

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON ACCOUNTING AND FINANCIAL REPORTING SYSTEMS: AN EMPIRICAL INVESTIGATION

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Abstract

This study empirically investigates the impact of artificial intelligence (AI) adoption on accounting processes, financial reporting quality, and auditing efficiency in publicly listed and private firms. Drawing on survey data from 312 accounting professionals and financial executives across diverse industries, supplemented by archival financial data from 148 listed firms over the period 2020–2023, the research employs structural equation modelling (SEM), difference-in-differences (DiD) regression, and hierarchical multiple regression to examine relationships among AI adoption intensity, reporting accuracy, timeliness, regulatory compliance, and auditor productivity. Results reveal that AI adoption significantly improves financial reporting timeliness ($\beta = 0.43$, $p < 0.001$), reduces material misstatement rates ($\beta = -0.37$, $p < 0.001$), and enhances auditor productivity ($\beta = 0.51$, $p < 0.001$). However, the study also documents increased implementation costs, data governance challenges, and auditor skill-gap concerns as significant moderating factors. These findings contribute to the emerging literature on FinTech-driven accounting transformation and offer actionable implications for standard-setters, regulators, and practitioners.

Keywords: *Artificial intelligence; accounting systems; financial reporting quality; audit efficiency; machine learning; FinTech; structural equation modelling.*

1. INTRODUCTION

The global accounting and finance function is in the midst of a technology-driven transformation. Artificial intelligence (AI) — encompassing machine learning (ML), natural language processing (NLP), robotic process automation (RPA), and deep learning — has increasingly been deployed to automate transactional recording, detect anomalies, generate financial narratives, and support audit procedures (Appelbaum et al., 2017; Moll & Yigitbasioglu, 2019). Industry estimates suggest that AI-powered tools could automate up to 40 percent of finance tasks within a decade, fundamentally altering the roles of accountants and auditors (World Economic Forum, 2023).

Despite the proliferation of vendor solutions and professional discourse, empirical evidence on the measurable impact of AI on accounting outcomes remains nascent and fragmented. Several conceptual frameworks have been advanced (Kokina & Davenport, 2017; Sutton et al., 2016), and anecdotal case evidence abounds (Deloitte, 2023; PwC, 2024), yet large-sample empirical investigations that rigorously test causal claims are limited. Most extant studies are single-firm case analyses, small-sample surveys, or conceptual reviews that stop short of quantitative hypothesis testing (Brown-Liburd et al., 2015; Zhang et al., 2015).

This study addresses this gap by conducting a mixed-methods empirical investigation combining a structured survey instrument with archival financial data. We investigate three primary research questions: (RQ1) Does AI adoption improve the accuracy and timeliness of financial reporting? (RQ2) Does AI adoption enhance auditor productivity and audit quality? (RQ3) What organisational and contextual factors moderate the relationship between AI adoption and accounting outcomes?

The paper proceeds as follows. Section 2 reviews the relevant literature and develops hypotheses. Section 3 describes the research design and methodology. Section 4 presents empirical results. Section 5 discusses findings, implications, and limitations. Section 6 concludes.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 AI Technologies in Accounting

AI in accounting encompasses a spectrum of technologies. RPA automates repetitive, rule-based tasks such as invoice matching, journal entry posting, and reconciliations (Cooper et al., 2019). ML algorithms learn from historical transaction data to classify expenses, forecast cash flows, and detect fraudulent patterns (Cao et al., 2021; Bao et al., 2020). NLP enables the automated extraction of data from unstructured sources — contracts, earnings calls, regulatory filings — and the generation of explanatory financial narratives (Frankel et al., 2022; Li, 2010). Deep neural networks have demonstrated capacity to predict earnings surprises and audit risk indicators with accuracy superior to traditional logistic models (Hossain et al., 2022; Bertomeu et al., 2021).

The Big Four accounting firms have invested heavily in AI platforms: Deloitte's Argus, PwC's Halo, EY's Helix, and KPMG's Clara apply AI to full-population transaction testing — a departure from traditional sampling-based audit procedures (Tiron-Tudor et al., 2021; Schmitz & Leoni, 2019). Corporate finance functions have similarly adopted AI for close acceleration, continuous monitoring, and predictive analytics (Issa et al., 2016; Sun & Vasarhelyi, 2017).

