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Technological Investment, Auditor Revenue, and Discretionary Accruals: A Capability-Based Analysis of U.S. Indexed Companies

Fandi Kharisma[1*], Yang Qingxiang[1], Shama Urooj[2]

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ABSTRACT

Investment in technology enhances audit quality or signals modernization; its existing audit technology research examines the subject of technological investment as homogenous, but does not discuss whether these improvements are due to digital infrastructure, technology-oriented human capital, or organizations' capacity. In this study, we explore if audit-firm technological investment is associated with lower discretionary accruals and whether auditor revenue and audit firm size moderate that relationship. Analyses a sample of 2,550 firm-year observations from publicly-held Nasdaq100 and S&P500 firms from the years of study (2019-2023) using Two-Stage Least Squares regression, Sobel testing, Heckman correction, Propensity Score Matching, Dechow-based accrual measures and client-complexity tests. The output also indicates that capital expenditures on technological assets and technology human capital are associated with a reduction in discretionary accruals, with regression coefficients of -0.206 and -0.348, respectively. Auditor revenue reinforces these interactions in relation to IT_AS (Technological Investment in assets) × AR (Auditor Revenue) (-0.181) and IT_HC (Technological Investment in Human Capital) × AR (Auditor Revenue) (-0.232), while the size of the audit firm is negatively related to discretionary accruals (-0.247). After taking account of endogeneity and selection concerns, robustness analyses confirm these effects. Theoretically, the study expands on Resource-Based View and Dynamic Capability Theory, arguing that audit technology delivers value as long as it is backed by human expertise, economic capacity and organizational structure. In practice, the findings encourage audit firms and regulators to consider technological capability a substantive resource for audit quality.

1. Introduction

Advanced digital technologies (artificial intelligence, big data analytics, blockchain, and cloud computing) are rapidly diffusing across businesses and fundamentally changing the informational environment in which auditors plan and

[1] Huazhong University of Science and Technology, Wuhan, China
[2] Lahore Garrison University, Department of Management Sciences, Pakistan
*Corresponding Author: i202122004@hust.edu.cn

evaluate audits (Elommal & Manita, 2022; Otia & Bracci, 2022). Audit firms are increasingly expected to leverage these technologies for greater efficiency, broader audit coverage, anomaly detection and enhanced assurance over the reliability of financial reporting. However, it is still an open question whether technological investment improves audit quality (Thottoli, 2023). Our research issue illustrates a broader paradox of digital transformation: while audit technologies are becoming more capable, their application in judgment-intensive professional services is not an automatic fit, nor value-enhancing. In auditing, where professional scepticism and qualitative evaluation of evidence, focusing on risk assessment, retain their preeminent positions (Barr‐Pulliam et al., 2023), technology could enhance outcomes only when embedded in audit routines and bolstered by other organizational capabilities.

However, it is difficult for audit firms to link technology spending directly to observable enhancements in audit quality (Wu et al., 2023). Implementing advanced audit technologies involves financial investment, organizational preparedness or ownership, specialized skills, and adjusting to rapidly evolving digital systems. Even though many firms invest in technologies, such as auditing software, analytics platforms, AI tools, and digital infrastructure (Georgiou et al., 2024; Kabashkin et al., 2023). These may see low adoption rates if auditors lack technical competence, workflows are misdesigned, or technology is treated as symbolic rather than substantive. This misalignment may undermine audit effectiveness through inefficient procedures, overreliance on output from automated processes, or failure to utilize evidence generated by technology. Thus, an investment in technology should be regarded not only as the introduction of new digital technologies but rather as a human capital and organizational capability development (El-Bassel et al., 2025).

Prior research raises mixed evidence on whether technology even affects our auditing (Georgiou et al., 2024; Thottoli, 2023). One stream suggests that big data analytics, artificial intelligence (AI), and blockchain will enhance audit quality by enabling broader testing, improving anomaly detection, increasing transparency, and reducing verification costs. One stream warns that technological tools do not guarantee higher-quality audit outcomes, especially when auditors have limited expertise or when algorithm aversion, automation bias, cybersecurity risk, and diminished professional scepticism undermine the quality of judgment. The contrasting findings suggest that investment in technology is not necessarily quality-enhancing. Its impact is dependent on the ability of audit firms to transform technology inputs into productive processes and professional judgment (al-Ma'aitah et al., 2024).

However, despite these advancements, three gaps continue to persist. First, existing studies tend to measure technological investment in a much more homogeneous manner and do not distinguish between investment into technology-oriented human capital and investment into technical assets. This distinction is important as digital infrastructure may enhance audit capacity, whereas technology-targeted human capital determines whether auditors are capable of appropriating and integrating digital evidence in the audit judgement (Rahman & Ziru, 2022). Second, previous empirical results are still exposed to endogeneity, self-selection and omitted-variable issues (Fang et al., 2023). Third, there is little knowledge regarding the organizational contexts within which technology investment has a greater impact on costs, specifically auditor economic capability, as well as audit firm structure (Elommal & Manita, 2022).

This study helps fill these gaps by examining the empirical question that remains unanswered: whether audit firms' technological investment yields positive consequences for audit quality. Although prior research has highlighted the relevance of audit technologies, little is known about how investments in technology translate into improvements in audit quality. This study examines U.S.-based publicly traded firms because the United States is a world leader in technology-centricity and digital transformation, and because of the SEC-required financial reporting disclosures in 10-K and 10-Q filings. The study uses a sample of U.S.-listed companies from 2019 to 2023, comprising 2,550 firm-year observations, to capture the accelerated adoption of AI, digital systems, and IT infrastructure following the COVID-19 pandemic. The baseline fixed-effect regression results show that auditor technology asset investment and auditor technology human capital are negatively and significantly associated with discretionary accruals, indicating that higher auditor technological investment is associated with lower earnings management. The novelty of this study, therefore, lies not only in distinguishing technological investment into asset-based and human-capital-based dimensions, but also in extending prior audit technology literature by explaining the capability-conversion process through which audit firms translate digital resources into audit quality. Specifically, this study introduces auditor revenue as a boundary condition that reflects the economic capacity of audit firms to absorb, maintain, and scale digital technologies. It also positions audit firm size as an organizational mechanism by which technology-oriented human capital translates into improved audit outcomes. In doing so, this study moves beyond examining whether audit technology matters and provides a more nuanced explanation of when, how, and under what organizational conditions technological investment enhances audit quality.

The study, therefore, asks three research questions: Do asset-based and human-capital-based technological investments influence audit quality? Does auditor revenue strengthen the effect of technological investment on audit quality? Does audit firm size mediate the relationship between technology-oriented human capital and audit quality? In line with these questions, the objectives of this study are to examine the direct effects of technological investment on audit quality, analyse the moderating role of auditor revenue, and evaluate the mediating role of audit firm size. The scope of the study is confined to U.S.-listed companies and focuses on audit-firm technological investment, auditor economic capacity, audit firm structure, and audit quality, measured using discretionary accruals as an inverse proxy. To strengthen empirical credibility, the study employs 2SLS, Heckman correction, Propensity Score Matching, and alternative accrual measures.

The remainder of this paper is organized as follows. Section 1 develops the introduction. Section 2 develops the theoretical framework and research hypotheses. Section 3 describes the research design, data, variable measurement, and empirical methodology. Section 4 presents the empirical results. Section 5 presents the discussion, and Section 6 presents the conclusion, implications, limitations, and suggests avenues for future research.

2. Literature Review and Hypothesis Development

The theoretical foundation of this study is grounded in the Resource-Based View (RBV) and Dynamic Capability Theory (Paipa-Sanabria et al., 2024). RBV argues that superior organizational outcomes arise from valuable, rare, inimitable, and well-organized resources, whereas Dynamic Capability Theory emphasizes firms' ability to integrate, reconfigure, and deploy resources in response to environmental change. These theories are relevant to auditing because advanced technologies do not automatically improve audit quality simply by being acquired (Gonzalez, 2022). Audit technologies such as artificial intelligence, big data analytics, blockchain-based verification systems, and cloud-based audit platforms become strategic resources only when embedded into audit routines, evidence evaluation, risk assessment, and professional judgment.

Although prior studies generally suggest that audit technologies can improve audit efficiency, risk assessment, evidence collection, and anomaly detection, the empirical and theoretical implications of these findings remain unsettled (Fedyk et al., 2022; Qader & Çek, 2024). While some studies depict digital technologies as quality-enhancing resources that increase audit coverage and bolster analytical procedures, others warn that technology adoption can create modest or even negative outcomes to audit quality when auditors are inadequately skilled, when decision-making is overly reliant on automated outputs or when technological tools are adopted for their symbolic rather than substantive value (Georgiou et al., 2024; Samiolo et al., 2023). This discrepancy suggests that the audit-quality impact of technology cannot be solely driven by the mere availability of digital resources. Instead, it depends on whether audit firms have the complementary capabilities to integrate, interpret and reconfigure technological resources in the service of professional audit judgment. The current study contributes theoretically by connecting RBV and Dynamic Capability Theory to address this still-unresolved debate, arguing that technological assets are indeed strategic resources, but that technology-oriented human capital captures the dynamic capability needed to exploit those resources to achieve higher levels of audit quality.

