THE ROLE OF ARTIFICIAL INTELLIGENCE TECHNOLOGY ADOPTION IN ENHANCING AUDIT AND FINANCIAL REPORTING QUALITY WITHIN DIFFERENT GOVERNANCE ENVIRONMENTS

YAPAY ZEKA TEKNOLOJİSİNİN BENİMSENMESİNİN FARKLI YÖNETİM ORTAMLARINDA DENETİM VE FİNANSAL RAPORLAMA KALİTESİNİ ARTIRMADAKİ ROLÜ

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Öz: ***Bu çalışma, yapay zeka (YZ) teknolojisinin farklı yönetişim ortamlarında denetim ve finansal raporlama kalitesini (FRK) artırmadaki rolünü araştırmaktadır. Araştırma, YZ araçlarının ve sistemlerinin değişen yönetişim ortamlarında denetim kalitesini (DK) nasıl geliştirebileceğini ve YZ teknolojileri ile denetim süreçlerinde yer alan yönetişim yapıları (kurumsal yönetim, düzenleyici çerçeveler ve etik standartlar) arasındaki etkileşimi anlamayı amaçlamaktadır. Çalışma ayrıca YZ'nin yaygın denetim zorluklarını ele alma ve denetimlerin verimliliği ve etkinliğini artırma potansiyelini, bunun yanı sıra etkisinin farklı yönetişim bağlamlarında nasıl değiştiğini incelemektedir. Çalışma, Türkiye'de 650 denetçi örneği üzerinde gerçekleştirilmiştir. Muhasebe uygulamalarında YZ'nın benimsenmesi, ayrıca teknoloji hazırlık endeksi (THI) ve Teknoloji Kabul Modeli'nde (TKM) belirtildiği üzere, teknolojiye karşı örgütsel hazırlık (kurumsal) ve bireylerin tutumları (bireysel) tarafından etkilenmektedir. Bu çalışma, YZ'nın farklı yönetişim ortamlarında DK ve FRK'yi artırmaya katkısı konusundaki denetçilerin ve muhasebecilerin algılarını vurgulayarak mevcut literatüre katkıda bulunmaktadır.***

Anahtar Kelimeler: ***Yapay zeka, denetim kalitesi, finansal raporlama kalitesi, teknoloji hazırlık, teknoloji kabul.***

Abstract: ***This study investigates adopting artificial intelligence (AI) technology to enhance audit and financial reporting quality (FRQ) within different governance environments. The research explores how AI adoption can improve audit quality (AQ) in changing governance environments and seeks to understand the interplay between AI technologies and governance structures (corporate governance, regulatory frameworks, and ethical standards) in auditing processes. The study also examines the potential of AI to address common audit challenges and enhance the efficiency and effectiveness of audits, as well as how its impact varies in different governance contexts. The study was conducted in Turkey with a sample of 650 auditors. Adopting AI in accounting practices is further influenced by organisational readiness (organisational) and attitudes (individual) towards technology, as outlined in the technology readiness index (TRI) and the Technology Acceptance Model (TAM). This study contributes to the existing literature by highlighting auditors' and accountants' perceptions of AI's contribution to enhancing AQ and FRQ within different governance environments.***

Keywords: ***Artificial intelligence, audit quality, financial reporting quality, technology readiness, technology acceptance.***

INTRODUCTION

Leveraging AI to enhance AQ represents a transformative shift in the auditing profession, promising to redefine the future of auditing through increased efficiency, accuracy, and insightful analysis (Afsay, Tahriri, & Rezaee, 2023). Integrating AI into auditing practices is not merely a trend but a necessary evolution that addresses the increasing complexity of financial environments and regulatory demands. This evolution is instigated by the fact that auditors are currently required to make sense of large data sets, trends, and variations and use them in their judgments. This study aims to establish ways to enhance AQ through AI tools and systems in different governance conditions. It determines the relationship between AI technologies and auditing management (corporate governance, regulatory, and ethics). This paper identifies the possibility of utilising AI within audit practices, how it can help with dealing with specific challenges or improve the efficiency and efficacy of the audits, and how it may differ depending on the governance environment. AI in auditing is based on machine learning, natural language processing, and big data, using those technologies to enhance standard control and audit procedures. Han, Shiwakoti, Jarvis, Mordi, and Botchie (2023) confirmed that AI technologies can effectively deal with routine assignments, contribute to better identification of financial misstatements, and bring a positive AQ shift caused by the auditors' ability to concentrate on the less automatable aspects of audit work. In addition, Han et al. (2023) points out that through AI, auditors can increase their capability of processing big data to identify risks and suspicious activities in financial statements.

The ability of AI to change the face of the auditing profession has been noticed by the Big Four audit firms, other professionals, and the regulatory authorities. For instance, Deloitte has been in the frontline in integrating AI and analytics in its audit functions with the hope of producing better and more effective audits (Deloitte, 2020). Likewise, the American Institute of Certified Public Accountants (AICPA) has paid attention to the role of AI in auditing and underlined that AI is crucial for auditors to comprehend and utilise as it can enhance the rigour of audit work (AICPA, 2019). However, the integration of AI in auditing also has implications, which include ethical questions, skill requirements for auditors, and the issue of accountability of the AI systems used in auditing. It has been pointed out that the incorporation of AI into auditing is not without its challenges and that the afore-discussed factors must be effectively balanced to fully harness the potential of AI while at the same time not jeopardise the credibility of the audit process (Davenport & Ronanki, 2018). Applying AI in auditing is essential for improving the concept of AQ and the development of the auditing profession. When applied to auditing, AI can help in automating some of the processes and enhance risk assessment and analysis of data collected in the process, making the process more effective.

