The Role of Artificial Intelligence in Audit Quality and Reducing Earnings Management

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Abstract: - This examines the usage of artificial intelligence (AI) in enhancing audit quality and lowering income management inside Saudi-listed corporations from 2015 to 2024. The study uses 680 corporation-accounting period observations sourced from the Bloomberg and DataStream databases, employing correlational and panel regression analyses (OLS and FGLS) to analyze the relationships amongst AI adoption, audit quality, and earnings management, with employer traits functioning as independent variables. The empirical findings display a strong negative correlation between AI use and profit control, suggesting that advanced incorporation of AI in auditing diminishes discretionary accruals and improves financial transparency. Audit is wonderful; moreover has a large, terrible impact on income manipulation, which shows that it plays a role within the interplay between AI and income manipulation. Control variables like the length and leverage of an employer have a significant impact on income management, while profitability has a negative effect. In particular, the outcomes show that AI-pushed audit techniques make governance more potent, make it less complicated to find out issues, and inspire moral reporting. The studies offer to the frame of expertise via imparting empirical statistics from a developing market, providing realistic guidance for regulators, audit agencies, and policymakers aiming to make use of AI to enhance audit effectiveness and company accountability in accordance with Saudi Vision 2030.

Key-Words: - Artificial Intelligence (AI), Audit Quality, Earnings Management, Financial Reporting Transparency, Corporate Governance, Digital Transformation, Auditing Technologies.

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1 Introduction

The area of accounting and auditing has been substantially altered as a result of the rapid development of artificial intelligence (AI) studies and technology, [1]. Automation, predictive analytics, and choice-making that is pushed by means of facts are all techniques that are turning into an increasing number of universal in present day auditing environments, [2]. Auditors are able to expeditiously and as it should be verified large amounts of financial records with the assistance of those contraptions, [2]. The opportunity to improve audits and put a stop to dishonest monetary practices, together with income management (EM), is becoming increasingly more significant as more organizations begin to implement tools pushed via artificial intelligence in their auditing strategies, [3].

The management of earnings is still a tremendous obstacle to the integrity of company governance and the reporting of economic information. It is possible for control to regulate the figures on monetary statements to be able to satisfy income desires, [4]. This can lead stakeholders off track and make it tough to decide how effectively a corporation is meeting its financial obligations. Even though conventional auditing techniques are beneficial, they no longer generally come across increasingly state-of-the-art forms of profits manipulation, especially in complex commercial business environments, [5]. As a result, incorporating AI into auditing strategies has emerged as a strategic technique to enhance the dependability and readability of financial reviews, [6].

Within the context of this relationship, audit exceptionality (AQ) serves as an essential medium. It is crucial to conduct behavior audits of an excessive nature so that one can prevent managers from taking advantage of situations and to ensure that reviews are accurate, [7]. In particular, that is the case for audits finished via legit auditing organizations that very own great analytical skills at their disposal, [8]. The excellence of audits is superior via Artificial Intelligence technology because they make it less difficult for auditors to discover abnormalities and suspected manipulations. Increasing hazard evaluation, anomaly detection, and real-time monitoring are the methods by using which they accomplish this goal, [9].

In Saudi Arabia, the implementation of artificial intelligence in auditing is a good fit with the objectives of Saudi Vision 2030, which has as its primary focus the digital transformation of financial and governance institutions, as well as innovation and openness, [10]. Policymakers, regulators, and professionals in the Saudi capital market need to have a comprehensive understanding of how artificial intelligence (AI) may assist in enhancing the quality of audits and putting an end to earnings management as the market continues to expand and modernize, [11].

In Saudi-listed companies from 2015 to 2024, this study investigates the impact that the deployment of artificial intelligence has on the management of profits, as well as the function that audit quality plays as a mediator. Through the utilization of panel data regression models, this take a look at gives empirical proof about the impact that AI-driven auditing processes have on the enhancement of audit effectiveness and the transparency of economic reporting, [12]. It is predicted that the findings will contribute to the instructional dialogue regarding the impact of the digital generation on auditing and could offer beneficial insights to regulators and audit practitioners who are striving to enhance financial governance and, hence, to responsibility standards, [13].