Technological investment in assets relates to investments made by an audit firm in both physical and digital infrastructure associated with developing new audit software, data analytics systems, artificial intelligence applications, blockchain-enabled verification tools or cybersecurity systems, including cloud-based audit platforms (Silva et al., 2022). Based on the Resource-Based View (RBV), these audit resources can improve audit quality in terms of increasing coverage, data-processing capacity, evidence acquisition and anomaly detection. Importantly, their quality effect is contingent upon methodological integration, auditor comprehension and governance mechanisms that inhibit the mere symbolic adoption.

Auditor’s digital competencies, analytics expertise, artificial intelligence literacy, cybersecurity knowledge, technology-related training and the ability to interpret technology-generated evidence are part of auditors’ technological investment in human capital (Domínguez et al., 2022; Radu et al., 2023). The Dynamic Capability Theory aligns well with this dimension, as it focuses on auditors' capacity to learn, absorb, and redeploy technological knowledge. Advanced tools can make the audit process more efficient, but they may also reduce audit quality through overreliance on poorly understood technology if the requisite technology-oriented human capital is not available.

Lower discretionary accruals indicate a higher quality of an audit (Kyriakou, 2024), and therefore, discretionary accruals are used as a proxy for audit quality. Consequently, technology assets may lower discretion in accruals by enhancing audit scope and precision, while human capital may augment auditors' ability to interpret less-understood digital evidence. Thus, the relation is socio-technical: evidence transformed into an audit assertion through human expertise facilitated by technology augmentation (Lou et al., 2024; Rahman & Ziru, 2022). Moreover, earlier research indicates that big data analytics, AI, blockchain, and computer-assisted audit techniques improve the efficiency of audits and risk assessment while enhancing transparency in governmental accounting practices by leveraging technical expertise to obtain more evidence for the design of audit procedures with greater consistency.

The hypothesis proposed in the study gains deeper theoretical grounding from RBV and Dynamic Capability Theory, as audit quality depends not only on possessing such technological resources but also on the capacity to deploy them effectively. The Technological Asset portion of RBV states that, when they are valuable, not easily imitable and embedded in firm-specific audit processes, technological assets can generate value, while Dynamic Capability Theory reveals how auditors' technology-oriented human capital enhances the ability of audit firms to integrate, adapt and reconfigure these resources as required by complex client environments. The degree to which resources may interact with capabilities is crucial in an auditing context, as whilst large volumes of data and analytical outputs are likely produced through digital tools, the quality of audits will ultimately depend on auditors' ability to assess the relevance, reliability and implications of such evidence. Thus, the theoretical rationale for hypothesizing the negative association between investment in technology and discretionary accruals is two-fold: asset-based investment increases audit-related technological infrastructure, while human-capital-based investment enhances auditors' ability to translate technological outputs into high-quality audit judgments. Accordingly, this study predicts that digital audit assets reduce discretionary accruals. This leads to the following hypotheses:

H*$_1$*: Technological investment in audit assets is negatively associated with discretionary accruals.

Hypothesis 2 is grounded in Dynamic Capability Theory, which suggests that auditors' digital expertise, training, and analytical capability improve the effective use of technology and strengthen professional judgment (Alsaif et al., 2025; Samiolo et al., 2023; Varma et al., 2023). Together, these hypotheses challenge the assumption that technological investment is a single uniform construct and instead predict that both infrastructure-based and human-capital-based investments contribute to audit quality through distinct but complementary channels. This leads to the following hypotheses:

H*$_2$*: Technological investment in human capital is negatively associated with discretionary accruals.

The effectiveness of technological investment is also likely to depend on the audit firm's economic capacity (AL-Akheli et al., 2025; Gonçalves & Basso, 2024; González-Ruíz et al., 2024; Thottoli, 2023). Auditor revenue can strengthen the relationship between technological investment and audit quality because higher-revenue auditors are more likely to have financial slack, specialized personnel, advanced audit methodologies, and quality-control systems that enable technology to be deployed more effectively. In lower-revenue audit firms, technological investments may be constrained by limited training, weaker integration, or insufficient specialist support, reducing their ability to affect audit outcomes. Therefore, auditor revenue is best conceptualized as a moderating condition that determines whether technological resources are converted into audit-quality improvements. This leads to the following hypotheses:

H*$_3$*: Auditor revenue strengthens the negative association between technological investment in assets and discretionary accruals.

H*$_4$*: Auditor revenue strengthens the negative association between technological investment in human capital and discretionary accruals.

Finally, audit firm size is theoretically relevant as an organizational mechanism linking technology-oriented human capital to audit quality (Abdallah et al., 2024). Larger audit firms typically have standardized methodologies, specialist pools, internal training systems, formal quality-control procedures, and reputational incentives to constrain aggressive reporting. However, when audit firm size is measured as a Big 4 indicator, it should be interpreted with caution because this measure is relatively stable and unlikely to reflect short-term human capital investment. Thus, technology-oriented human capital is expected to reduce discretionary accruals more effectively within larger audit-firm structures that can standardize, supervise, and scale technology-enabled audit practices (Bansal, 2023a; Herranz et al., 2022).

The mediation mechanism is based on the argument that technology-oriented human capital does not improve audit quality in isolation, but must be embedded within an organizational structure that enables such expertise to be coordinated, standardized, monitored, and deployed across audit engagements. From a Dynamic Capability Theory perspective, auditors' digital skills represent a reconfiguring capability, while audit firm size reflects the organizational platform through which this capability can be institutionalized into audit methodologies, specialist support units, training systems, review procedures, and quality-control routines (Azambuja & Islam, 2023; Tanchangya et al., 2025). Empirically, larger audit firms are more likely to possess the financial resources, reputational incentives, industry specialization, and internal governance systems needed to transform individual auditors' technological expertise into consistent audit-quality outcomes (He et al., 2025). Thus, technology-oriented human capital may contribute to audit quality partly because it is associated with audit-firm structures that can scale and supervise technology-enabled audit practices. In this sense, audit firm size serves as a mediating channel through which human-capital-based technological investment is translated into lower discretionary accruals. This leads to the following hypotheses:

H_5*: *Audit firm size mediates the negative association between technological investment in human capital and discretionary accruals.

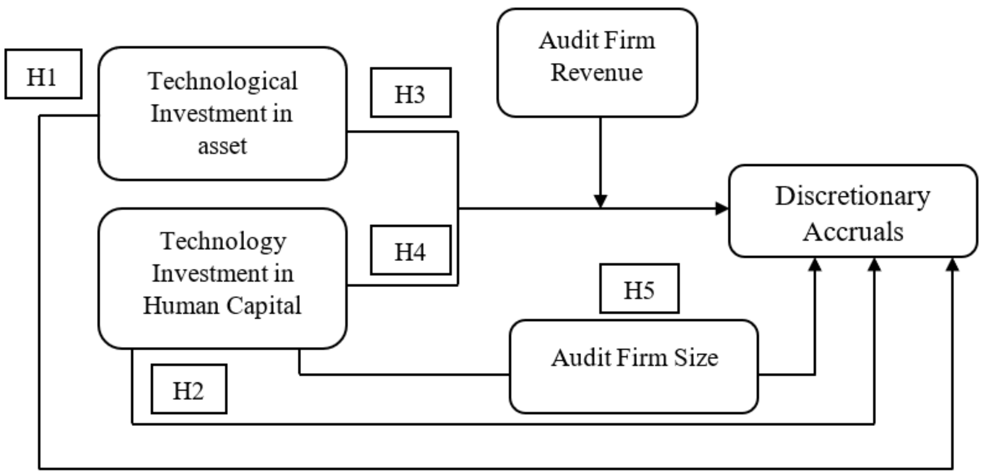

Figure 1. Conceptual Framework

3. Methodology

This study employs a quantitative archival research design to examine whether audit-firm technological investment is associated with audit quality among U.S.-listed companies. The empirical setting is structured at the client firm–auditor–year level, where each client firm-year observation is matched with its external auditor, and audit-firm technological investment variables are assigned accordingly. This design enables the study to assess whether auditor-side technological resources influence client-level financial reporting outcomes. Before conducting the main analysis, this study first performs the Hausman test to determine whether to use a fixed-effects or random-effects panel data model. The Hausman test results will be used to estimate the baseline regression. To address potential endogeneity from reverse causality, omitted variables, and endogenous auditor-client matching, the study uses Two-Stage Least Squares (2SLS) as the main estimation methodproposed by, complemented by a Heckman two-stage correction, Propensity Score Matching, alternative accrual-quality measures, and cross-sectional tests.