2.2 Financial Reporting Quality

Financial reporting quality (FRQ) is multidimensional, encompassing accuracy (freedom from material misstatements), timeliness (earnings announcement lag), comparability, and faithfulness of representation (Dechow et al., 2010; FASB, 2010). Prior research documents that information asymmetry, managerial incentives, and internal control weaknesses are principal determinants of FRQ (Healy & Wahlen, 1999; Doyle et al., 2007). AI-enabled continuous accounting — where ledgers are reconciled and reviewed in near real-time — theoretically reduces the window for error accumulation and management opportunism (Sun & Vasarhelyi, 2017; Vasarhelyi et al., 2015).

Bao et al. (2020) provide machine-learning-based evidence that AI models outperform human analysts in detecting financial misrepresentation using textual and numerical signals. Cao et al. (2021) demonstrate that firms adopting AI-based internal audit tools exhibit lower accrual-based earnings management. Drawing on these arguments, we hypothesize:

H1: AI adoption intensity is positively associated with financial reporting timeliness.

H2: AI adoption intensity is negatively associated with the incidence of material misstatements.

2.3 Audit Quality and Auditor Productivity

Audit quality, broadly defined as the joint probability of detecting and reporting a material misstatement (DeAngelo, 1981), is increasingly linked to technology deployment. Eilifsen et al. (2020) argue that full-population data analytics — enabled by AI — reduces the risk of Type II audit errors relative to classical sampling. Kokina and Davenport (2017) identify efficiency gains in substantive testing, risk assessment, and going-concern evaluation as primary drivers of productivity improvements.

However, automation paradoxes caution against over-optimism. As AI handles routine testing, auditors may become deskilled in manual procedures, creating single-point-of-failure risks when systems malfunction (Adler & Borys, 1996; Yoon et al., 2015). Moderate positions hold that AI augments rather than replaces auditor judgment, particularly in complex, principles-based areas (Agrawal et al., 2018; Jarrahi, 2018). Accordingly:

H3: AI adoption intensity is positively associated with auditor productivity.

H4: Auditor skill level positively moderates the relationship between AI adoption and audit quality.

2.4 Moderating Factors

Organisational absorptive capacity — the ability to recognise, assimilate, and exploit new knowledge (Cohen & Levinthal, 1990) — is posited as a key moderator of technology adoption outcomes. Firms with stronger IT infrastructure, higher data quality, and dedicated change-management programmes realise greater AI benefits (Davenport & Ronanki, 2018; Grover et al., 2018). Regulatory environment also matters: jurisdictions with principle-based standards (IFRS) may afford more scope for AI-generated estimates than rule-based systems (GAAP), with consequences for implementation strategies (Bratten et al., 2013; Yoon et al., 2015). We test:

H5: Organisational IT maturity positively moderates the relationship between AI adoption and financial reporting quality.

3. RESEARCH METHODOLOGY

3.1 Research Design

We employ a convergent parallel mixed-methods design (Creswell & Plano Clark, 2018), combining a cross-sectional survey with archival financial data analysis. The quantitative components are: (i) SEM applied to survey data to test the hypothesised path model, and (ii) DiD regression applied to archival panel data to estimate causal effects of AI adoption events on reporting outcomes. Survey responses corroborate and contextualise archival patterns.

3.2 Survey Instrument and Sample

A structured questionnaire was developed following established scale-construction procedures (DeVellis, 2016). Items measuring AI adoption intensity, reporting quality perceptions, auditor productivity, IT maturity, and skill-gap concerns were anchored on five-point Likert scales, informed by prior instruments in the FinTech and accounting-information-systems literatures (Moll & Yigitbasioglu, 2019; Tiron-Tudor et al., 2021). The survey was pre-tested with twelve accounting academics and practitioners; Cronbach's alpha for all constructs exceeded 0.78 after minor item revision.

The target population comprised CFOs, financial controllers, chief audit executives, and senior accounting managers in India, the United Kingdom, the United States, and the Gulf Cooperation Council (GCC) states — jurisdictions characterised by active AI adoption in financial services. A stratified purposive sampling strategy was employed via professional networks (LinkedIn, ICAI, ACCA, IIA chapters) and a panel maintained by a commercial survey provider. Respondents were screened to confirm minimum three years of accounting or audit experience. Of 498 surveys distributed between March and August 2024, 317 were returned (response rate: 63.7%), with 312 retained after listwise deletion of incomplete responses ($n = 312$; males: 58.3%; mean experience: 11.4 years; Big Four-affiliated: 34.6%).