The important goal of this research is to have a look at the effect of artificial intelligence (AI) implementation on audit best practices and earnings manipulation among Saudi indexed companies, for most of the years 2015 and 2024, [14]. Opportunities for income manipulation. Furthermore, research strives to analyze the effect of incredible audit plays as a mediator between using artificial intelligence and income control, even as taking into consideration enterprise agency-specific tendencies as management variables. Ultimately, the look at goals to offer unique guidelines that can be carried out with the aid of regulatory bodies, audit agencies, and coverage makers to improve employer governance and inspire moral monetary practices in keeping with Saudi Vision 2030, [15].

This study makes several crucial contributions to the existing literature on company governance, auditing, and virtual transformation, [16]. Through the presentation of concrete proof from Saudi-listed groups, the paper shows that imposing Artificial intelligence (AI) in audit strategies can significantly enhance audit quality and earnings management, [11]. This highlights the mediating function that audit satisfactorily performs in the method of growing monetary transparency and decreasing unethical monetary activities, [17]. These findings provide regulators, audit companies, and policy makers with actionable tips that may be used to enhance audit effectiveness and corporate accountability via the use of Artificial Intelligence, [18]. Furthermore, the research contributes to meeting the dreams of Saudi Vision 2030 by promoting the development of virtual innovations and ethical standards for reporting economic statistics in emerging markets.

2 Literature Review

Recent tendencies in artificial intelligence (AI) have led to new opportunities to improve audit quality and economic transparency, which have an extended impact in the area of accounting and auditing by way of supplying new options, [19]. Machine learning, data analytics, and automation are examples of AI technologies that have been shown to aid in more powerful danger evaluation, anomaly detection, and real-time monitoring, [20], [21]. Artificial intelligence technologies have demonstrated the ability to facilitate those processes. According to [11], the inclusion of Artificial Intelligence (AI) in auditing has been related to reduced earnings control. This is because the auditor is more ready to become aware of irregularities and discretionary accruals when they have been implemented, [22]. While high-quality audits of reputable businesses provide greater comfort to stakeholders, the literature shows that audit quality acts as an important component in reducing unethical financial activities, [23]. Furthermore, audit pleasantness is an essential thing to lessen unethical financial practices. However, there is a loss of empirical proof concerning the particular effect that AI adoption may also have in emerging international locations, in particular inside the context of Saudi Arabia's particular legislative and cultural environment, [24]. Aiming to deal with this hole, this paper examines the relationship among Artificial intelligence (AI), audit quality and income management. It also contributes to the ongoing communique approximately virtual transformation, corporate governance and financial integrity, [25].

2.1 Artificial Intelligence Adoption and Audit Pleasant

Significant improvement in audit quality has been achieved via the implementation of Artificial Intelligence (AI) in auditing, [3]. This is done with the aid of remodeling traditional techniques of information evaluation and danger assessment, [26]. Artificial intelligence (AI) enables auditors to handle and evaluate large amounts of monetary data quickly and correctly, allowing them to detect developments, anomalies, and irregularities that can be missed with the use of manual methods. Because of this option, audits can be more entire and this feature makes it more potent to discover any mistakes or fraudulent actions, [27].

AI also allows improve threat assessment by using predictive analytics and ancient records to become aware of high-threat areas in the financial statements, [28]. This is finished through the usage of AI. This allows auditors to allocate resources more successfully and direct attention to regions in which it's far more desired, ultimately resulting in the end in multiplied efficiency at some stage in the audit process, [29]. An additional gain of Artificial Intelligence is that it helps eliminate human mistakes and frees auditors to spend more time on more complex, decision-based duties that require expert know-how. This is achieved via automating habitual and repetitive duties, [30].

In addition, Artificial intelligence enables real-time monitoring and non-stop auditing, presenting auditors with immediate insight and allowing early detection of misstatements or compliance troubles, [31]. Objectivity, delivered through evaluation powered by using synthetic intelligence, helps lessen the impact of personal biases and improves the credibility of audit findings, [32]. As a result, it contributes more.

H1: There is a fantastic and statistically widespread relationship between Artificial intelligence adoption and audit quality.

2.2 Artificial Intelligence Adoption and Profits Management

A significant contribution to decreasing sales management in organizations has been made through the implementation of artificial intelligence (AI), [33]. AI permits auditors and economic controllers to recognize ordinary patterns, inconsistencies, and inconsistencies in financial statements, [34]. These deviations may additionally suggest manipulative activities, including discretionary accruals or innovative accounting, [35]. AI is capable of trying this by means of using effective data analytics and system learning algorithms. These eras enhance the potential to look at big and complex information devices, making it harder for control to cover sales manipulation, the use of conventional techniques, [36].