The use of 2SLS is appropriate because audit-firm technological investment may be endogenously determined by audit quality or by unobserved client and auditor characteristics. Therefore, instrumental variables are used to isolate the exogenous component of technological investment. The Heckman two-stage correction is employed to reduce potential selection bias arising from non-random auditor-client matching, while Propensity Score Matching helps ensure that firms with different levels of technological investment are compared with observationally similar firms. Alternative accrual-quality measures are used to confirm that the findings are not driven by a single audit-quality proxy, and cross-sectional tests are conducted to examine whether the results vary across different organizational and economic conditions.

The sample consists of U.S. firms found in the Nasdaq100 and S&P 500 stock indices during the time span of 2019-2023, a period characterized as one with a rapid diffusion of digital technology after COVID-19. We selected Nasdaq100 and S&P 500 firms because they include some of the largest publicly traded US firms that face higher levels of disclosure regulation, greater investor scrutiny, and more complex audit environments. These firms are also more likely to engage with audit firms that have the resources and incentives to adopt advanced audit technologies, making them a relevant setting for examining the relationship between audit-firm technological investment and audit quality. From an initial population of 3,855 firm-year observations from technology-related firms listed on NYSE and NASDAQ, firms not continuously included in the indices and observations with missing data were excluded, resulting in 2,550 firm-year observations. Audit quality is measured using discretionary accruals, with higher values indicating lower audit quality. Audit quality is measured using discretionary accruals because discretionary accruals capture the extent to which managers exercise accounting discretion in reporting earnings.

High-quality audits are expected to constrain opportunistic earnings management by requiring more reliable, conservative, and verifiable financial reporting. Therefore, when auditors perform effective audit procedures, detect unusual accrual patterns, and challenge aggressive accounting choices, the level of discretionary accruals should be lower. For this reason, discretionary accruals are widely used as an inverse proxy for audit quality: higher discretionary accruals indicate greater managerial discretion and earnings management, which reflect lower audit quality, whereas lower discretionary accruals suggest stronger auditor monitoring and higher financial reporting reliability. The main dependent variable is DA, while a Dechow-based accrual measure is used for robustness. The main independent variable, IT_AS, is technological investment in assets. It is operationalized as the natural logarithm of one plus the audit firm's annual technology-asset investment:

$$IT\_AS_{j,t} = \ln(TechnologyAssetInvestment_{j,t}) \tag{1}$$

where $j$denotes the audit firm and $t$denotes year. Technological investment in human capital (IT_HC) captures audit firms' investment in technology-related training, digital audit expertise, analytics capabilities, AI-related personnel, cybersecurity training, and professional development in digital audit competencies. It is operationalized as the natural logarithm of one plus the audit firm's annual technology-oriented human-capital investment:

$$IT\_HC_{j,t} = \ln(Technology\ Human\ Capital\ Investment_{j,t})$$

(2)

To test whether auditor revenue strengthens the effect of technological investment in assets on discretionary accruals, the following moderation model is estimated:

$$DA_{i,j,t} = \beta_0 + \beta_1 IT\_AS_{j,t} + \beta_2 AR_{j,t} + \beta_3 (IT\_AS_{j,t} \times AR_{j,t}) + \beta_4 SIZE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 TURN_{i,t} + \beta_7 GRW_{i,t} + \beta_8 ROA_{i,t} + \beta_9 QR_{i,t} + \beta_{10} REC_{i,t} + \varepsilon_{i,j,t} \quad (3)$$

To test whether auditor revenue strengthens the effect of technological investment in human capital on discretionary accruals, the following moderation model is estimated:

$$DA_{i,j,t} = \beta_0 + \beta_1 IT\_HC_{j,t} + \beta_2 AR_{j,t} + \beta_3 (IT\_HC_{j,t} \times AR_{j,t}) + \beta_4 SIZE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 TURN_{i,t} + \beta_7 GRW_{i,t} + \beta_8 ROA_{i,t} + \beta_9 QR_{i,t} + \beta_{10} REC_{i,t} + \varepsilon_{i,j,t} \quad (4)$$

To examine the mediating role of audit firm size in the relationship between technology-oriented human capital and discretionary accruals, the following model is estimated:

$$DA_{i,j,t} = \beta_0 + \beta_1 IT\_HC_{j,t} + \beta_2 AU\_SIZE_{j,t} + \beta_3 SIZE_{i,t} + \beta_4 LEV_{i,t} + \beta_5 TURN_{i,t} + \beta_6 GRW_{i,t} + \beta_7 ROA_{i,t} + \beta_8 QR_{i,t} + \beta_9 REC_{i,t} + \varepsilon_{i,j,t} \quad (5)$$

Because technological investment may be endogenous, the study estimates the models using Two-Stage Least Squares. In the first stage, technological investment is predicted using instrumental variables, namely, leave-one-out peer auditor technological investment and local technology labour supply:

$$IT\_AS_{j,t} = \alpha_0 + \alpha_1 PeerIT\_AS_{-j,g,t} + \alpha_2 LocalTechLabor_{r,t} + \alpha_3 Controls_{i,t} + \mu_{j,t} \quad (6)$$

$$IT\_HC_{j,t} = \gamma_0 + \gamma_1 PeerIT\_HC_{-j,g,t} + \gamma_2 LocalTechLabor_{r,t} + \gamma_3 Controls_{i,t} + \nu_{j,t} \quad (7)$$

The predicted values from the first-stage regressions are then used in the second-stage outcome model:

$$DA_{i,j,t} = \delta_0 + \delta_1 \widehat{IT\_AS}_{j,t} + \delta_2 \widehat{IT\_HC}_{j,t} + \delta_3 Controls_{i,t} + \omega_{i,j,t} \quad (8)$$

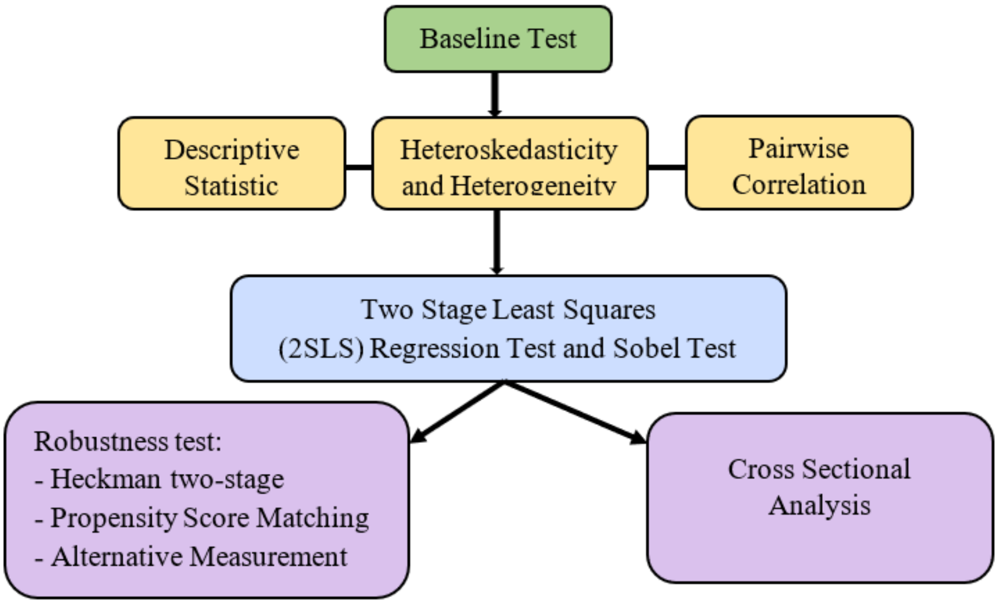

Figure 2. Methodological flow chart

The study focuses on U.S.-listed companies because the United States is a global hub of technological innovation and digital transformation, with firms such as Apple, Microsoft, Google, Amazon, and Meta leading AI adoption across industries. The U.S. uses transparent and accessible financial reporting through SEC-mandated 10-K and 10-Q forms, enabling reliable, comparable data collection by Bloomberg, Yahoo Finance, and the NASDAQ Data Portal. We chose 2019-2023 because it reflects a period of accelerated digital adoption due to COVID-19 and the subsequent increased investments in AI, digital systems, and IT infrastructure. This context allows for a more objective assessment of technology adoption and business outcomes.

