advanced technologies but also emphasize their effective integration into audit processes to maximize their contribution to audit quality.

IMPLICATIONS

Theoretical Implications

This study addresses a key gap in prior research by moving beyond a direct-effect perspective and demonstrating that advanced audit technology capability influences audit quality through a process-based mechanism. The findings confirm that audit process efficiency functions as a critical explanatory pathway, consistent with TTF. These findings provide empirical support for TTF by suggesting that technological capabilities are more likely to contribute to favorable audit outcomes when they are aligned with the requirements of audit tasks. Importantly, the results reveal that different technologies play distinct roles. Artificial intelligence and continuous auditing affect audit quality only indirectly, while data analytics and blockchain technology exhibit both direct and indirect effects. This indicates that technological capability does not operate uniformly but depends on how it is embedded in audit processes. By integrating a multidimensional view of technology with a mediating mechanism, this study refines the theoretical explanation of how digital capabilities are translated into audit outcomes and strengthens the application of TTF in the auditing context.

Practical Implications

The findings suggest that improving audit quality requires more than technology adoption. Audit firms should focus on aligning technologies with audit processes to enhance efficiency. The results show that artificial intelligence and continuous auditing do not generate direct benefits unless they are integrated into workflow design. Therefore, firms should emphasize process restructuring, standardization, and auditor capability development. In addition, audit firms should strengthen their technology readiness to support the effective integration of advanced audit technologies into

audit processes. In contrast, data analytics and blockchain technology provide both immediate and process-driven benefits, indicating that investment strategies should vary across technologies. Particular attention should also be given to smaller audit firms, which may face resource and capability constraints in adopting advanced audit technologies. Overall, the value of advanced audit technologies depends on effective implementation within audit processes, not on adoption alone.

Limitations and Directions for Future Research

1. This study employs cross-sectional data, which limits the ability to establish causal relationships over time. Future research may adopt longitudinal or panel data to examine the dynamic effects of advanced audit technology capability and audit process efficiency on audit quality.

2. The data were collected from certified public accountants in Thailand, which may constrain the generalizability of the findings. Future studies could extend the analysis to different institutional settings or conduct cross-country comparisons to enhance external validity.

3. This study focuses on audit process efficiency as the primary mediating mechanism. However, other relevant mechanisms, such as auditor judgment, professional skepticism, or audit effort, were not included. Future research may incorporate these variables to provide a more comprehensive explanation.

4. Advanced audit technology capability was examined as a multidimensional construct, but the interaction effects among different technologies were not explored. Future studies could investigate how combinations of technologies jointly influence audit outcomes using configurational or interaction-based approaches.

REFERENCES

- Abdelwahed, A. S., Abu-Musa, A. A. E. S., Badawy, H. A. E. S., & Moubarak, H. (2025). Investigating the impact of adopting big data and data analytics on enhancing audit quality. *Journal of Financial Reporting and Accounting*, 23(2), 472–495. <https://doi.org/10.1108/JFRA-12-2023-0724>
- Akuoko-Sarpong, R., Gyasi, S. T., & Affram, H. (2024). Audit quality and its determinants: Study the factors that influence audit quality, including auditor independence, firm size, and regulatory environment. *International Journal of Innovative Science and Research Technology*, 9(8), 1584–1598. <https://doi.org/10.38124/ijisrt/IJISRT24AUG1058>
- Alles, M. A., Brennan, G., Kogan, A., & Vasarhelyi, M. A. (2006). Continuous monitoring of business process controls: A pilot implementation of a continuous auditing system at Siemens. *International Journal of Accounting Information Systems*, 7(2), 137–161. <https://doi.org/10.1016/j.accinf.2005.10.004>