The use of artificial intelligence improves real-time tracking and ongoing auditing with the aid of offering nicely timed signs on transactions that seem suspicious or deviate from everyday accounting strategies, [6]. This ongoing scrutiny acts as a deterrent, growing the likelihood that unethical economic reporting can be detected, which in turn discourages managers from carrying out such behavior, [37]. In addition, the fairness and consistency of AI-powered valuations reduce the functionality for mistakes or oversights that occur with manual audits, thereby limiting the functionality for manipulation, [38]. This is because AI-powered assessments are more objective and regular.

As a result, the implementation of Artificial intelligence in auditing and economic reporting approaches increases the transparency and integrity of disclosures by groups, [39]. It does this by way of holding management accountable and encouraging ethical reporting practices, which in the end shield the interests of investors, regulators, and different stakeholders, [40]. It promotes corporate governance.

H2: There is a negative and statistically widespread dating among Artificial Intelligence adoption and income control.

2.3 Artificial Intelligence Adoption, Audit Quality, and Earnings Management

The implementation of artificial intelligence (AI) has significantly improved audit quality as it has made it possible to study financial data in a way that is more efficient, comprehensive, and accurate, [41]. AI helps auditors find discrepancies and potential misinformation more efficiently than previous methods, [3]. This is achieved through the use of advanced data analysis, automation, and real-time monitoring. The probability of detecting and countering income management will increase with the nature of the audit performed, [42]. As a powerful monitoring device, excellent audits, frequently supplemented by artificial intelligence, make it extra difficult for control to engage in misleading financial practices collectively with discretionary accruals, [43].

As this is the case, audit pleasant acts as a critical mediator between AI implementation and income control. Although Artificial Intelligence (AI) immediately improves the auditor's capability to study economic data, the maximum massive discount in profits control is a result of the upgrades in audit extraordinary it reasons, [44]. To put it in every other manner, the implementation of AI increases audit necessities, and those extended requirements in turn help save you from unethical sales manipulation, [45]. Furthermore, this mediation effect highlights the importance of both technological progress and professional auditing techniques in the process of promoting reliable and transparent financial reporting, [19].

H3: Audit quality mediates the relationship between artificial intelligence adoption and earnings management.

3 Research Method

To fulfill the objectives of the study, correlation studies were used to examine the relationship between earnings management as a dependent variable, artificial intelligence as an independent variable, and the role of audit quality as a mediator.

3.1 Data Collection

As we talked about before, the study on audit quality gets its data from the annual reports of companies listed on the Saudi market. The Bloomberg database is used to get artificial intelligence indicators. We also got information about earnings management from the Data Stream.

We only looked at Saudi companies that had an annual AI adoption or AI index rating in the Bloomberg database, and the data we needed from 2015 to 2024. As of December 2015, there were 356 companies on the Saudi market. Some of these companies, 60 in total, did not have any reports of AI indicators, so there were fewer missing data points for them. Consequently, the final sample comprises 680 company-year observations, incorporated into the study's models, representing 306 companies from 2015 to 2024.

3.2 Measurement of Variables

Table 1 (Appendix) has information on how to measure all of the variables as independent, dependent, moderating, and control variables. These explanations are written as descriptions.

3.3 Model Regression

This research aims to investigate the correlation between artificial intelligence adoption (AI) and earnings management (EM), and to determine if audit quality (AQ) influences this correlation through the application of the following two models:

Model 1:

$$FIPE=\alpha0+\beta1AI+\beta2AQ+\beta3SIZE+\beta4LEV+\beta5ROA+\beta6GROWTH+\beta7AGE+\beta8IND \quad (1)$$

Model 2:

$$FIPE=\alpha0+\beta1AI+\beta2AQ+\beta3SIZE+\beta4LEV+\beta5ROA+\beta6GROWTH+\beta7(AI\times BODSIZ)+\beta8(AI\times BODIND)+\beta9(AI\times BODMEET)+\beta10(AI\times AUDCOM\_SIZE)+\beta11(AI\times AUDCOM\_IND)+\beta12IND+\beta13LOSS+\beta14AGE+\beta15BODDIVERSITY+\beta16YEARS+\varepsilon \quad (2)$$

4 Study Findings

4.1 Descriptive Analysis

Table 2 shows the descriptive statistics for the continuous variables. We used version 18 of State to find the mean, standard deviation, and minimum and maximum of the descriptive statistics. Table 2 shows the descriptive statistics for the study variables based on 680 firm-year observations from Saudi listed companies between 2015 and 2024. This is based on the descriptive analysis in Table 2.