Table 1: Sample Selection

Procedures	**(Observations)**
Technology companies listed on NYSE and NASDAQ over the period 2019-2023	3,855
Less:	
Firms not continuously included in NASDAQ-100 and S&P 500 Index from 2019-2023	400
Firms with missing data on main and control variables	905
Final Sample	**2,550**

4. Data Analysis-Results

4.1 Descriptive statistics

Table 2 presents the descriptive statistics for 2,550 firm-year observations from Nasdaq100 and S&P 500 indexed companies. Discretionary accruals (DA) showed a low positive mean (M = 0.068, SD = 0.993), although the wide range from -25.626 to 18.769 indicates substantial variation in earnings management practices across firms. Investment in technology assets (IT_AS) averaged 13.184 (SD = 4.174), while investment in technology human capital (IT_HC) had a relatively low mean of 0.175 (SD = 0.111), suggesting variation in firms' technology investment characteristics.

Table 2: Descriptive Statistics for Nasdaq100 and SP500 Indexed Company Data

Variable	Obs	Mean	Std. Dev.	Min	Max
DA	2,550	0.068	0.993	-25.626	18.769
IT_AS	2,550	13.184	4.174	4.000	27.000
IT_HC	2,550	0.175	0.111	-0.200	0.487
AR	2,550	16.118	0.959	12.682	19.866
AU_SIZE	2,550	0.989	0.100	0.000	1.000
IT_AS*AR	2,550	5.294	0.405	3.993	6.229
IT_HC*AR	2,550	2.824	1.817	-2.803	7.850
SIZE	2,550	15.751	2.868	3.810	24.440
LEV	2,550	0.478	0.247	0.057	1.779
TURN	2,550	0.655	0.368	0.082	3.537
GRW	2,550	2.504	1.682	-6.032	12.876
ROA	2,550	0.473	0.336	-0.437	1.095
QR	2,550	2.009	0.911	0.036	13.914
REC	2,550	0.468	0.394	0.008	2.507
Peer IT	2,550	13.067	3.892	4.500	26.250
LocalTechLabor	2,550	0.184	0.096	0.012	0.523

4.2 Pairwise Correlation

Table 3 reports the Pearson correlation matrix and variance inflation factor (VIF) values for the Nasdaq100 and S&P 500 indexed company data. The results show that DA is positively correlated with IT_AS, IT_HC, Peer IT, and LocalTechLabor, suggesting that auditor technological investment and technology-related labor market factors are associated with discretionary accruals. Moreover, some control variables are related to the dependent variable and are significantly correlated with the main variables, suggesting that firm characteristics such as size, profitability, leverage, liquidity, and receivables can also be determinant factors in explaining discretionary accruals. The extreme relationships amongst IT_AS, IT_HC, AR, Peer IT, and LocalTechLabor additionally imply that auditor technology-related measures merchandise are integrated with audit-related and market-level technology stipulations.

Table 3: The Correlation Matrix for Nasdaq100 and SP500 Indexed Company Data

Variables	**VIF**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
(1) DA		1.000															
(2) IT_AS	1.498	0.214 **	1.000														
(3) IT_HC	1.449	0.187*	0.342***	1.000													
(4) AR	2.333	-0.126	0.215**	0.198**	1.000												
(5) AU_SIZE	1.382	-0.118	0.183*	0.176*	0.154*	1.000											
(6) IT_AS*AR	1.956	0.162*	0.486***	0.274***	0.531***	0.142	1.000										
(7) IT_HC*AR	1.965	0.139	0.263***	0.492***	0.518***	0.137	0.437***	1.000									
(8) SIZE	1.755	-0.081	0.294***	0.218**	0.176*	0.164*	0.251***	0.223**	1.000								
(9) LEV	1.801	0.119	-0.164*	-0.137	0.092	0.086	-0.128	-0.116	0.246***	1.000							
(10) TURN	1.399	-0.104	0.188*	0.203**	-0.145	-0.132	0.172*	0.181*	0.219**	-0.284***	1.000						
(11) GRW	1.248	0.096	0.231**	0.176*	0.158*	0.121	0.214**	0.197**	0.267***	-0.102	0.256***	1.000					
(12 ROA	1.557	-0.212**	0.247***	0.224**	-0.097	0.146	0.203**	0.196**	0.304***	-0.356***	0.329***	0.271***	1.000				
(13) QR	1.490	-0.078	0.143	0.121	-0.183*	0.109	0.109	0.117	0.162*	-0.412**	0.226**	0.194**	0.318***	1.000			
(14) REC	1.271	0.134	-0.096	-0.118	0.207**	-0.104	-0.084	-0.102	0.141	0.228**	-0.176*	0.086	-0.153*	-0.247***	1.000		
(15) Peer IT	1.684	0.151*	0.438***	0.306***	0.226**	0.188*	0.462***	0.318***	0.241**	-0.137	0.173*	0.208**	0.235**	0.128	-0.112	1.000	
(16) LocalTechLabor	1.732	0.151*	0.392***	0.354***	0.184*	0.207**	0.337***	0.362***	0.216**	-0.121	0.159*	0.186*	0.224**	0.141	-0.095	0.287***	1.000

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

The multicollinearity diagnostics show that the regression models are not severely affected by multicollinearity problems. The above correlations are all below the thresholds most people would agree are a good level of correlation. 80, where particularly high correlations are observed for the corresponding interaction terms and the variables related to them. Also, the VIF values vary from 1.248 to 2.333 and are all below the threshold value of 5. The results imply that multicollinearity issues are not scrutinized through the regression models since the explanatory variables can be included together in the same operational model context, thereby adding confidence to such subsequent regression analyses.

4.3 Roubstness Analysis

Table 4 presents the results of the Breusch–Pagan/Cook–Weisberg test for heteroscedasticity. The test result showed that the assumption of constant variance was not violated (χ^2 (1) = 12.438, p = 0.182). Since the reported *p*-value was greater than the conventional significance level of 0.05, the null hypothesis of homoscedasticity was not rejected. This indicates that the regression model did not suffer from heteroscedasticity, and the variance of the error terms can be considered constant across observations. Therefore, the model satisfies the homoscedasticity assumption and is appropriate for further regression analysis.

Table 4: Breusch–Pagan/Cook–Weisberg test for heteroscedasticity

Ho: constant variance	χ2(1)	p-value	Decision
Breusch–Pagan/ Cook–Weisberg test for heteroscedasticity	12.438	0.182	No heteroscedasticity

4.4 Hausman Test

As shown in Table 5, the Hausman test was conducted to determine the appropriate panel data model between the fixed-effect and random-effect models. The result shows a chi-square statistic of 25.188 with a p-value of 0.005. Since the p-value is below the 5% significance level, the null hypothesis that the random-effect model is appropriate is rejected. Therefore, the fixed-effect model is preferred and used as the baseline regression model in this study.

Table 5: Hausman Test for Model Selection

Model Specification	Chi-square Statistic	d.f.	p-value	Preferred Model
Fixed Effect vs. Random Effect	25.188	10	0.005	Fixed Effect

4.5 Baseline Regression (Fix Effect Model)

Table 6 presents the baseline regression results using the fixed-effect model. The results show that IT_AS had a negative and significant effect on discretionary accruals, β = -0.196, *SE* = 0.058, $p < 0.01$. Similarly, IT_HC was negatively and significantly associated with discretionary accruals (β = -0.328, SE = 0.074, p < 0.01). These results suggest that greater investment in technology assets and human capital by auditors is negatively associated with discretionary accruals. As for the control variables, only SIZE, TURN, GRW, ROA, and REC were statistically significant; LEV and QR were not. Firm and year fixed effects included (N = 2,550; adjusted R^2 = 0.402).

Table 6: Result of Baseline Regression (Fixed Effect Model)

Variables	DA (Fix Effect Model)
IT_AS	-0.196***
	(0.058)
IT_HC	-0.328***
	(0.074)
SIZE	0.071*
	(0.039)
LEV	-0.024
	(0.031)
TURN	0.052**
	(0.023)
GRW	0.014*
	(0.008)
ROA	0.241***
	(0.066)
QR	-0.009
	(0.013)
REC	-0.081**
	(0.040)
Constant	-1.684***
	(0.552)
Firm fixed effects	Yes
Year fixed effects	Yes
Observations	2.550
Adjusted R2	0.402

Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

4.6 Regression with Two Stage Least Squares (2SLS) and Sobel Test

Table 7 presents the 2SLS regression and Sobel test results. In Model 1, IT_AS was negatively and significantly associated with discretionary accruals (β = -0.206, SE = 0.061, p < 0.01), and IT_HC also had a negative and significant effect (β = -0.348, SE = 0.079, p < 0.01). In Model 2, the interaction terms IT_AS × AR, $\beta = -0.139$, $SE = 0.049$, $p < 0.01$, and IT_HC × AR, $\beta = -0.194$, $SE = 0.062$, $p < 0.01$, were both negative and significant, indicating that AR strengthens the negative relationship between auditor technological investment and discretionary accruals. In Model 3, AU_SIZE had a negative and significant effect on DA (β = -0.247, SE = 0.062, p < 0.01), and the Sobel test was significant (Z = 3.764, p = 0.012), supporting the mediating role of AU_SIZE. The adjusted R^2 values range from 0.394 to 0.438, indicating that the models explain a significant portion of the error variance for each discretionary accrual measure. This level of explanatory power seems reasonable, as the models include both audit-firm technological investment variables and established firm-level determinants of accrual behaviour: SIZE, LEV, TURN, GRW, ROA, QR, and REC. The increase in adjusted R^2 across the specifications is gradual, implying incremental explanatory power from auditor revenue, interaction terms, and audit firm size.