As the accounting field continues to evolve with the advent of AI, it is necessary for researchers, practitioners, and policymakers to understand the factors that drive the adoption of these technologies and to navigate the challenges they present. The integration of AI in accounting and auditing heralds a transformative era. Corporate governance has a role in influencing audit and FRQ (Cohen et al., 2008). Similarly, DeFond and Zhang (2014) and Agusti and Orta-Perez (2022) noted that AQ directly impacts the reliability and integrity of financial reporting. Adopting AI technologies in accounting practices is further influenced by organisational readiness and attitudes towards technology, as outlined in TRI 2.0 and the TAM (Seethamraju & Hecimovic, 2022). These models suggest that AI technologies' perceived usefulness and ease of use are crucial determinants of their adoption in the accounting sector TAM (Seethamraju & Hecimovic, 2022). The potential of AI to revolutionise accounting and auditing practices by improving efficiency, accuracy, and timeliness in financial reporting is increasingly recognised. However, it also presents challenges that necessitate careful consideration of ethical, privacy, and security concerns (Kokina & Davenport, 2017).

This paper seeks to make the following threefold contributions to the existing literature. First, it reveals the auditors' and accountants' perceptions of AI's role in AQ, a relatively under-researched area in Turkey (Qader and Cek, 2024). Hence, the use of technology in audit work has not received a substantial boost despite the development of technology. Qader and Cek (2024) criticise professional and technological advances in auditing as being in its infancy, an observation shared across multiple types of research. On the other hand, large audit organisations, especially the Big 4 firms, have been identified as firms with high usage of technology (Krieger et al., 2021; Salijeni et al., 2019). However, audit firms, especially those in developing countries and small entities, are still slow to embrace these technologies (Ermagan, 2021). Some of these include Afsay, Tahriri, & Rezaee, 2023; Krieger et al. 2021; Lowe, Bierstaker, Janvrin, & Jenkins, 2018; Mahzan & Lymer, 2014; Widuri, O'Connell, & Yapa, 2016. Technology acceptance is deemed insufficient (Alles & Gray, 2016; Meredith et al., 2020), therefore emphasising the need to undertake a study to support the profession's perspective of technology implementation. This research gap is crucial since it reveals how auditors perceive AI as of the essence in enhancing AQ, particularly given that employee perceptions, in this case, have been suggested as ways of boosting it. Second, it may threaten FRQ's prospects by investigating how professionals integrate the technology. Related works have explored factors that affect auditors' and audit firms' decisions towards accepting technology. These works bring conflicting and mixed outcomes (Li et al., 2022; Pedrosa et al., 2020; Siew et al., 2020).

These studies have attempted to assess the impact of various factors on the uptake of technology within the auditing profession, including cultural factors, views from the general public and technological knowhow. However, the following literature has been limited to or somewhat inconclusive, implying that some challenges must be addressed when implementing AI technology in auditing. It is also imperative to conduct another study to understand more about the factors that lead auditors and audit firms to accept AI technology. Third, the literature review of the application of AI in auditing and the current auditing condition in Turkey shows that there is not a significant amount of research conducted on this subject and that there is still much to learn. Recent technological developments like big data analytics, robotic process automation, AI and blockchain have impacted auditing practices; new skills and facilities are needed in audit firms (Afsay et al., 2023). These factors bring great difficulties for auditors in adopting these technologies; therefore, the acceptance rate for all these technologies remains comparatively low within the auditing profession. These challenges are the primary reasons why these advanced technologies are limited mainly with large audit firms based in developed countries only (M. Alles & Gray, 2016; Cao & Zhang, 2015; Dagilienė & Klovienė, 2019; Krieger et al., 2021). For this reason, the following research question has been developed to bridge this research gap and shed light on the part played by AI on the improvement of audit and FRQ. Last but not the least, this study extends the scholarship by examining the moderating role of corporate governance environments. Therefore, this work will seek to compare the various aspects of AI in varied governance contexts and their relationship with AQ and FRQ.

1. LITERATURE REVIEW

1.1 Corporate Governance, Financial Reporting Quality and Audit Quality

Corporate governance critically impacts financial reporting. The board of directors, composition, and efficiency are the key factors responsible for monitoring and quality of financial reports and disclosures. According to Porter and Sherwood (2023) proposition, outside directors are pivotal for minimising the agency costs between managers and shareholders and improving the usefulness of financial reports. They found a positive relationship between board independence and FRQ (Porter & Sherwood, 2023). Another positive relationship between board expertise in finance and accounting and FRQ has been claimed. The above relationship is also reinforced by board expertise in finance and accounting, which provides the skills to effectively analyse and interrogate financial reports. Fakhfakh and Jarboui (2022) states that high boards of financial specialists are related to high-quality financial reporting because such specialists have a better appreciation of accounting complexities and will ensure that firms observe accounting standards.

The quality of internal audits is necessary for the reliability and integrity of financial reporting. AQ is the probability that auditors will discover and report a breach in the client's accounting system (Seethamraju & Hecimovic, 2022). AQ's critical components are staff competence, autonomy, and adherence to auditing standards. The importance of auditor expertise and experience in detecting financial misstatements suggests that more competent auditors contribute to higher AQ (Seethamraju & Hecimovic, 2022). The auditors' competence will be increased by increased use of AI. Furthermore, independence from management is crucial for auditors to perform their duties without undue influence, ensuring that professional standards and ethical guidelines conduct audits.