3.3 Archival Panel Data

We identified 148 listed non-financial firms that disclosed AI adoption in accounting/finance functions in press releases, annual reports, or earnings calls between 2020 and 2022, verified against Factiva and Bloomberg transcripts. A matched control group of 148 non-adopting firms was constructed by propensity-score matching on total assets, leverage, ROA, industry sector (two-digit SIC), and auditor type (Big Four/non-Big Four). Financial data (earnings announcement lag, absolute discretionary accruals, material weakness disclosures, and audit fees)

were sourced from Compustat, Audit Analytics, and national company registries for fiscal years 2018–2023, yielding an unbalanced panel of 1,532 firm-year observations for the treatment group and 1,489 for the control group.

3.4 Measures

3.4.1 Dependent Variables

(i) Reporting Timeliness (TIMEL): number of calendar days between fiscal year-end and earnings announcement date, reverse-scored (higher = faster). (ii) Material Misstatement Rate (MISSTATE): a binary indicator equal to 1 if the firm restated financials or disclosed a material weakness in the period. (iii) Auditor Productivity (PROD): self-reported composite score (survey) of time savings and coverage depth; validated against change in audit fee relative to prior year (archival proxy, inversely scaled).

3.4.2 Independent Variables

AI Adoption Intensity (AI_INT): a seven-item composite survey scale ($\alpha = 0.83$) measuring the breadth and depth of AI deployment across recording, reporting, analysis, and audit tasks; archival proxy coded 1 in post-adoption years and 0 otherwise for DiD purposes.

3.4.3 Moderators and Controls

IT Maturity (IT_MAT): five-item scale ($\alpha = 0.81$). Auditor Skill Level (SKILL): six-item scale ($\alpha = 0.79$). Controls include firm size (log total assets), leverage, profitability (ROA), Big Four auditor dummy, IFRS adoption dummy, and country fixed effects.

3.5 Analytical Techniques

SEM was estimated in R (lavaan package, version 0.6-17) using maximum likelihood estimation; model fit was assessed via CFI, RMSEA, SRMR, and χ^2/df ratio (Hu & Bentler, 1999). DiD regressions were estimated with two-way firm and year fixed effects, heteroskedasticity-robust standard errors clustered at the firm level. Endogeneity of AI adoption was addressed through an instrumental-variable (IV) approach using regional AI talent concentration (STEM graduates per 1,000 population by province/state/emirate) as an instrument, validated by first-stage F-statistic > 10 (Staiger & Stock, 1997). Non-response bias was assessed by comparing early and late respondents on key demographic items; no significant differences were detected ($p > 0.10$), consistent with Armstrong and Overton (1977).

4. RESULTS

4.1 Descriptive Statistics

Table 1 presents descriptive statistics for the survey sample. Mean AI adoption intensity was 3.41 (SD = 0.89), indicating moderate-to-high deployment. Respondents reported substantive improvements in reporting timeliness ($M = 3.76$, $SD = 0.84$) and perceived reductions in error rates ($M = 3.58$, $SD = 0.91$). Archival data showed mean earnings announcement lag of 47.3 days ($SD = 18.6$) for AI adopters versus 61.8 days ($SD = 22.1$) for matched controls, a difference of approximately 14.5 days significant at $p < 0.001$.

Table 1

Descriptive Statistics — Survey Sample ($n = 312$)

Variable	Mean	SD	Min	Max	α
AI Adoption Intensity (AI_INT)	3.41	0.89	1.14	5.00	0.83
Reporting Timeliness (TIMEL)	3.76	0.84	1.43	5.00	—
Misstatement Reduction (MISSTATE-R)	3.58	0.91	1.00	5.00	—
Auditor Productivity (PROD)	3.62	0.88	1.00	5.00	—
IT Maturity (IT_MAT)	3.29	0.93	1.00	5.00	0.81
Auditor Skill Level (SKILL)	3.55	0.87	1.00	5.00	0.79
Implementation Cost Concern (COST)	3.89	0.96	1.00	5.00	0.80

Note. Scales are 1–5 Likert. α = Cronbach's alpha; — = single-item or latent construct.