This supports the validity of the 2SLS estimates, as indicated by the diagnostic tests. The F-statistics of 24.318 and 21.096 from our first-stage regression exceed the conventional threshold of 10, suggesting that the instruments are sufficiently strong by this criterion. The large LM statistics imply that the models are not just-identified, and the insignificant Hansen J p-values of 0.327 and 0.214 indicate that the instruments fulfill the overidentifying restrictions. The results obtained demonstrate that the instruments are relevant, valid, and highly suitable for the 2SLS estimation.

Table 7: Result of 2SLS Regression and Sobel Test

Variables	Dep. Variable: DA		
	(1)	(2)	(3)
IT_AS	-0.206***	-0.181***	
	(0.061)	(0.056)	
IT_HC	-0.348***	-0.232***	-0.183***
	(0.079)	(0.067)	(0.055)
AR		-0.407***	
		(0.079)	
IT_AS*AR		-0.139***	
		(0.049)	
IT_HC *AR		-0.194***	
		(0.062)	
AU_SIZE			-0.247***
			(0.062)
SIZE	0.086*	0.081**	0.080**
	(0.044)	(0.037)	(0.039)
LEV	-0.026	-0.020	-0.022
	(0.029)	(0.022)	(0.022)
TURN	0.047**	0.040**	0.042**
	(0.021)	(0.018)	(0.020)
GRW	0.018*	0.015	0.019*
	(0.010)	(0.009)	(0.011)
ROA	0.251***	0.231***	0.234***
	(0.069)	(0.067)	(0.066)
QR	-0.012	-0.013	-0.011
	(0.015)	(0.014)	(0.013)
REC	-0.086*	-0.070*	-0.077**
	(0.044)	(0.038)	(0.038)
Constant	-1.746***	-1.601***	-1.526***
	(0.610)	(0.513)	(0.498)
First-stage F-statistic	24.318	21.096	
Wald F-statistic	18.014	16.672	
LM statistic	31.105***	28.412***	
Hansen J-statistic	2.236	3.081	
Hansen J p-value	0.327	0.214	
Sobel Z			3.764**
Sobel Z p-value			0.012
Observations	2.550	2.550	2.550
Adjusted R2	0.394	0.412	0.438

Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Our results imply that in more technologically intensive industries, both asset and human capital technological investment are positively correlated with audit quality, as shown by lower discretionary accruals. This aligns with the monitoring and efficiency views, which suggest that companies investing more in technology are better monitored, enjoy increased data processing capabilities and improved transparency, resulting in a lower chance of income manipulation (Abraham et al., 2024; Neiroukh & Çağlar, 2025). The negative and significant effect of auditor revenue reinforces the notion that tighter auditor control is a precursor to curtailing managerial discretion in financial reporting (again, the harder they work, the less latitude managers have).

The impact of interaction terms indicates that auditor-related factors reinforce the disciplining effect of technological investment on earnings management. The impact of governance is stronger with more powerful audits, highlighting the complementarity between asset technology and human capital investments. The inverse relation between firm size and discretionary accruals substantiates that bigger audit firms are successful in identifying managers' opportunistic reporting behaviour or constrain it by their increased expertise, resources and reputation (Micale, 2025).

4.7 Robustness Test

4.7.1 Alternative measurement of Audit Quality (Discretionary Accruals Dechow Model)

Table 8 presents the robustness results using the Dechow model as an alternative measure of audit quality. The results show that IT_AS was negatively and significantly associated with DA_DM in Model 1, β = -0.209, *SE* = 0.063, $p < 0.01$, and Model 2, β = -0.221, *SE* = 0.063, $p < 0.01$. Similarly, IT_HC had a negative and significant effect across all models, β = -0.281, *SE* = 0.072, $p < 0.01$; β = -0.305, *SE* = 0.074, $p < 0.01$; and β = -0.191, *SE* = 0.055, $p < 0.01$. The interaction terms IT_AS × AR, β = -0.161, *SE* = 0.060, $p < 0.01$, and IT_HC × AR, β = -0.199, *SE* = 0.066, $p < 0.01$, were also negative and significant, indicating that AR strengthens the negative effect of auditor technological investment on discretionary accruals. In Model 3, AU_SIZE was negatively and significantly associated with DA_DM, β = -0.210, *SE* = 0.060, $p < 0.01$. The Sobel test was significant, Z = 3.742, p = 0.012, supporting the mediating role of AU_SIZE.

Table 8: Alternative measurement of Audit Quality (Dechow Model) using 2SLS Regression and Sobel Test

Variables	Dep. Variable: DA_DM		
	(1)	(2)	(3)
IT_AS	-0.209***	-0.221***	
	(0.063)	(0.063)	
IT_HC	-0.281***	-0.305***	-0.191***
	(0.072)	(0.074)	(0.055)
AR		-0.188***	
		(0.057)	
IT_AS*AR		-0.161***	
		(0.060)	
IT_HC*AR		-0.199***	
		(0.066)	
AU_SIZE			-0.210***

Variables	Dep. Variable: DA_DM		
	(1)	(2)	(3)
			(0.060)
SIZE	0.092**	0.087**	0.085**
	(0.043)	(0.042)	(0.039)
LEV	-0.030	-0.022	-0.021
	(0.027)	(0.023)	(0.022)
TURN	0.043**	0.044**	0.041**
	(0.019)	(0.018)	(0.019)
GRW	0.018	0.016*	0.014
	(0.011)	(0.009)	(0.009)
ROA	0.233***	0.249***	0.229***
	(0.069)	(0.068)	(0.065)
QR	-0.014	-0.018	-0.012
	(0.016)	(0.016)	(0.013)
REC	-0.075**	-0.071**	-0.070**
	(0.037)	(0.034)	(0.035)
Constant	-1.706***	-1.619***	-1.438***
	(0.579)	(0.504)	(0.509)
Sobel Z			3.742***
Sobel Z p-value			0.012
Observations	2.550	2.550	2.550
Adjusted R2	0.398	0.411	0.439

Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

The same holds true for the results based on the Dechow Model, thereby further supporting that our main findings are not sensitive to the discretionary accruals measure selection. The coefficients of IT_AS and IT_HC are statistically significant and negative across various specifications, implying that technological investment in both physical assets and human capital contributes to higher financial reporting quality regardless of the alternative accrual estimation model employed. This bolsters its claim that the observed effects are not simply model-specific artifacts but economically meaningful (Fazio et al., 2022).

The positive impact of auditor revenue and the interaction terms (IT_AS × AR and IT_HC × AR) remain significant, further suggesting that audit-related mechanisms continue to exert a stable moderating effect, reinforcing the governance advantages associated with technology investment. In support of this hypothesis, we find that larger audit firms impose stronger constraints on discretionary reporting behaviour due to their superior monitoring capacity and reputational incentives.

4.7.2 Heckman two-stage analysis

Table 9 presents the results of the Heckman two-stage analysis. In the first-stage probit model, SIZE was positively and significantly associated with TECH_INTS (β = 0.389, SE = 0.099, $p < 0.01$), while ROA was also positive and marginally significant (β = 0.198, SE = 0.103, $p < 0.10$). In the second-stage outcome model, the Inverse Mills Ratio was not statistically significant (β = 0.126, SE = 0.133), suggesting that sample selection bias is not a major concern. The results further show that IT_AS had a negative and significant effect on discretionary accruals (β = -0.211, SE = 0.077, $p < 0.05$), and IT_HC also had a negative and significant effect (β = -0.229, SE = 0.083, $p < 0.01$).