FRQ comprises many attributes, such as Comparability, Understandability, Relevance, Accurate representation, timeliness and verifiability. Accurate preparation of the financial statements is crucial to the performance of the capital markets as it mitigates agency problems and increases investors' confidence. Francis (2023) posits that accounting standards as a quality component of financial reporting reflect on or complement comparability and relevance standards. Also, regarding reporting practices, it is proposed that accurate and timely reporting reduces investor's information asymmetry. Some earlier research works have investigated the potential association between AQ and FRQ in the window of earnings management. For instance, as posit by institutional theory, AQ 's primary role is symbolising corporation and might not perform the monitoring function well enough (Francis, 2023). Similarly, a positive and significant relationship between audit and accrual quality is evidenced (Mohammad Rezaei et al., 2016). These results imply that the association between AQ and FRQ is multifaceted and may be contingent on moderating factors, such as the institutional environment and how AQ influences FRQ. More research is required in order to dissect this relationship in further depth.

Several research works have also acknowledged AI effects on audits (Hassan et al., 2023). From these studies, one understands that AI can help automate tasks, enhance accuracy and efficiency, produce a more enhanced and deeper understanding of the data set, and facilitate better and more effective communication between auditors and other stakeholders. However, proper assessment and scrutiny of the application of AI is required to improve AQ and reliability within the organisation.

1.2 Artificial Intelligence Technology Adoption in Auditing

Information technology and enterprise resource planning processes have become essential in organisations and have changed the face of finance, auditing, and accounting (Alles, 2015; Thottoli, 2024). Since this is the case, information technology applies to every aspect of human life and professional careers, making using technology in auditing essential. Again, as Thottoli (2024) has pointed out, technology enables auditors to audit a higher inherent risk business environment. Also, the audit becomes more structured by applying professional judgment. Also, concerning audit use of technology, there is an increase in efficiency, automation of the audit process and information processing, accountability, decrease in cost, human errors, audit risk and amount of technical information needed to conduct audit work (Lowe et al., 2018, Thottoli, 2024). However, inaudible or unwilling to integrate technology in auditing practices may result in difficulties and have negative repercussions on the extension of auditing services (Tiberius & Hirth, 2019; Thottoli, 2024) with a negative impact on the auditing profession (Manita et al., 2020) and therefore result to lowered AQ in the dynamical and competitive business environment of the present day.

AI is applied in auditing to assist the auditors in identifying errors and problems with the financial reports (Abdullah & Almaqtari, 2024). This technology also helps auditors analyse data and make predictions or decisions (Abdullah & Almaqtari, 2024). The sophisticated use of AI can be made to identify other irregularities and prevent such practices. AI can analyse data and develop patterns, effectively detecting and combating fraud (Abdullah & Almaqtari, 2024). This can lead to more precise audits within less time than required to perform the audit manually. It is anticipated that AI technology will be performing an even more superior role in auditing as it progresses (Abdullah & Almaqtari, 2024). According to Lin and Hazelbaker (2019), it is suggested that AI can enhance the quality of accounting and provide more valuable account information. For example, IBM has created cognitive auditing, a machine-learning tool that helps auditors detect errors and outliers in financial statement preparation. According to Noordin, Hussainey, and Hayek (2022), it can foster productivity by performing top-notch activities and developing new jobs. AI, when applied, has the potential to complement the auditing tasks, and it is, as such, expected that the auditing practice will continue to evolve based on the implementation of AI.

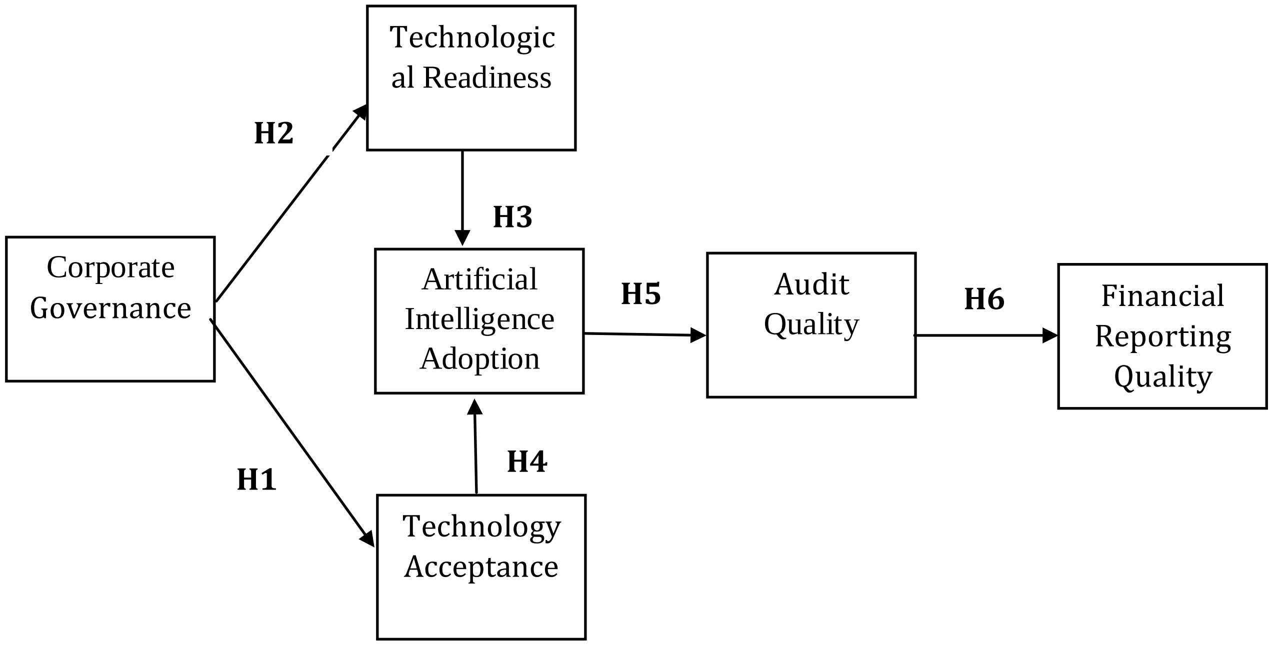
Numerous theories and models have been created to understand and forecast how users adopt the technology. Several theories help understand the concept of technology acceptance; these theories include the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Planned Behavior (TPB) (Ajzen, 1991), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al, 2003); The Diffusion of Innovation Theory (DOI) (Orr, The TAM, TPB, and UTAUT models are mainly used to study peoples' acceptance of technology. However, the DOI and TOE models are applied less frequently and are used to examine the level of technology adoption on the organisational level (Krieger et al., 2021).