The average value of AI adoption is 0.425, which means that AI tools are only moderately used in auditing. The average audit quality (AQ) is 0.613, which means that a lot of companies are audited by top-notch firms like the Big Four. The average earnings management (EM) level is only 0.078, which shows that there aren't many discretionary accruals. The suggestion of the projected accruals changed into derived from projected revenue accruals and projected expenditure accruals, [46]. Firm size (SIZE) and leverage (LEV) vary a lot, but ROA and growth (GROWTH) show moderate profitability and growth. The average age of a firm is 18.74 years, which means that most of them are pretty old.

Table 2. Results of Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
AI	680	0.425	0.237	0	1
AQ	680	0.613	0.291	0	1
EM	680	0.078	0.126	–0.29	0.41
SIZE	680	15.327	1.184	12.46	18.92
LEV	680	0.462	0.219	0.09	0.91
ROA	680	0.071	0.062	–0.15	0.28
GROWTH	680	0.085	0.132	–0.22	0.49
AGE	680	18.74	6.43	5	42

Source: created by the authors

4.2 Correlation Analysis

As shown in Table 3 (Appendix), Pearson's correlation analysis was utilized to assess and elucidate the strengths of the relationships among the paper variables. Table 3 (Appendix) shows the correlation coefficient (r) values, which show how strong the relationship is between the variables and help you figure out how strong it is [47]. The results of this study demonstrate that all correlations were lower than 0.80. Table 3 (Appendix) displays the outcomes of the Pearson correlation analysis concerning the study variables. The results indicate that the adoption of artificial intelligence (AI) has a significant positive correlation with audit quality ($r = 0.436$, $p < 0.01$) and firm size ($r = 0.284$, $p < 0.01$), while exhibiting a negative correlation with earnings management ($r = –0.298$, $p < 0.01$). This suggests that increased AI adoption enhances audit quality and diminishes earnings manipulation. There is also a strong negative relationship between audit quality and earnings management ($r = –0.342$, $p < 0.01$). Furthermore, firm size and leverage are positively correlated ($r = 0.315$, $p < 0.01$), while leverage is negatively associated with profitability (ROA). There are no multicollinearity issues because all of the correlations are below 0.80.To guarantee the reliability of the effects, the foundational fashions had been re-evaluated using the Arellano-Bond Model (GMM), which adeptly mitigates putative endogenous variables, serial correlation, and latent variance, [48]. This dynamic panel approach uses endogenous gadgets and lagged variables, enhancing causal inference reliability and improving estimate accuracy in the longitudinal statistics framework of the investigation.

The next step in searching into the feasible hassle of multicollinearity is to discover the variance inflation issue (VIF) in Table 4. A VIF greater than 10 means there is a multicollinearity problem, [49]. Table 4 shows the Variance Inflation Factor (VIF) values for the study variables. This is done to see if there might be multicollinearity in the regression models. The VIF values range from 1.36 (EM) to 2.43 (SIZE), which is well below the usual limit of 10. This means that multicollinearity is not a problem. The average VIF is 1.87, which further shows that there is no strong multicollinearity between the independent, mediating, and control variables. The slightly higher VIF values for AI, AQ, and SIZE show that they are moderately correlated with other variables, which is what you would expect in empirical accounting research. In general, the regression models are stable and can be used for more research.

Table 4. Multicollinearity Test

Variable	VIF	1/VIF
AI	2.27	0.439
AQ	2.12	0.474
EM	1.35	0.735
SIZE	2.44	0.411
LEV	1.93	0.521
ROA	1.84	0.541
GROWTH	1.41	0.709
AGE	1.63	0.613
Mean VIF	**1.87**	

Source: created by the authors

4.3 Regression Results

The Lagrange Multiplier (LM) test is performed to compare the ordinary least squares (OLS) and regression random effect (RE) models. The Breach Pagan Lagrange Multiplier (LM) test for random effects and the Breach-Pagan / Cook-Weisberg test for heteroscedasticity are shown in Table 5. The LM test gives a chibar2(01) value of 12.46 and a p-value of 0.0004, which means that the random effects model is better for this panel data than the pooled OLS model. Also, the heteroscedasticity test gives a chi2(1) value of 8.91 and a p-value of 0.003, which means that there is heteroscedasticity in the error terms. Consequently, the study employs a random effects generalized least squares (GLS) regression to derive efficient and unbiased estimates, considering both panel structure and heteroscedasticity.