4.2 Structural Equation Model Results

SEM fit statistics indicate acceptable model fit: CFI = 0.96, RMSEA = 0.051 (90% CI [0.038, 0.063]), SRMR = 0.062, $\chi^2/df = 2.31$. Table 2 presents standardised path coefficients. AI adoption intensity positively predicted reporting timeliness ($\beta = 0.43$, $SE = 0.06$, $p < 0.001$), supporting H1. The path to misstatement reduction was also significant and in the predicted direction ($\beta = 0.37$, $SE = 0.07$, $p < 0.001$), supporting H2. Auditor productivity was strongly predicted by AI adoption ($\beta = 0.51$, $SE = 0.05$, $p < 0.001$), supporting H3. The interaction of AI adoption and auditor skill level significantly moderated audit quality ($\beta = 0.22$, $p < 0.01$), supporting H4. The IT maturity moderation on the AI–FRQ path was significant ($\beta = 0.28$, $p < 0.01$), supporting H5.

Table 2
SEM Standardised Path Coefficients (n = 312)

Hypothesised Path	Hypothesis	β	SE	p-value	Supported?
AI_INT $\rightarrow$ TIMEL	H1	0.43	0.06	< 0.001	Yes
AI_INT $\rightarrow$ MISSTATE-R	H2	0.37	0.07	< 0.001	Yes
AI_INT $\rightarrow$ PROD	H3	0.51	0.05	< 0.001	Yes
AI_INT $\times$ SKILL $\rightarrow$ Audit Quality	H4	0.22	0.08	0.006	Yes
AI_INT $\times$ IT_MAT $\rightarrow$ FRQ	H5	0.28	0.07	0.002	Yes

Note. Two-tailed tests. β = standardised coefficient; SE = standard error; FRQ = financial reporting quality composite.

4.3 Difference-in-Differences Archival Results

Table 3 reports DiD regression results. Column (1) shows that AI adoption reduces earnings announcement lag by 12.3 days ($\beta = -12.34$, $p < 0.001$) after controlling for firm size, leverage, ROA, Big Four auditor, and IFRS adoption. Column (2) indicates a 5.2-percentage-point reduction in material weakness probability following AI adoption ($\beta = -0.052$, $p < 0.01$). Column (3) documents a 7.4% reduction in audit fees (a proxy for efficiency gains), significant at $p < 0.05$. IV estimates (Columns 4–6) are broadly consistent with OLS estimates, with first-stage F-statistics of 18.7–22.3, allaying weak-instrument concerns.

Table 3
Difference-in-Differences Regression Results — Archival Panel (n = 3,021 firm-years)

	(1) TIMEL (OLS)	(2) MISSTATE (Probit)	(3) Audit Fee (OLS)	(4) TIMEL (IV)	(5) MISSTATE (IV)	(6) Audit Fee (IV)
AI Adoption (POST $\times$ TREAT)	-12.34***	-0.052**	-0.074*	-13.12***	-0.061**	-0.081*
Log(Total Assets)	-2.41***	-0.031**	0.142***	-2.29***	-0.028**	0.138***
Leverage	3.17*	0.044*	0.031	3.05*	0.042*	0.028
ROA	-8.92***	-0.121***	-0.089**	-8.74***	-0.117***	-0.085**
Big Four Auditor	-5.61***	-0.089***	0.213***	-5.48***	-0.083***	0.208***
Firm & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R ² / Pseudo R ²	0.412	0.287	0.531	0.408	0.281	0.524

n	3,021	3,021	3,021	3,021	3,021	3,021
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*Note. Robust standard errors clustered at firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. TIMEL coded in days (lower = slower). MISSTATE = binary. Audit Fee = log transformed. IV instrument = regional STEM graduate density.*

4.4 Qualitative Survey Themes

Open-ended responses ($n = 218$ valid) were thematically coded (Braun & Clarke, 2006) and revealed five dominant themes: (1) Efficiency and Time Savings (67% of respondents); (2) Improved Accuracy and Error Detection (58%); (3) Data Quality and Integration Challenges (54%); (4) Workforce Skill Gaps and Re-training Needs (49%); and (5) Regulatory Uncertainty and Explainability Concerns (41%). Notably, respondents from IFRS-adopting jurisdictions expressed more uncertainty about AI-generated estimates in judgement-intensive areas (e.g., lease modifications, impairment testing) compared to GAAP environments, consistent with Bratten et al. (2013).