- Almasoudi, R. S. Z. K., & Al-Refiay, H. A. N. (2023). The impact of continuous auditing on the quality of auditing and its reflection on investors' decisions. *Kurdish Studies*, 11(2), 746–757. <https://doi.org/10.58262/ks.v11i02.054>
- Alsughayer, S. A. (2021). Impact of auditor competence, integrity, and ethics on audit quality in Saudi Arabia. *Open Journal of Accounting*, 10(4), 125–140. <https://doi.org/10.4236/ojacct.2021.104011>
- Anis, A. (2023). Blockchain in accounting and auditing: Unveiling challenges and unleashing opportunities for digital transformation in Egypt. *Journal of Humanities and Applied Social Sciences*, 5(4), 359–380. <https://doi.org/10.1108/JHASS-06-2023-0072>
- Arianpoor, A., & Borhani, S. A. (2025). The interaction of blockchain technology, audit process, and the International Financial Reporting Standards. *Accounting Research Journal*, 38(1), 35–58. <https://doi.org/10.1108/ARJ-01-2024-0020>
- Bellucci, M., Cesa Bianchi, D., & Manetti, G. (2022). Blockchain in accounting practice and research: Systematic literature review. *Meditari Accountancy Research*, 30(7), 121–146. <https://doi.org/10.1108/MEDAR-10-2021-1477>
- Binh, N. T. T. (2025). Transforming auditing in the AI era: A comprehensive review. *Information*, 16(5), Article 400. <https://doi.org/10.3390/info16050400>
- Bonsón, E., & Bednárová, M. (2019). Blockchain and its implications for accounting and auditing. *Meditari Accountancy Research*, 27(5), 725–740. <https://doi.org/10.1108/MEDAR-11-2018-0406>
- Bonyuet, D. (2020). Overview and impact of blockchain on auditing. *The International Journal of Digital Accounting Research*, 20, 31–43. https://doi.org/10.4192/1577-8517-v20_2
- Cameran, M., Campa, D., & Francis, J. R. (2022). The relative importance of auditor characteristics versus client factors in explaining audit quality. *Journal of Accounting, Auditing & Finance*, 37(4), 751–776. <https://doi.org/10.1177/0148558X20953059>
- Celestin, M. (2020). The role of data analytics in enhancing the effectiveness of audit procedures and financial statement reviews. *Brainae Journal of Business, Sciences and Technology*, 4(8), 835–845. <https://doi.org/10.5281/zenodo.15056688>
- Christensen, B. E., Glover, S. M., Omer, T. C., & Shelley, M. K. (2016). Understanding audit quality: Insights from audit professionals and investors. *Contemporary Accounting Research*, 33(4), 1648–1684. <https://doi.org/10.1111/1911-3846.12212>
- Ditkaew, K., & Suttipun, M. (2023). The impact of audit data analytics on audit quality and audit review continuity in Thailand. *Asian Journal of Accounting Research*, 8(3), 269–278. <https://doi.org/10.1108/AJAR-04-2022-0114>

- Eulerich, M., Masli, A., Pickerd, J., & Wood, D. A. (2023). The impact of audit technology on audit task outcomes: Evidence for technology-based audit techniques. *Contemporary Accounting Research*, 40(2), 981–1012. <https://doi.org/10.1111/1911-3846.12847>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>
- Friska, R., & Agustia, D. (2025). Enhancing auditor judgment quality: A review of evidence from experimental research. *Journal of Risk and Financial Management*, 18(3), Article 115. <https://doi.org/10.3390/jrfm18030115>
- Gokoglan, K., Cetin, S., & Bilen, A. (2022). Blockchain technology and its impact on audit activities. *Journal of Economics, Finance and Accounting*, 9(2), 72–81. <https://doi.org/10.17261/Pressacademia.2022.1567>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
- Huang, F., No, W. G., Vasarhelyi, M. A., & Yan, Z. (2022). Audit data analytics, machine learning, and full population testing. *Journal of Finance and Data Science*, 8, 138–144. <https://doi.org/10.1016/j.jfds.2022.05.002>
- Isa, H., & Subramanian, U. (2024). The impact of big data in auditing. *Procedia Computer Science*, 238, 841–848. <https://doi.org/10.1016/j.procs.2024.06.101>
- Kokina, J., Blanchette, S., Davenport, T. H., & Pachamanova, D. (2025). Challenges and opportunities for artificial intelligence in auditing: Evidence from the field. *International Journal of Accounting Information Systems*, 56, Article 100734. <https://doi.org/10.1016/j.accinf.2025.100734>
- Lee, J. W., Kang, M., Oh, Y., & Pyo, G. (2014). Does continuous auditing enhance the quality of financial reporting? Korean evidence. *Asia-Pacific Journal of Accounting & Economics*, 21(3), 284–307. <https://doi.org/10.1080/16081625.2014.884483>
- Manita, R., Elommal, N., Baudier, P., & Hikkerova, L. (2020). The digital transformation of external audit and its impact on corporate governance. *Technological Forecasting and Social Change*, 150, Article 119751. <https://doi.org/10.1016/j.techfore.2019.119751>
- Meiryani, Sujanto, M., Lindawati, A. S. L., Zulkarnain, A., & Liawatimena, S. (2021). Auditor’s perception on technology transformation: Blockchain and CAATs on audit quality in Indonesia. *International Journal of Advanced Computer Science and Applications*, 12(8), 526–533. <https://doi.org/10.14569/IJACSA.2021.0120861>
- Milad, M. M. A. (2022). Advanced auditing: Techniques and tools for the modern auditor. *Stallion Journal for Multidisciplinary Associated Research Studies*, 1(1), 56–64. <https://doi.org/10.55544/sjmars.1.1.9>