Table 9: Result of Heckman Two-Stage Analysis

Heckman Analysis			
First Stage (Probit)		**Second Stage (Outcome)**	
Variable	**TECH_INTS**	**Variable**	**DA**
	(1)		(2)
SIZE	0.389***	*Inverse Mills Ratio*	0.126
	(0.099)		(0.133)
ROA	0.198*	IT_AS	-0.211**
	(0.103)		(0.077)
		IT_HC	-0.229***
			(0.083)
		Control Var.	Included
Observations	2.550	Observations	2.550
Pseudo R^2	0.379	Adj. R^2/Pseudo R^2	0.839
Wald Chi-sq.	50.462	F Value	29.417

Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

The first-stage probit results suggest that firm characteristics are an important determinant of whether a firm has engaged in technology-intensive activities. The positive and significant coefficients on firm size and return on assets indicate that larger and more profitable firms have greater financial capacity, resources, and organizational capacity to adopt superior technology investments. This aligns with resource-based and efficiency theories, arguing that successful firms are better able to invest in innovation and technology-related capabilities (Chen & Srinivasan, 2023; Zapadka et al., 2022).

Sample selection bias is less worrisome in this empirical model as indicated by the non-significance of the inverse Mills ratio in the second-stage results. This supports the validity of our baseline estimates as it shows that these observed relationships are not driven by non-random sample selection. Most importantly, the consistently negative and statistically significant coefficients of IT_AS and IT_HC on discretionary accruals strongly support the earlier finding of a robust relationship, even after accounting for potential endogeneity bias.

4.7.3 Propensity Score Matching Analysis

We present the results of the propensity score matching analysis in Table 10. Panel A: First-stage selection model Panel A presents a first-stage selection model showing that SIZE was positively and significantly related to treatment selection ($\beta = 0.087$, $SE = 0.031$, p < 0.01. Compared to non-excluded articles, ROA ordained $\beta = 0.816$; *SE* 40.4; $p <$ 0. 05. We also note the matched-sample mean difference, which shows that SIZE and ROA continue to be significantly different between treated and control groups while LEV, TURN and GRW are not significant. The second-stage regression in Panel B reveals a negative and significant effect of IT_AS on discretionary accruals ($\beta = -0.019$, $SE = 0.010$, $p < 0.05$. Thus, this empirical analysis suggests that within this framework, both IT_HC and IT_SI had a significant negative effect (β = -0.083, SE = 0.040, p < 0.05). After propensity score matching, these results demonstrate that auditors' investments in technology are associated with lower discretionary accruals.

Table 10: Result of Propensity Score Matching Analysis

Panel A: PSM- First Stage Regression					
	(1) Selection Model		(2) The Mean Difference of Matched Sample		
	Coefficients	Standard Errors	Treated	Control	t-Statistics
SIZE	0.087***	(0.031)	18.096	17.584	2.083**
LEV	-0.071	(0.067)	0.604	0.659	-0.982
ROA	0.816**	(0.404)	0.188	0.154	1.876*
TURN	0.041	(0.050)	0.704	0.668	0.913
GRW	-0.026	(0.031)	3.142	3.229	-0.806
Observations	2.550				
Pseudo-R2	0.046				
Panel B: PSM - The second stage regression					
Dep. Var: DA					
IT_AS	-0.019**				
	(0.010)				
IT_HC	-0.083**				
	(0.040)				
Controls	Included				
Observations	1.275				
Pseudo-R2	0.162				

Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

4.8 Additional Analysis

4.8.1 Cross-Sectional Analysis Based on The Client Complexity

As shown in Table 11, the negative effect of auditor technological investment on discretionary accruals is greater for high-complexity clients than for low-complexity clients. Panel A shows that both IT_AS and IT_HC have negative and significant coefficients on DA in the high- and low-complexity groups, with a significant difference in coefficients (β = -0.016, p = 0.041). Panel B shows that the results are qualitatively similar when using DA_DM, and the coefficient difference is also statistically significant (β = -0.011, p = 0.048). Overall, the results suggest that auditor technological investment leads to a reduction of discretionary accruals only in client firms with high complexity.

Table 11: Cross-sectional analysis based on the Client Complexity

Panel A. Dep. Var. = DA		
	(1)	**(2)**
	High	**Low**
IT_AS	-0.026***	-0.010**
	(0.009)	(0.005)
IT_HC	-0.022***	-0.008**
	(0.008)	(0.004)
Difference of coef.	-0.016**	
p-value	0.041	
Controls	Included	Included
Observations	1.080	1.470
Adj-R^2	0.168	0.139
Panel B. Dep. Var. = DA_DM		

	(1)	(2)
	High	**Low**
IT_AS	-0.019**	-0.007*
	(0.008)	(0.004)
IT_HC	-0.017**	-0.006*
	(0.008)	(0.004)
Difference of coef.	-0.011**	
p-value	0.048	
Controls	Included	Included
Observations	1.080	1.470
Adj-R^2	0.156	0.135

Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

5. Discussion

Our empirical results provide strong, robust evidence that audit-firm investment in technology is negatively related to discretionary accruals, consistent with the view that greater technological investment is associated with higher audit quality. The technological investment in assets and in human capital produces similarly large negative effects on discretionary accruals, regardless of the empirical specification (2SLS baselines; alternative Dechow-based accrual measures; Heckman selection correction; propensity score matching; and cross-sectional analyses based on client complexity). The substantial consistency across various methodological approaches reinforces the validity of these results by reducing concerns about model dependence or estimation bias.

These results broadly complement prior evidence showing that audit technology enhances efficiency, improves anomaly detection, and limits earnings management (Cardona et al., 2024; Hazaea et al., 2025; Sadman et al., 2022). More specifically, prior studies highlighted that digital technologies such as data analytics, artificial intelligence and advanced information systems enhance auditors' effectiveness in identifying misstatements and evaluating the risk of financial reporting. The overall pattern of a negative association between technological investment and discretionary accruals in this study supports some general conclusions about technology improving audits.

The results also contribute to and somewhat refine the audit literature by demonstrating that technology, in isolation, does not improve audit outcomes. Previous research has often emphasized technology adoption as a direct determinant of audit quality, whereas the current results point to complementary factors including auditor revenue, human capital investment and organizational size (Fedyk et al., 2022). Consistent with prior research (Bansal, 2023b; Ege et al., 2024), the financial capacity afforded by auditor revenue determines whether firms have the ability and sustainability to adopt technological systems. Likewise, audit firm size has received considerable attention, as larger firms with more established structures are thought to develop stronger institutional mechanisms for integrating technology into auditing practices (Seethamraju & Hecimovic, 2022).

The findings are generally in line with previous literature but extend it with a capabilities-based rationale for audit quality improvement. Instead of considering technology as an isolated factor, the results support the Resource-Based View and Dynamic Capability Theory, which hold that improvements in audit quality arise from the interplay among a firm's technological resources, human expertise, financial capacity, and organizational structure (Li et al., 2025). This integrated view helps reconcile previously inconsistent findings in the literature and argues for an understanding of audit technology that situates it within a broader bundle of complementary firm capabilities.

6. Conclusion

The main contribution of this study is to answer the research questions, which show that audit-firm technological investment reduces discretionary accruals as a measure of audit quality. More specifically, both technological investment in assets and in human capital are negatively related to discretionary accruals, indicating that audit firms with strong digital infrastructure and technological expertise more effectively constrain earnings management. Results also reveal that auditor revenue moderates the relationship between technological investment and audit quality, while audit firm size is negatively associated with discretionary accruals. This set of results remains robust across multiple estimation methods (2SLS, Dechow-based accrual-measures alternative tests, Heckman two-stage modelling, propensity score matching, and various client-complexity subsample tests). This study contributes to the audit technology literature by showing that simply incorporating new technology into the case does not automatically improve audit quality. Its value, in fact, relies on the audit firm integrating digital assets, technology-skilled human capital, economic capacity, and organizational structure. This study, by examining the implicit investment in audit technology where such investments are separated into asset-based and human-capital-based measures of technological investment, provides a more nuanced explanation for the relationships between audit technology and financial reporting quality as compared to the general literature, while explaining why these benefits might be stronger in environments with complex audits.

This study provides evidence that judicious use of technological and human capital resources at audit firms improves the quality of individual audits, resulting in greater reliability of financial reporting and greater efficiency in capital markets. Higher-quality audits mitigate information asymmetry between firms and investors, thereby facilitating more efficient capital allocation and enhancing investor confidence. From a social perspective, higher audit quality promotes greater transparency and accountability in corporate reporting, reducing the costs of financial misstatements and earnings manipulation for stakeholders such as employees, creditors, and minority shareholders.

From a cultural perspective, our findings underscore the need to promote an audit culture that combines technological competence with professional scepticism and critical thinking. Instead of merely relying on automated systems, audit professionals are challenged to adopt a data-centric perspective and apply professional scepticism and accountability in interpreting machine-generated output.