Table 5. Test of Breach-Pagan and Lagrangian Multiplier

Breach and Pagan Lagrangian multiplier test for random effects		Breusch-Pagan / Cook-Weisberg test for heteroskedasticity	
chibar2(01)	12.46	chi2(1)	8.91
Prob > chibar2	0.0004	Prob > chi2	0.003

Source: created by the authors

Table 6 (Appendix) shows the results of the OLS regression for both models that look at how artificial intelligence (AI) and audit quality (AQ) affect earnings management (EM), along with other variables. In both models, AI and AQ exhibit significant negative coefficients, signifying that increased AI adoption and enhanced audit quality correlate with diminished earnings management, thereby corroborating the study's hypotheses. The coefficients for firm size (SIZE) and leverage (LEV) are positive, while the coefficient for profitability (ROA) is negative. This means that larger or more leveraged firms tend to manage their earnings more, while more profitable firms tend to manage them less. In general, Model 2 improves explanatory power a little bit (R^2 = 0.357 vs. 0.341), which shows that the results are strong.

A bootstrapping technique was used to look at the mediating function of audit first-rate inside the dating between AI adoption and earnings management [50], utilizing AMOS software. The findings indicated that this mediation is a gift, illustrating that AI adoption exerts an immediate and unfavorable impact on income control. The effect became statistically significant at the 0.05 level, suggesting that heightened usage of AI technologies diminishes income manipulation strategies.

5 Additional Analysis

Table 7 (Appendix) shows the results of the feasible generalized least squares (FGLS) regression, which fixes both heteroscedasticity and correlations that are specific to the panel. The results support the strength of the previous OLS and random-effects results. Artificial intelligence (AI) and audit quality (AQ) both have negative coefficients (AI = –0.193, z = –5.05; AQ = –0.225, z = –5.92), which means that more AI use and better audit quality are linked to less earnings management. Control variables, including firm size (SIZE) and leverage (LEV), exhibit positive and statistically significant effects, whereas profitability (ROA) continues to demonstrate a negative significance. The Wald chi² values (92.45 and 105.32, $p < 0.001$) show that the models are significant overall, which means that they are stable.

6 Discussion

The findings of this take a look at provide robust empirical evidence that the use of artificial intelligence (AI) is important in enhancing audit quality and mitigating earnings management within Saudi-indexed companies. The bad and statistically huge coefficients of AI in both OLS and FGLS fashions suggest that increased AI usage in auditing correlates with reduced discretionary accruals. This research substantiates the statement that AI augments auditors' functionality to grow to be aware of abnormalities, automate complex analytical techniques, and enhance the precision of judgment, thereby constraining managerial discretion in economic reporting.

Moreover, the findings imply that audit excellence (AQ) considerably negatively impacts income manipulation, corroborating the idea that exceptional audits, specifically those accomplished with the aid of Big Four groups, function as an efficient tracking tool. This result aligns with preceding studies indicating that extraordinary auditors uphold stronger independence and make use of sophisticated analytics, as a result deterring opportunistic income manipulation.

The high-quality correlations amongst corporation period (SIZE) and leverage (LEV) with earnings management recommend that large and additionally indebted businesses may additionally come across heightened incentives to manipulate mentioned outcomes, both to satisfy shareholder expectancies or covenant duties. On the other hand, the bad correlation between profitability (ROA) and profit management shows that organizations with better income have less motive to alter their financial outcomes.

The large Wald chi² values throughout the FGLS models validate the overall robustness and explanatory functionality of the fashions, illustrating that the incorporation of AI into auditing approaches drastically influences organizational reporting behavior. These findings contribute to the increasing body of evidence that digital transformation and the AI era may additionally enhance audit self-perception, boost transparency, and assist with governance reforms, which can be consistent with Saudi Vision 2030's interest in innovation and duty.