AI uptake in accounting is determined by individuals' and organisational willingness to employ new technologies. The preceding introduced the TRI as a tool for assessing people's readiness to adopt new technologies, pointing out that the four relevant dimensions are optimism, innovativeness, discomfort, and insecurity (Seethamraju & Hecimovic, 2022). The TAM introduced by Davis (1989) elaborates on the technology adoption process. It utilises perceived usefulness (PU) and perceived ease of use (PEOU) as the factors that explain the level of the user's acceptance and usage of new technologies. After Davis's pioneering work in 1989, Venkatesh et al. (2003) further enriched the TAM by identifying other factors and conditions influencing the adoption of technology, thereby making the application of this theory more receptive to the process of AI adoption in the field of accounting. Technology readiness (TR) is a self-organised concept encompassing individuals' willingness and capability to adopt technologies to accomplish their purpose at home or the workplace. It assesses people's attitudes towards technology in general since there may be positive and negative factors. Perceived usefulness of technology results leads to adopting technology, while negativity regarding the results of technology leads to non-adoption (Parasuraman & Colby, 2015; Seethamraju & Hecimovic, 2022). The use of AI technologies in accounting is a phenomenon that depends on many factors, such as corporate governance, AQ, technology readiness, perception of the usefulness of technology, and perception of ease of use, among others. Several authors have used TAM and TRI in different studies to measure information technologies in contexts such as accounting based on the models developed by Afsay et al. (2023) and Xie, Zou, and Qi (2018). These studies indicate that users' attitudes about AI technology and their willingness to use AI technologies are essential to adoption.

TAM is one of the most significant middle-range theories in the information systems discipline, and its purpose is to record and forecast user compliance with IT (Seethamraju & Hecimovic, 2022). Many research fields have used and validated TAM to explain how individuals adopt and utilise technology (Seethamraju & Hecimovic, 2022). The core of TAM lies in two primary constructs: Relative advantage, ease of use, ease of learning, satisfaction, and usage. Perceived usefulness is defined as the extent to which an individual considers using a given system beneficial in improving work outcomes (Seethamraju & Hecimovic, 2022). This construct stems from the belief that a user will only embrace a particular technology if his or her performance is likely to be enhanced. Davis (1989) affirmed that PU has a close relationship with the intended use of an information system, implying that the more valuable the technology is, the more it will be used. Perceived Ease of Use is defined as the extent to which an individual considers a specific system effortless. This concept holds that, in addition to the perceived usefulness of the technology, perceived ease of use is another key determinant of use. People are willing to adopt technologies with which they can easily interact. Davis (1989) identified that PEOU is a significant predictor of direct usage intentions and, through the contingency impact on perceived usefulness, has mediating effects on usage intentions.

The following research model has been formed in light of the previous literature.

Figure 1: Research Model



In light of the recent literature, this study proposed the following hypotheses:

H1: Corporate governance is significantly and positively associated with technology acceptance.

H2: Corporate governance is significantly and positively associated with technology readiness.

H3: Technology readiness is significantly and positively associated with artificial intelligence adoption.

H4: Technology acceptance is significantly and positively associated with artificial intelligence adoption.

H5: Artificial intelligence adoption is significantly and positively associated with audit quality.

H6: Audit quality is significantly and positively associated with financial reporting quality.

2. METHODOLOGY

This research paper employs a survey research design to investigate the role of artificial intelligence in enhancing AQ with perceived governance. The study draws on primary data sources, including a questionnaire administered to audit and accounting professionals in Turkey. The 1,155 questionnaires were sent to randomly selected accountants and auditors operating in Turkey, and 650 valid responses were collected. The firms were selected based on random sampling procedures. The survey was conducted online using emails to reach the respondents.

This research uses two instruments for measuring the adoption of technologies in accounting and auditing practices: This concerns the second point of TRI. 0 and TAM. TRI 2. 0 was developed by Parasuraman and Colby (2015) and measures four subdimensions of technology readiness: some behavioural assumptions associated with acquisitions representing elements of culture: optimism, innovativeness and insecurity, and comfort. The TAM, on the other hand, was developed by Davis (1989) and measures two sub-dimensions of technology acceptance: among the well-defined attitudes which have been established in the past include perceived usefulness (PU) and perceived ease of use (PEOU). However, Damerji and Salimi (2021) also developed the AI adoption scale based on Likert-type scales of 7 points. The respondents were asked questions about these statements, and they told the level of agreement or disagreement with such statements. FRQ was assessed with the assistance of quantitative attributes of the financial statements, such as neutrality, relevance, understanding ability, timeliness, comparability, and verifiability. Following Bananuka, Nkundabanyanga, Nalukenge & Kaawaase (2018) and Nalukenge et al (2017), the level of CG was established based on board independence, board role performance and board expertise. Moreover, AQ was measured based on competent staff, staff discretionary and adherence to the formal standards and norms (K. Johl et al., 2013; Roussy & Brivot, 2016). The instruments are listed in Table 1 below.