From a public policy perspective, the results suggest regulators and standard-setting bodies ought to encourage policies that facilitate digital transformation in audit firms, including investments in audit technologies, training programs for auditors, and governance frameworks that direct the prudent use of advanced analytical tools. Regulators should go beyond just firm-level evaluation of audit quality and take into account the tech landscape and human capital development, as complex audits may rely more on these factors.

Theoretically, this study contributes to the Resource-Based View (RBV) literature by concluding that technological assets are viable resources for audit-firm competitive advantage only when complemented by requisite capabilities. This also contributes to the Dynamic Capability Theory by showing that technology-oriented human capital in audit firms can convert digital infrastructure into strong, valuable audit judgment, thereby increasing audit quality. This helps elevate the discussion of audit technology away from mere adoption and toward deploying capabilities, as the authors show that while audit firms own these technologies, their usefulness emerges only when they are integrated, interpreted, and governed in relation to each audit engagement. In practice, the findings suggest that audit firms should not treat digital transformation as merely the acquisition of software. Instead, they need to simultaneously invest in audit analytics platforms, AI-enabled tools, cybersecurity systems, auditor training, digital specialist teams, and robust quality-control procedures for technology-generated evidence. For clients and investors, an auditor's technological capability and economic capacity may serve as relevant signals of audit quality, particularly in complex reporting environments where advanced analytical capabilities are critical. This study is limited to U.S. Nasdaq100 and S&P 500 firms during 2019-2023, which may restrict generalizability. Although 2SLS, Heckman correction, PSM, and alternative accrual measures are applied, endogeneity and measurement error may remain. Moreover, proxies for technological investment and discretionary accruals may not fully capture actual technology use or all dimensions of audit quality. A further limitation of this study is that technological investment may not fully capture actual technology utilization in audit engagements. Although investment in technological assets and technology-oriented human capital reflects an audit firm's digital capacity, expenditure on audit technologies does not necessarily mean that these tools are effectively used in audit planning, risk assessment, evidence collection, anomaly detection, or professional judgment. Some technologies may be underutilized, adopted symbolically, or unevenly implemented across engagement teams. Therefore, the findings should be interpreted as evidence on the relationship between audit-firm technological investment capacity and audit quality, rather than direct evidence that actual technology use improves audit quality.

This study may be limited, but it could lead to analytical directions for important aspects of our research. Cross-country analyses would help examine whether the link between audit-firm investment in technology and audit quality is moderated by institutional environments, regulatory regimes, and the level of technological infrastructure development. Comparative studies like these may deepen understanding of how country-specific factors shape the impact of audit technology adoption.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Fabrication/Falsification Statement

The author(s) declare that no data have been fabricated, falsified, or manipulated in this study.

Participant Consent

This study is based on secondary data obtained from publicly available sources and did not involve any human participants. Therefore, no participant consent was required, and all data were used in accordance with ethical standards for secondary data research.

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References

Abdallah, A. S., Amin, H., Abdelghany, M., & Elamer, A. A. (2024). Assessing Competitiveness Through Intellectual Capital Research: A Systematic Literature Review and Agenda for Future Research. *Competitiveness Review, an International Business Journal*, *35*(1), 190–220. https://doi.org/10.1108/cr-10-2023-0262

Abraham, R., El-Chaarani, H., & Deari, F. (2024). Does Audit Oversight Quality Reduce Insolvency Risk, Systematic Risk, and ROA Volatility? The Role of Institutional Ownership. *Journal of Risk and Financial Management*, *17*(8), 335. https://doi.org/10.3390/jrfm17080335

al-Ma'aitah, R., Al-Hajaya, K., Sawan, N., & Alzeban, A. (2024). The Impact of Remote Auditing on Audit Quality: The Moderating Role of Technology Readiness. *Managerial Auditing Journal*, *39*(6), 624–647. https://doi.org/10.1108/maj-02-2024-4210

AL-Akheli, A., Tan, H., Hazaea, S. A., Elfarra, B., & Al-Zubairi, A. (2025). Mapping the Literature Trends of Corporate Social Responsibility and Cost of Capital: A Systematic Literature Review. *Corporate Social Responsibility and Environmental Management*, *32*(3), 3383–3407. https://doi.org/10.1002/csr.3137

Alsaif, M., Phan, D. H. T., Kend, M., & Alharbi, M. G. (2025). Emerging Technologies in External Audit and How They Are Challenging Auditors' Judgements and Decision-Making Processes. *Accounting and Finance*, *65*(4), 3347–3360. https://doi.org/10.1111/acfi.70043

Azambuja, R., & Islam, G. (2023). Middle-Managerial Deviance as a Response to Structural Strain: Rescoping, Reconfiguring and Replacing Norms. *Journal of Management Studies*, *61*(3), 994–1035. https://doi.org/10.1111/joms.12911

Bansal, M. (2023a). Earnings Management: A three-Decade Analysis and Future Prospects. *Journal of Accounting Literature*, *46*(4), 630–670. https://doi.org/10.1108/jal-10-2022-0107

Bansal, M. (2023b). Predictors of revenue shifting and expense shifting: Evidence from an emerging economy. *Journal of Contemporary Accounting and Economics*, *19*(1). https://doi.org/10.1016/j.jcae.2022.100339

Barr-Pulliam, D., Calvin, C. G., Eulerich, M., & Maghakyan, A. (2023). Audit Evidence, Technology, and Judgement: A Review of the Literature in Response to ED-500. *Journal of International Financial Management and Accounting*, *35*(1), 36–67. https://doi.org/10.1111/jifm.12192

Cardona, L. F., Luna, J. A. G., & Restrepo-Carmona, J. A. (2024). Bibliometric Analysis of Intelligent Systems for Early Anomaly Detection in Oil and Gas Contracts: Exploring Recent Progress and Challenges. *Sustainability*, *16*(11), 4669. https://doi.org/10.3390/su16114669

Chen, W., & Srinivasan, S. (2023). Going Digital: Implications for Firm Value and Performance. *Review of Accounting Studies*, *29*(2), 1619–1665. https://doi.org/10.1007/s11142-023-09753-0

Domínguez, F. I. R., Antequera, J. G., Pérez, A. G., Rodríguez, M. I. P., & González-

Fernández, A. (2022). Digital Teaching Competence: A Systematic Review. *Sustainability*, *14*(11), 6428. https://doi.org/10.3390/su14116428
Ege, M., Kim, Y. H., & Wang, D. (2024). Auditor Distraction: The Case of Outside Job Opportunities for External Auditors and Audit Quality. *Contemporary Accounting Research*. https://doi.org/10.1111/1911-3846.12994
El-Bassel, N., David, J., Mukherjee, T. I., Aggarwal, M., Wu, E., Gilbert, L., Walters, S. T., Chandler, R., Hunt, T., Frye, V., Campbell, A., Goddard-Eckrich, D., Keyes, K. M., Benjamin, S. N., Balise, R. R., Muresan, S., Aragundi, E., Lounsbury, D. W., Sabounchi, N. S., … Zheng, T. (2025). The Practical, Robust Implementation and Sustainability (PRISM)-capabilities Model for Use of Artificial Intelligence in Community-Engaged Implementation Science Research. *Implementation Science*, *20*(1). https://doi.org/10.1186/s13012-025-01447-2
Elommal, N., & Manita, R. (2022). How Blockchain Innovation Could Affect the Audit Profession: A Qualitative Study. *Journal of Innovation Economics & Management*, *N° 37*(1), 37–63. https://doi.org/10.3917/jie.pr1.0103
Fang, Q., Yu, N., & Xu, H. (2023). Governance effects of digital transformation: from the perspective of accounting quality. *China Journal of Accounting Studies*, *11*(1), 77–107. https://doi.org/10.1080/21697213.2023.2148944
Fazio, S. de A., Grande, E. U., & Estébanez, R. P. (2022). The "Secret Life" of the Statement of Cash Flow: A Bibliometric Analysis. *Cuadernos De Gestión*, *22*(1), 143–159. https://doi.org/10.5295/cdg.211481rp
Fedyk, A., Hodson, J., Khimich, N. V, & Fedyk, T. (2022). Is Artificial Intelligence Improving the Audit Process? *Review of Accounting Studies*, *27*(3), 938–985. https://doi.org/10.1007/s11142-022-09697-x
Georgiou, I., Sapuric, S., Lois, P., & Thrassou, A. (2024). Blockchain for Accounting and Auditing—Accounting and Auditing for Cryptocurrencies: A Systematic Literature Review and Future Research Directions. *Journal of Risk and Financial Management*, *17*(7), 276. https://doi.org/10.3390/jrfm17070276
Gonçalves, M. N., & Basso, L. F. C. (2024). Bibliometric Analysis Into a Decade of Academic Research on Innovation, Value Creation, and Sustainability (2013-2023). *International Journal of Innovation*, *12*(2), 1–71. https://doi.org/10.5585/2024.26353
González-Ruíz, J. D., Marín-Rodríguez, N. J., & Weber, O. (2024). New Insights on Social Finance Research in the Sustainable Development Context. *Business Strategy & Development*, *7*(1). https://doi.org/10.1002/bsd2.342
Gonzalez, R. V. D. (2022). How Do Learning Culture and Dynamic Capability Interfere With Team Performance? *Gestão & Produção*, *29*. https://doi.org/10.1590/1806-9649-2022v29e134
Hazaea, S. A., Cai, C., Al-Matari, E. M., Al-Bukhrani, M. A., & Chong, H. G. (2025). Mapping the Literature Trends of Internal Auditing in the United States: A Systematic Review and Directions for Future Research. *Sage Open*, *15*(1). https://doi.org/10.1177/21582440251318071
He, M., Mirza, S. S., & Huang, C. (2025). When Technology Meets Turbulence: The Impact of Digital Transformation and Policy Uncertainty on Audit Opinions. *Journal of Corporate Accounting & Finance*. https://doi.org/10.1002/jcaf.70011
Herranz, C. Z., Alvarado, N. R., & López-Iturriaga, F. J. (2022). Audit Committee Competence and Earnings Management in Europe. *Revista De Contabilidad –*