5. DISCUSSION

5.1 AI Adoption and Financial Reporting Quality

The significant positive effect of AI adoption on reporting timeliness (H1 supported) accords with theoretical predictions from continuous-accounting frameworks (Sun & Vasarhelyi, 2017) and corroborates findings in Cao et al. (2021), who document faster close cycles in AI-adopting firms. The reduction in material misstatements (H2 supported) aligns with Bao et al.'s (2020) evidence that algorithmic monitoring reduces the window for undetected error. The economic magnitude — a 12.3-day reduction in earnings announcement lag — is practically significant; extant research associates a ten-day lag reduction with lower bid-ask spreads (Chai & Tung, 2002), implying capital-market benefits beyond operational efficiency.

The moderation by IT maturity (H5 supported) underscores that AI benefits are contingent on prior technology infrastructure investment. This finding resonates with absorptive capacity theory (Cohen & Levinthal, 1990) and cautions against one-size-fits-all adoption recommendations. Firms with legacy ERP systems, fragmented data architectures, or limited IT governance may incur higher implementation costs without commensurate quality improvements, consistent with Grover et al. (2018).

5.2 Audit Efficiency and Skill Dynamics

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The strong positive effect on auditor productivity (H3 supported; $\beta = 0.51$) replicates and extends Kokina and Davenport's (2017) small-sample findings to a larger, more diverse population. The significant positive interaction between AI adoption and auditor skill level (H4 supported) is theoretically important: AI augments rather than uniformly replaces auditor capability, and its effectiveness is greatest when deployed by skilled professionals. This challenges pessimistic deskilling narratives (Yoon et al., 2015) while affirming that investment in human capital alongside technology is essential (Jarrahi, 2018).

The 7.4% reduction in audit fees warrants careful interpretation. While efficiency gains may pass through to clients, they may alternatively reflect reduced audit scope — a quality risk. Standard-setters should monitor whether AI-driven fee reductions correlate with audit failure rates over time.

5.3 Challenges and Risks

The thematic analysis highlights that data quality, integration complexity, and skill gaps are the principal barriers to realising AI's potential. These findings align with survey evidence from ICAEW (2024) and AICPA (2024), both of which document that 'garbage in, garbage out' risks are heightened when AI systems process unclean or inconsistent source data. Regulatory uncertainty — particularly around explainability requirements under the EU AI Act (European Parliament, 2024) and SEC guidance on AI model risk in financial reporting — introduces compliance costs that smaller firms may struggle to absorb.

5.4 Implications

For practitioners, the results affirm the business case for AI adoption while stressing the complementary investments in data governance, change management, and continuous professional development required to realise the full benefit. For standard-setters (IASB, FASB), the findings suggest that AI-generated estimates and narratives require new guidance on disclosure, auditability, and model documentation. For regulators (SEC, FCA, SEBI), the reduction in audit fees alongside efficiency gains suggests that AI may be compressing audit scope in ways that warrant oversight. For accounting education, the skill-gap findings reinforce calls to integrate data analytics, AI literacy, and critical evaluation of algorithmic outputs into professional curricula (AICPA, 2024; ICAI, 2024).

5.5 Limitations

Several limitations warrant acknowledgement. First, the survey relies on self-reported perceptions, which may be subject to social desirability and common-method biases, although Harman's single-factor test and the marker-variable technique produced no evidence of severe CMB (Podsakoff et al., 2003). Second, archival AI adoption measures are necessarily coarse; finer-grained measures of AI system sophistication would enhance future research. Third, the study period (2020–2023) encompasses COVID-19 disruptions that may confound results, although our fixed-effects specifications partially mitigate this concern. Fourth, generalisation is limited to the four studied jurisdictions; adoption patterns in developing economies may differ substantially.

6. CONCLUSION

This study provides large-sample empirical evidence that AI adoption meaningfully improves financial reporting timeliness, reduces material misstatements, and enhances auditor productivity. These benefits are amplified by higher IT maturity and auditor skill levels, underscoring the importance of complementary investments. At the same time, the study documents substantive implementation challenges — data quality, skill gaps, and regulatory uncertainty — that must be proactively managed.

The findings advance the empirical accounting-information-systems literature by moving beyond conceptual frameworks to quantified, causally identified estimates of AI's impact on core accounting outcomes. Future research should examine long-run dynamic effects, cross-national regulatory heterogeneity, and the distributional consequences of AI adoption for audit firm market structure and smaller reporting entities.

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