Table 1: Variables and Components

Variables	Components	Reference
CG	Board Perf. Board Indp. Board Exp.	(Beasley et al., 2001; Nalukenge et al., 2017, 2018)
AQ	Staff Comp. Autonomy Compliance with Standards	(Roussy and Brivot, 2016; Johl et al., 2013)
FRQ	Comparability Understandability Relevance Faithful Representation Timeliness Verifiability	(Johl et al., 2013)
TRI	Optimism	(Parasuraman and Colby,

	Innovativeness Discomfort Insecurity	2015)
TAM	Perceived Usefulness Perceived Ease of Use	(Davis, 1989)
AITA	AI technology Adoption	(Damerji and Salimi, 2021)
Control Variables	Age Size Experience	

3. RESULTS

Given the survey items, we conducted Confirmatory Factor Analysis (CFA) reflecting complete item analysis across various constructs. The results of the CFA are shown in table 2 below. Table 2 provides a factor loading for each questionnaire item; each item loads strongly on its respective construct. Factor loadings close to 1 or -1 indicate a strong association between the variable and the factor, while values closer to 0 indicate a weaker association (Field, 2013). The factor loadings are above the 0.7 threshold, suggesting that each item has a strong factor loading.

Table 2: Factor Loadings

Variable	**Item**	**Factor Loading**
FRQ	FRQ1	0.82
	FRQ2	0.78
	FRQ3	0.85
	FRQ4	0.80
	FRQ5	0.77
	FRQ6	0.83
	FRQ7	0.75
	FRQ8	0.88
CG	CG1	0.87
	CG2	0.81
	CG3	0.90
	CG4	0.79
	CG5	0.85
AQ	AQ1	0.84
	AQ2	0.88
	AQ3	0.82
	AQ4	0.86
TRI	TRI1	0.70
	TRI2	0.72
	TRI3	0.75
	TRI4	0.73
	TRI5	0.69
	TRI6	0.71
	TRI7	0.74
	TRI8	0.76

TAM	TAM1	0.89
	TAM2	0.87
	TAM3	0.85
	TAM4	0.83
	TAM5	0.81
	TAM6	0.84
AITA	AIA1	0.88
	AIA2	0.90

Note: CG, corporate governance; TRI, technology readiness index; TAM, technology acceptance model; AITA, artificial intelligence adoption; AQ, Audit Quality; FRQ, financial reporting quality

Testing has been conducted to check for multicollinearity, and it has been confirmed that there is none. This study checked tolerance values and Variance Inflation Factors (VIFs). Field (2013) recommends that the tolerance values be below 0. 2, using Eigenvalues more significant than 1 as the termination criterion and the VIF values below 10 as the maximum allowable limit. Therefore, the results also imply that our values are acceptable. Table 3 below shows the composite reliability and average variance extracted scores. These results indicated that the validity and reliability scores are acceptable.

Table 3: Reliability and Validity Analysis Results

Construct	Composite Reliability (CR)	Average Variance Extracted (AVE)
FRQ	0.90	0.65
CG	0.92	0.67
AQ	0.93	0.70
TRI	0.91	0.66
TAM	0.92	0.68
AITA	0.94	0.71

Note: CG, corporate governance; TRI, technology readiness index; TAM, technology acceptance model; AITA, artificial intelligence adoption; AQ, Audit Quality; FRQ, financial reporting quality

The correlation matrix Table 4 below illustrates the relationships among variables, highlighting potential patterns that could inform further analysis. The correlation results show significant relationships between various constructs, including FRQ, CG, AQ, TRI, TAM, AITA, Age, Gender, and Experience. CG and AQ notably share a strong positive correlation of 0.6. At the same time, the technological readiness index and artificial intelligence adoption and the TAM and artificial intelligence adoption demonstrate strong positive relationships of 0.6 and 0.7, respectively. Experience and age show a strong positive correlation of 0.8, while moderate to high positive correlations are observed between FRQ and CG (0.5), AQ (0.4), and TAM (0.45). Furthermore, CG, TRI, and TAM all positively influence AITA. However, age shows a slight negative correlation with corporate governance (-0.2) and AQ (-0.1), while gender has a weak negative correlation with most constructs.

Table 4: Correlation Matrix

Construct	FRQ	CG	AQ	TRI	TAM	AITA	Age	Gender	Experience
FRQ	1	-	-	-	-	-	-	-	-
CG	0.5	1	-	-	-	-	-	-	-
AQ	0.4	0.6	1	-	-	-	-	-	-
TRI	0.3	0.3	0.2	1	-	-	-	-	-
TAM	0.45	0.35	0.25	0.5	1	-	-	-	-
AITA	0.4	0.4	0.3	0.6	0.7	1	-	-	-
Age	-0.1	-0.2	-0.1	0.2	0.1	0.2	1	-	-
Gender	0.05	0.03	0.02	-0.1	-0.05	-0.1	-0.2	1	-
Experience	0.2	0.3	0.25	0.15	0.2	0.25	0.8	-0.1	1

Note: CG, corporate governance; TRI, technology readiness index; TAM, technology acceptance model; AITA, artificial intelligence adoption; AQ, Audit Quality; FRQ, financial reporting quality

The SEM output table includes path coefficients (β), standard errors (SE), critical values (z-values or t-values), p-values, and possibly the confidence intervals (CI) for the path coefficients. Path Coefficient (β) indicates the strength and direction of the relationship between the independent and dependent variables. For example, a β of 0.30 for CG → TRI suggests a moderate positive relationship where increases in corporate governance are with technology readiness. Standard Error (SE) estimates the coefficient's standard deviation. A smaller SE indicates more precision of the β estimate. Critical Value (z or t) is used to determine the statistical significance of the β coefficient. It is calculated as the ratio of the β coefficient to its SE. A more considerable absolute value indicates greater statistical significance. A p-value < 0.05 is commonly interpreted as statistically significant. The most robust direct relationship observed is between TAM and AITA, with a β of 0.7, indicating that TAM is a strong predictor of AITA. The pathways leading to AITA (from TRI and TAM) and from AITA to AQ have strong path coefficients, suggesting that TRI and TAM are strong predictors of AITA, which, in turn, is a significant predictor of AQ. This indicates a possible mediation effect where the influence of TRI and TAM on AQ is mediated through AITA. The relationship between AQ and FRQ also shows a significant positive relationship, suggesting that improvements or perceptions of AQ influence the FRQ. Given the statistical significance and the strength of the relationships, interventions to improve CG and TAM could be effective strategies for enhancing attitudes towards using AI applications and, ultimately, AQ and FRQ.