Spanish Accounting Review, *25*(1), 121–135. https://doi.org/10.6018/rcsar.385331
Kabashkin, I., Mišņevs, B., & Zervina, O. (2023). Artificial Intelligence in Aviation: New Professionals for New Technologies. *Applied Sciences*, *13*(21), 11660. https://doi.org/10.3390/app132111660
Kyriakou, M. I. (2024). Modelling the Impact of Turbulent Economic Conditions on Non-Audit Services Provision and Audit Quality During the Global Financial Crisis. *International Journal of Accounting and Information Management*, *32*(4), 730–746. https://doi.org/10.1108/ijaim-02-2023-0031
Li, K., Kongkuah, M., & Alessa, N. (2025). Beyond Compliance: How Board–Ownership Structures and Eco-Technology Intensity Drive Circular Economy Performance In <scp>MENA</Scp> Firms. *Corporate Social Responsibility and Environmental Management*, *32*(5), 6658–6679. https://doi.org/10.1002/csr.70045
Liao, K., Liu, H., & Liu, F. (2023). Digital transformation and enterprise inefficient investment: Under the view of financing constraints and earnings management. *Journal of Digital Economy*, *2*, 289–302. https://doi.org/https://doi.org/10.1016/j.jdec.2023.12.001
Lou, Z., Li, M. S., Shan, Y. G., & Ye, A. (2024). Does Corporate Digitalisation Moderate Real Earnings Management? *Accounting and Finance*, *64*(4), 4157–4196. https://doi.org/10.1111/acfi.13301
Micale, J. A. (2025). Can Individual Auditors' Career Advancements Predict Audit Partner Quality? *Contemporary Accounting Research*, *43*(1), 136–168. https://doi.org/10.1111/1911-3846.70014
Neiroukh, N., & Çağlar, D. (2025). Unveiling the Nexus Between Audit Quality and Financial Performance: A Strategic Adaptation Approach Through Earnings Management and Corporate Governance. *Sage Open*, *15*(4). https://doi.org/10.1177/21582440251391115
Otia, J. E., & Bracci, E. (2022). Digital Transformation and the Public Sector Auditing: The SAI's Perspective. *Financial Accountability and Management*, *38*(2), 252–280. https://doi.org/10.1111/faam.12317
Paipa-Sanabria, E., Escalante-Torres, F., Jaimes, W. A., & Coronado-Hernández, J. R. (2024). Exploring Innovation Capabilities in Organizations Through a Scientometric Approach in the Context of Manufacturing Industry. *Journal of Innovation Management*, *12*(1), 109–138. https://doi.org/10.24840/2183-0606_012.001_0006
Qader, K. S., & Çek, K. (2024). Influence of Blockchain and Artificial Intelligence on Audit Quality: Evidence From Turkey. *Heliyon*, *10*(9), e30166. https://doi.org/10.1016/j.heliyon.2024.e30166
Radu, E., Dima, A., Dobrota, E. M., Badea, A.-M., Madsen, D. Ø., Dobrin, C., & Stanciu, S. (2023). Global Trends and Research Hotspots on HACCP and Modern Quality Management Systems in the Food Industry. *Heliyon*, *9*(7), e18232. https://doi.org/10.1016/j.heliyon.2023.e18232
Rahman, M. J., & Ziru, A. (2022). Clients' Digitalization, Audit Firms' Digital Expertise, and Audit Quality: Evidence From China. *International Journal of Accounting and Information Management*, *31*(2), 221–246. https://doi.org/10.1108/ijaim-08-2022-0170
Sadman, N., Ahsan, M. M., Rahman, A., Siddique, Z., & Gupta, K. D. (2022). Promise of AI in DeFi, a Systematic Review. *Digital*, *2*(1), 88–103.

https://doi.org/10.3390/digital2010006

Samiolo, R., Spence, C., & Toh, D. (2023). Auditor Judgment in the Fourth Industrial Revolution. *Contemporary Accounting Research*, *41*(1), 498–528. https://doi.org/10.1111/1911-3846.12901

Seethamraju, R., & Hecimovic, A. (2022). Adoption of Artificial Intelligence in Auditing: An Exploratory Study. *Australian Journal of Management*, *48*(4), 780–800. https://doi.org/10.1177/03128962221108440

Silva, R., Inácio, H., & Marques, R. P. (2022). *Blockchain Implications for Auditing: A Systematic Literature Review and Bibliometric Analysis*. 163–192. https://doi.org/10.4192/1577-8517-v22_6

Tanchangya, T., Siddiqi, K. O., Dhar, B. K., Rahman, J., & Islam, N. (2025). Leveraging Green Capabilities and Digital Accounting Under <scp>ESG</Scp> Pressure: Strategic Insights From an Emerging Market's Global Value Chains. *Thunderbird International Business Review*, *68*(4), 579–592. https://doi.org/10.1002/tie.70058

Thottoli, M. M. (2023). The Tactician Role of FinTech in the Accounting and Auditing Field: A Bibliometric Analysis. *Qualitative Research in Financial Markets*, *16*(2), 213–238. https://doi.org/10.1108/qrfm-11-2021-0196

Varma, A., Mancini, D., & Kaushik, S. (2023). *Professional Skepticism for Green Reputation Clients: A Mixed Method Study of Technology-Enabled Audits*. *23*(6), 137–179. https://doi.org/10.4192/1577-8517-v23_6

Wu, Y., Li, Z., Zhang, M., & Zhai, S. (2023). Auditor Assignments and Audit Quality. *Australian Accounting Review*, *33*(2), 160–187. https://doi.org/10.1111/auar.12400

Zapadka, P., Hanelt, A., & Firk, S. (2022). Digital at the Edge – Antecedents and Performance Effects of Boundary Resource Deployment. *The Journal of Strategic Information Systems*, *31*(1), 101708. https://doi.org/10.1016/j.jsis.2022.101708

Appendix

Variables Definition and Measurement

Variables	Definition	Measurement
DA	The absolute value of performance discretionary accruals.	Discretionary Accruals = Total Accruals - Non-Discretionary Accruals.
IT_AS	Technological Investment on asset in audit firm.	(∑) Total of Technological Investment on asset in audit firm.
IT_HC	Technological Investment on human capital in audit firm.	(∑) Total of Technological Investment on Human Capital in audit firm.
AR	Auditor Revenue	Auditor Revenue.
AU_SIZE	The relative size of an audit firm, reflecting its capacity and resources to conduct audit engagements.	Audit Firm Size is measured using min–max normalization of the audit firm size indicator.
SIZE	The natural logarithm of the book value of total assets	(∑) Total Asset of Auditee.
LEV	Leverage is the ratio of total debts to total assets in line with audit risk.	Leverage = Total Debts / Total Assets.
TURN	Asset Turn Over ratio.	Sales / Lagged Total Assets
GRW	One-year percentage growth in sales.	Current Year Sales - Previous Year Sales) / Previous Year Sales * 100
ROA	Return on Asset Ratio.	Net Income / Average Total Assets.
QR	Quick Ratio.	(Current Assets - Inventory) / Current Liabilities.
REC	Account Receivable.	Account Receivable / Total Assets.
Peer IT	leave-one-out peer auditor technological investment	Peer IT is measured as the average technological investment of other auditors in the same peer group and year.
LocalTechLabor	local technology labour.	Proportion of technology-related workers available in the local labour market where auditor operates.