- Noordin, N. A., Hussainey, K., & Hayek, A. F. (2022). The use of artificial intelligence and audit quality: An analysis from the perspectives of external auditors in the UAE. *Journal of Risk and Financial Management*, 15(8), Article 339. <https://doi.org/10.3390/jrfm15080339>
- Nugraha, G. C. H. (2024). Perception of artificial intelligence adoption on audit quality. *ABIS: Accounting and Business Information Systems Journal*, 12(1), 16–43. <https://doi.org/10.22146/abis.v12i1.89329>
- Nwadior, E. O., & Obi, T. N. (2020). Effect of big data on the quality of audit reports in Anambra State. *International Journal of Advanced Academic Research (Social and Management Sciences)*, 6(10), 48–65. <https://doi.org/10.46654/ij.24889849.s6107>
- Oraka, A. O., & Okegbe, T. O. (2015). The impact of professional accounting ethics in quality assurance in audit. *International Journal of Academic Research in Business and Social Sciences*, 5(8), 64–78. <https://doi.org/10.6007/IJARBS/v5-i8/1761>
- Pristiwanto, B., 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. *Journal Research of Social Science Economics and Management*, 5(3), 3454–3471. <https://doi.org/10.59141/jrssem.v5i3.1109>
- Qader, K. S., & Cek, K. (2024). Influence of blockchain and artificial intelligence on audit quality: Evidence from Turkey. *Heliyon*, 10(9), Article e30166. <https://doi.org/10.1016/j.heliyon.2024.e30166>
- Qatawneh, A. M. (2025). The role of artificial intelligence in auditing and fraud detection in accounting information systems: Moderating role of natural language processing. *International Journal of Organizational Analysis*, 33(6), 1391–1409. <https://doi.org/10.1108/IJOA-03-2024-4389>
- Rahman, M. J., Zhu, H., & Yue, L. (2024). Does the adoption of artificial intelligence by audit firms and their clients affect audit quality and efficiency? Evidence from China. *Managerial Auditing Journal*, 39(6), 668–699. <https://doi.org/10.1108/MAJ-03-2023-3846>
- Rajgopal, S., Srinivasan, S., & Zheng, X. (2021). Measuring audit quality. *Review of Accounting Studies*, 26, 559–619. <https://doi.org/10.1007/s11142-020-09570-9>
- Rezaee, Z., Sharbatoghlie, A., Elam, R., & McMickle, P. L. (2002). Continuous auditing: Building automated auditing capability. *Auditing: A Journal of Practice & Theory*, 21(1), 147–163. <https://doi.org/10.2308/aud.2002.21.1.147>
- Rikhardsson, P., Singh, K., & Best, P. (2019). Exploring continuous auditing solutions and internal auditing: A research note. *Accounting and Management Information Systems*, 18(4), 614–639. <https://doi.org/10.24818/jamis.2019.04006>
- Sari, W. K. (2024). A qualitative study on the use of data analytics in auditing. *Golden Ratio of Auditing Research*, 4(1), 33–42. <https://doi.org/10.52970/grar.v4i1.387>

- Sayal, A., Johri, A., Chaithra, N., Alhumoudi, H., & Alatawi, Z. (2025). Optimizing audit processes through open innovation: Leveraging emerging technologies for enhanced accuracy and efficiency. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(3), Article 100573. <https://doi.org/10.1016/j.joitmc.2025.100573>
- Sewpersadh, N. S. (2025). Adaptive structural audit processes as shaped by emerging technologies. *International Journal of Accounting Information Systems*, 56, Article 100735. <https://doi.org/10.1016/j.accinf.2025.100735>
- Sharma, D., & Jarial, R. (2024). The impact of modern technology on accounting line of work. *International Journal of Humanities Social Science and Management*, 4(2), 1233–1239. <https://doi.org/10.2139/ssrn.4990630>
- Shazly, M. A., Abd ElAlim, K., & Zakaria, H. (2024). The impact of artificial intelligence on audit quality: A field study on audit firms in Egypt. *International Journal of Current Research*, 16(5), 28273–28278. <https://doi.org/10.24941/ijcr.47187.05.2024>