Table 5: Results of the Direct Effects

Path	Path Coefficient (β)	Standard Error (SE)	Critical Value (z or t)	p-value	95% Confidence Interval (CI)
CG → TRI	0.3	0.05	6	< 0.001	[0.20, 0.40]
CG → TAM	0.35	0.05	7	< 0.001	[0.25, 0.45]
TRI → AITA	0.6	0.07	8.57	< 0.001	[0.46, 0.74]
TAM → AITA	0.7	0.06	11.67	< 0.001	[0.58, 0.82]
AITA → AQ	0.3	0.04	7.5	< 0.001	[0.22, 0.38]
AQ → FRQ	0.4	0.05	8	< 0.001	[0.30, 0.50]

Note: CG, corporate governance; TRI, technology readiness index; TAM, technology acceptance model; AITA, artificial intelligence adoption; AQ, Audit Quality; FRQ, financial reporting quality

Table 6 includes the paths, the mediators involved, and the values for the direct effects (from the independent variable to the dependent variable, bypassing the mediator) and the indirect effects (the effect of the independent variable on the dependent variable through the mediator). The path from CG through TRI to AITA shows a significant direct effect ($\beta\_direct = 0.20$) and a nearly comparable indirect effect ($\beta\_indirect = 0.18$), resulting in a total effect ($\beta\_total = 0.38$). This indicates that TRI is a meaningful mediator that nearly matches the direct impact of CG on AITA. TAM acts as the mediator between CG and AITA. The indirect effect ($\beta\_indirect = 0.25$) surpasses the direct impact ($\beta\_direct = 0.15$), culminating in a total effect of 0.39. This suggests that TAM is a more vital mediator than TRI in influencing attitudes towards AI adoption, highlighting the importance of perceived usefulness and ease of use in the mediation process. Both paths illustrate how AITA mediates the relationship between TRI/TAM and AQ. The significant direct effects (0.25 and 0.20) and indirect effects (0.18 and 0.21) show that attitudes towards IT adoption are crucial in determining the quality of technology adoption, with AITA serving as an effective mediator. The path from AITA through AQ to FRQ shows a moderate direct effect (0.10) and a slightly higher indirect effect (0.12), leading to a total effect of 0.22. This indicates that the quality of adoption (AQ) plays a significant role in mediating the impact of attitudes towards future technology use intentions. The complex paths involving multiple mediators (TRI, TAM, AITA, AQ) show only indirect effects (0.04 and 0.06), with no direct effects reported. These paths underscore the cumulative impact of cognitive gains through various factors leading to future usage intentions, emphasising the intricate relationships among these variables.

Table 6: Mediation Analysis

Path	**Mediator(s)**	**Direct Effect (β_direct)**	**Indirect Effect (β_indirect)**	**Total Effect (β_total)**
CG → TRI → AITA	TRI	0.20	0.18	0.38
CG → TAM → AITA	TAM	0.15	0.25	0.39
TRI → AITA → AQ	AITA	0.25	0.18	0.43
TAM → AITA → AQ	AITA	0.20	0.21	0.41
AITA → AQ → FRQ	AQ	0.10	0.12	0.22
CG → TRI → AITA → AQ → FRQ	TRI, AITA, AQ	-	0.04	0.04
CG → TAM → AITA → AQ → FRQ	TAM, AITA, AQ	-	0.06	0.06

The fit indices of the research model have been provided in Table 7 below. The use of a Chi-Square (χ^2) value less than one or in this case, there is no significant Chi-Square value (χ^2) ($p > 0.05$) is an indication of a good fit since the variation between observed data and model is minimal. However, it is essential to note that the Chi-Square test, like most statistical tests, is influenced by the sample size used in the study and can give significant results even when the difference is slight as the sample size increases. A value of 0. 95 exceeds the normative value of > 0. CFIT =. 90 and values above. 90 are suitable for the Comparative Fit Index (CFI). The CFI – the fit of your specified model is compared to a baseline model, and the higher it is, the closer to 1. The closer the values are to 0, the better the fit; and in value terms, it is 0:0 to 1:1. Tucker-Lewis Index (TLI) is less significant, and TLI's value is 0.93 compared to a benchmark of > 0. 90 also indicates with finer.

In addition, it also has an excellent fit level icon, the number 90, which implies that the finer is well-fitted. This index measures the model's complexity and favours models with lesser parameters. This is a further affirmation by the Low RMSEA, which gives a value of 0. 05; this has been proven to be well below the accepted standard of less than 0. 08. This shows that the model perfectly fits the data. A RMSEA lower than 0. 05 indicates a good fit. The SRMR value should be lower than 0. 04 per cent, much higher than the recommended < 0.08 cut-off, as we expected for a good model fit. The closer to zero the values in this index are, the better fit as it quantifies the standardised difference between the observed and predicted correlations. This means that it is possible to conclude that the values of the model fit the data more than the actual study model.