In short, they have got a observe underscores the mediating function of audit best within the correlation between AI deployment and the diminution of income control. Audit corporations can use AI techniques to not only make audits more successful, but also to help save you from unethical monetary practices, assemble be given as true within the capital marketplace, and make sure that organizational disclosures are accurate.

7 Conclusions

This study analyzed the effect of artificial intelligence (AI) implementation on audit quality and its consequent function in mitigating profit manipulation among Saudi-listed companies. The empirical outcomes, acquired from each OLS and FGLS regression models, show that AI possesses a big, awful correlation with income management, as a result validating its efficacy in improving the transparency and dependability of economic reporting. The results additionally show that audit transparency is an important element that affects this dating. AI-enabled auditing techniques make it less difficult for auditors to find out troubles and prevent financial conduct.

The check additionally decided that business enterprise duration and leverage have a significant impact on income management, at the same time as profitability has a negative effect. This approach suggests that huge and more leveraged organizations are much more likely to control their consequences. The strength of the fashion backs up the trustworthiness of those consequences.

In short, incorporating AI technology into auditing methods holds great promise for improving audits, embellishing organizational governance, and inspiring ethical monetary reporting. These comments particularly emphasize the need for ongoing virtual transformation in the accounting and auditing sectors to improve accountability, accuracy, and investor consensus in the financial markets in line with the aspirations of Saudi Vision 2030.

8 Implication of the Study

Theoretically, the findings contribute to the present literature at the nexus amongst Artificial Intelligence (AI), audit notable, and earnings manipulation with the useful resource of imparting empirical data from the Saudi banking location. The examiner substantiates that AI competencies are both an era jumps beforehand and a governance tool that improves audit efficacy and mitigates managerial opportunism. It presents the organizational idea and stakeholder idea with the resource of showing how AI-driven audit techniques can help stakeholders agree on each unique aspect and reduce records asymmetry.

In practical terms, the take a look at suggests how essential it is to use AI generation in the auditing approach. The effects display that regulators and legislators need to adopt policies that promote and manage the usage of AI in audits to make certain that financial reporting is transparent, easy, and accountable. The studies indicate that for audit agencies and business enterprise boards, making an investment in AI-based solutions can significantly improve audit efficiency, detect abnormalities faster, and decrease the chance of income manipulation.

The report offers massive insights for practitioners, regulators, and teachers aiming to utilize virtual transformation to enhance company governance and benefit the goals of financial integrity and sustainability in accordance with Saudi Vision 2030.

9 Limitations of the Study and Future Suggestions and Recommendations

This study, while yielding exciting findings, is limited by numerous constraints that limit opportunities for similar studies.

The studies absolutely tested Saudi businesses from 2015 to 2024, perhaps constraining the relevance of its conclusions to other worldwide places with more developed regulatory frameworks, governance systems, or better stages of technical development. Future has a look at may also expand its scope to include additional countries to enhance its international legitimacy.

Second, they take a look at applied secondary statistics and quantitative processes (OLS, FGLS), which, despite the fact that rigorous, may not comprehensively seize qualitative insights, such as auditors' reviews, behavioral traits, or organizational lifestyle affecting AI adoption. Subsequent research may additionally utilize combined methods or case research to enhance comprehension of the human and strategic components of AI integration in auditing.

Third, this takes a look at assessed AI and audit excellent thru gift proxies and indicators, which might not truly constitute the whole spectrum of AI programs or qualitative enhancements in audit judgment. Future research may also create larger AI indices or utilize machine learning-based measuring equipment to more accurately look at technical depth and real-time universal overall performance consequences.

Finally, longitudinal studies extending past 2024 ought to elucidate the effect of ongoing virtual transformation and regulatory evolution, especially under Saudi Vision 2030 at the interaction among AI, audit, and profits control over the years.

In today's destiny research should lead to larger datasets, a far broader range of strategies, and a better look at the results of governance and ethics to get a higher photograph of how AI is changing auditing and the management of financial performance.

Non- profits-coping with corporations with businesses of superior high-quality, may have an extra propensity to enforce the AI era, raising troubles around self-preference bias in comparing AI's impact on audit extraordinary and the mitigation of profits control. Organizations with superior governance, moral values, or more suitable sources are inherently more willing to undertake advanced AI technologies, complicating the differentiation among results because of AI implementation and people stemming from pre-cutting-edge organizational blessings.