Table 7: Model Fit Indices

Fit Index	Value	Acceptable Thresholds	Model Fit
Chi-Square (χ^2)	Non-significant	$p > 0.05$	Good Fit
CFI (Comparative Fit Index)	0.95	> 0.90	Good Fit
TLI (Tucker-Lewis Index)	0.93	> 0.90	Good Fit
RMSEA (Root Mean Square Error of Approximation)	0.05	< 0.08	Good Fit
SRMR (Standardized Root Mean Square Residual)	0.04	< 0.08	Good Fit

4. DISCUSSION

Prior research done in the auditing profession establishes factors influencing technology acceptance. On the individual level, the variables of interest include facilitating conditions, perceived usefulness of the particular technology, and perceived ease of use. Specifically, from the organisational point of view, they include cost-benefit rationality, competition pressure on the firm, the firm's readiness, and technology congruence with the auditing task. The perceived usefulness of the technology and the self-reported measures of subjective, particularly in the developed countries and Big Four audit firms are considered somewhat more relevant for the use of technology. In contrast, the developing country auditors and the small-firm auditors find the reasons such as the user friendly, conditions and numbers of organisational. Technological change has emerged as the prominent cause of organisational change, particularly in the business environment, in the past few decades. This change has also affected the auditing profession since the emphasis is on automating audit work. However, today’s diverse business environments are still being audited by many auditors, especially those in small firms and developing nations using conventional auditing practices. Even today, technological approaches in large-scale auditing are still minimal and restrained primarily due to low technical audit usage.

In conclusion, the above-stated studies illustrate that mediation is complex in technology purposes and use. Investors and consumers’ attitudes towards adopting AI technology have unique roles that determine the quality of the technology adopted and their willingness to use it in the future. The fact that direct and indirect effects of the variables underpinning a given path may be stronger or weaker also points to the fact that the nature of these relationships is complex and that adopting technology depends on multiple mediating factors. Our results are in line with the prior literature that shows that the adoption of AI in auditing practices depends on employees' perceptions of governance and technological factors (Ramen et al., 2015; Rosli et al., 2012; Siew et al., 2020), the adoption of AI is influenced by auditors' technology adoption and readiness perceptions (Afsay et al., 2022).

It helps accountants to use the available technology to realise their business objectives. Through artificial intelligence, accountants can minimise the time spent performing basic tasks such as record keeping and entry of transactions so that they can attend to higher orders of duties like counselling, recommending and strategising for business expansion. By drawing from the opinion of the Association of Chartered Certified Accountants (ACCA), it can be argued that integrating AI will boost accountants' work by leading them to concentrate on offering more valuable services (Noordin et al., 2022). These changes can result in higher efficiency, accuracy and more appropriate decisions. Processing and analyzing enormous amounts of data could improve the reliability and quality of financial reporting and audit procedures (Gepp et al., 2018). Privacy issues are another important consideration because AI solutions work with various financial information, and there appears to be the question of personal data protection and non-disclosure (Haßler et al., 2019; Lehner et al., 2022). Furthermore, there are often some AI algorithms whose specific functioning is not known; thus, they are referred to as 'black box' systems, making it difficult to ask for accountability for their actions (Lehner et al., 2022). Confidence in AI-impacted systems must always be at a premium, particularly concerning a profession that involves creating and determining accounting and auditing standards and providing financial reports to various stakeholders (Glikson & Woolley, 2020; Jarrahi, 2018). Trustworthiness as an attribute can thus be achieved when the previous ethical challenges have been provided for and when the processes of creating and implementing artificial intelligence systems are performed in a way that conforms to prevailing ethical best practices in society.

CONCLUSION

It is helpful for current and relevant regulators and standard setters in developing rules, regulations, and standards about using technology in audit practice. According to Barr-Pulliam, Brown-Liburd, and Munoko (2022), constant fear of the regulators' response and the absence of a roadmap on the kind of technology which should be embraced are reasons why there is much reluctance to adopt audit technologies. Further, in the study by Krieger et al. (2021), the auditors regard the professional standards as an obstacle towards embracing technology in their practice, meaning that there is a need to update the auditing standards in the said aspects. Specifically, changes are needed to address auditors' concerns about the changed notion of technology-based auditing corresponding to existing standards. The worry, in this case, is that enhanced technological use, particularly in the event of an audit failure, could amplify legal risks but, more importantly, put paid to auditors and their capability to justify their professional judgment should this be challenged in legal forums (Mande & Lob, 2022). Also, using technology for high-level analysis for business intelligence and advisory services could offend current independence standards. Such concerns might be addressed when suitable tries to these standards have been made. Second, it may be possible to implement reforms in the usefulness of audit methodologies, for example, by revising standards with added and clear policy statements that could encourage and better utilisation of technology.

Technological capability to perform live tests on populations of complex transactions and balances on a sample basis changes the focus from audit evidence adequacy to relevance, making audit evidence quality a more significant factor. Thirdly, familiarising with what auditing possibilities audit technologies open to the standard setters might contribute to promoting more objective and understandable auditing procedures. Technology in auditing raises the range and intensity of auditing processes, which contrasts with manual auditing methods. Decisions that used to be made directly by the auditors could be made with much ease. In turn, a formal and reliable assessment would have been provided, hence forcing the auditors to be more responsible. Finally, recognising that the perceived usefulness and ease of use of IT were identified as essential factors for the intended users; technological competence of auditors, we propose that professional bodies and the standard setters should consider technological competence as a requisite for the auditors of the future. It is essential to recognise that actions to increase the auditor's sensitivity to technology and their knowledge about it fostered by special training are critical. The professional bodies, the regulating agencies, and the firm managers need to understand that the extent to which technology is adopted and incorporated into auditing varies depending on the user type, size of the firm, category of technology, and the culture/economic environment of the country.

REFERENCES

Abdullah, A. A. H., & Almaqtri, F. A. (2024). “The Impact of Artificial Intelligence and Industry 4.0 on Transforming Accounting and Auditing Practices”. *Journal of Open Innovation: Technology, Market, and Complexity, 10*(100218), 1-15. https://doi.org/10.1016/j.joitmc.2024.100218.