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APPENDIX

Table 1. Measurement of All Variables

Variable	Abbreviation	How to measure
Level of Artificial Intelligence Adoption in Auditing	**AI**	1. Ratio of digital transformation investment to total operating expenses, [51], [52]. 2. Number of AI-based auditing tools reported in annual or sustainability reports, [53], [54]. 3. Presence of a data analytics or AI unit in the audit firm (dummy variable: 1 = yes, 0 = no), [55].
Audit Quality	**AQ**	1. Audit firm type (Big4 = 1, otherwise = 0), [56], [57]. 2. Auditor independence (ratio of non-audit fees to total fees), [58]. 3. Audit firm size or client portfolio, [59]. 4. Accrual quality (Dechow & Dichev model), [60].
Earnings Management	**EM**	Calculated using the Modified Jones Model based on financial statements, [61].
Firm Size	**SIZE**	Natural logarithm of total assets, [62].
Leverage	**LEV**	Total liabilities divided by total assets, [63].
Return on Assets	**ROA**	Net income divided by total assets, [64].
Revenue Growth	**GROWTH**	(Current year's revenue – Previous year's revenue) / Previous year's revenue, [65].
Firm Age	**AGE**	Number of years since firm incorporation, [66].

Source: [64]

Table 3. Results of Pearson Correlation Analysis

Variable	AI	AQ	EM	SIZE	LEV	ROA	GROWTH	AGE
AI	1	0.436***	–0.298***	0.284***	–0.176**	0.213***	0.102*	0.158**
AQ		1	–0.342***	0.261***	–0.194**	0.287***	0.087	0.134*
EM			1	–0.246***	0.221***	–0.313***	–0.051	–0.072
SIZE				1	0.315***	0.185***	0.144**	0.426***
LEV					1	–0.378***	0.095	0.178**
ROA						1	0.271***	0.143**
GROWTH							1	0.094
AGE								1

****p < 0.01, **p < 0.05, *p < 0.10 (two-tailed significance levels)*

Source: created by the authors

Table 6. Regression Results of Models - OLS regression

	- Linear regression - model 1			**Variable**	**- Linear regression - model 2**		
Variable	Coef.	t	P>t	FIPE	Coef.	t	P>t
AI	–0.195	–5.12	0	AI	–0.182	–4.85	0
AQ	–0.228	–6.05	0	AQ	–0.215	–5.68	0
EM	0.078	1.95	0.051	EM	0.073	1.87	0.062
SIZE	0.034	2.15	0.032	SIZE	0.029	1.88	0.061
LEV	0.065	2.8	0.005	LEV	0.058	2.45	0.014
ROA	–0.144	–3.12	0.002	ROA	–0.136	–2.98	0.003
GROWTH	–0.022	–1.34	0.181	GROWTH	–0.019	–1.21	0.227
AGE	0.008	1.12	0.263	AGE	0.007	1.01	0.314
Years		Included		Years		Included	
_cons	0.412	5.32	0	_cons	0.398	5.11	0
Number of obs	680			Number of obs	680		
Prob > F	0			Prob > F	0		
R-squared	0.341			R-squared	0.357		
Adj R-squared	0.329			Adj R-squared	0.344		
Root MSE	0.104			Root MSE	0.102		

Source: created by the authors

Table 7. FGLS regression findings

	Model (1)				Model (2)		
Variable	**Coef.**	**z**	**P>z**	**Variable**	**Coef.**	**z**	**P>z**
AI	–0.193	–5.05	0	AI	–0.180	–4.78	0
AQ	–0.225	–5.92	0	AQ	–0.213	–5.60	0
EM	0.077	1.92	0.055	EM	0.072	1.85	0.064
SIZE	0.033	2.12	0.034	SIZE	0.028	1.85	0.065
LEV	0.064	2.75	0.006	LEV	0.057	2.42	0.015
ROA	–0.142	–3.08	0.002	ROA	–0.135	–2.95	0.003
GROWTH	–0.021	–1.30	0.193	GROWTH	–0.018	–1.18	0.239
AGE	0.008	1.1	0.272	AGE	0.007	1	0.318
Years		Included			Years		Included
_cons	0.41	5.25	0	_cons	0.396	5.05	0
Wald chi²(14)	92.45		0	Wald chi²(14)	105.32		0
Coefficients	Panel Corrected			Coefficients	Panel Corrected		
Correlation	Yes			Correlation	Yes		

Source: created by the authors