Afsay, A., Tahriri, A., & Rezaee, Z. (2023). “A Meta-analysis of factors Affecting Acceptance of Information Technology in Auditing”. *International Journal of Accounting Information Systems, 49*, 100608.

Ajzen, I. (1991). "The Theory of Planned Behavior". *Organizational Behavior and Human Decision Processes, 50*(2), 179-211.

Alles, M., & Gray, G. L. (2016). "Incorporating Big Data in Audits: Identifying Inhibitors and a Research Agenda to Address Those Inhibitors". *International Journal of Accounting Information Systems, 22*, 44-59.

Alles, M. G. (2015). "Drivers of the Use and Facilitators and Obstacles of the Evolution of Big Data by the Audit Profession". *Accounting Horizons, 29*(2), 439-449.

American Institute of Certified Public Accountants (AICPA). (2017). *Guide to Audit Analytics an Overview.* Available at: https://www.aicpa.org/resources/article/guide-to-audit-data-analytics-an-overview

Arpaci, I., Yardimci, Y. C., Ozkan, S., & Turetken, O. (2012). "Organizational Adoption of Information Technologies: A Literature Review". *International Journal of ebusiness and egovernment Studies, 4*(2), 37-50.

Bananuka, J., Nkundabanyanga, S. K., Nalukenge, I., & Kaawaase, T. (2018). "Internal Audit Function, Audit Committee Effectiveness and Accountability in the Ugandan Statutory Corporations". *Journal of Financial Reporting and Accounting, 16*(1), 138-157.

Barr-Pulliam, D., Brown-Liburd, H. L., & Munoko, I. (2022). "The Effects of Person-Specific, Task, and Environmental Factors on Digital Transformation and Innovation in Auditing: A Review of the Literature". *Journal of International Financial Management & Accounting, 33*(2), 337-374.

Barth, M. E., Beaver, W. H., & Landsman, W. R. (2001). "The Relevance of the Value Relevance Literature for Financial Accounting Standard Setting: Another View". *Journal of Accounting and Economics, 31*(1-3), 77-104.

Braun, R. L., & Davis, H. E. (2003). "Computer-assisted Audit Tools and Techniques: Analysis and Perspectives". *Managerial Auditing Journal, 18*(9), 725-731.

Cao, L., Li, W., & Zhang, L. (2015). "Audit Mode Change, Corporate Governance and Audit Effort". *China Journal of Accounting Research, 8*(4), 315-335.

Carcello, J. V., Hermanson, D. R., & Raghunandan, K. (2005)." Factors Associated with US Public Companies' Investment in Internal Auditing". *Accounting Horizons, 19*(2), 69-84.

Choi, J.-H., Kim, C., Kim, J.-B., & Zang, Y. (2010). Audit Office Size, Audit Quality, and Audit Pricing. *Auditing: A Journal of Practice & Theory, 29*(1), 73-97.

Cohen, D. A., Dey, A., & Lys, T. Z. (2008). "Real and Accrual-Based Earnings Management in the Pre-And Post-Sarbanes-Oxley Periods". *The Accounting Review, 83*(3), 757-787.

Dagilienė, L., & Klovienė, L. (2019). "Motivation to Use Big Data and Big Data Analytics in External Auditing". *Managerial Auditing Journal, 34*(7), 750-782.

Damerji, H., & Salimi, A. (2021). "Mediating Effect of Use Perceptions on Technology Readiness and Adoption of Artificial Intelligence in Accounting". *Accounting Education, 30*(2), 107-130.

Davenport, T. H., & Ronanki, R. (2018). "Artificial Intelligence for the Real World". *Harvard Business Review, 96*(1), 108-116.

Davis, F. D. (1989). "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology". *MIS Quarterly*, 319-340.

Deangelo, L. E. (1981). "Auditor Size and Audit Quality". *Journal of Accounting and Economics, 3*(3), 183-199.

Defond, M., & Zhang, J. (2014). "A Review of Archival Auditing Research". *Journal Of Accounting And Economics, 58*(2-3), 275-326.

Deloitte. 2020. *The Window for AI Competitive Advantage is Narrowing How Can AI Adopters Keep Their Edge?* Https://Www2.Deloitte.Com/Us/En/Insights/Industry/ Technology/Ai-Competitive-Advantage-Narrowing.Html.

Eilifsen, A., Kochetova, N., & Messier Jr, W. F. (2019). "Mitigating the Dilution Effect in Auditors' Judgments Using a Frequency Response Mode". *Behavioral Research in Accounting, 31*(2), 51-71.

Fama, E. F., & Jensen, M. C. (1983). "Separation of Ownership and Control". *The Journal Of Law And Economics, 26*(2), 301-325.

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics*: Sage.

Fakhfakh, J., & Jarboui, A. (2022). *Two-Tier Board Characteristics and Audit Risk: Evidence from Expanded Audit Reporting. Review of Quantitative Finance and Accounting.*

Francis, J. R. (2024). "What Exactly Do We Mean by Audit Quality?" *Accounting In Europe, 21*(2), 123–133. https://Doi.Org/10.1080/17449480.2023.2247410

Gepp, A., Linnenluecke, M. K., O'Neill, T. J., & Smith, T. (2018). "Big Data Techniques in Auditing Research and Practice: Current Trends and Future Opportunities". *Journal Of Accounting Literature, 40*(1), 102-115.

Glikson, E., & Woolley, A. W. (2020). "Human Trust in Artificial Intelligence: Review Of Empirical Research". *Academy Of Management Annals, 14*(2), 627-660.

Han, H., Shiwakoti, R. K., Jarvis, R., Mordi, C., & Botchie, D. (2023). "Accounting and Auditing with Blockchain Technology and Artificial Intelligence: A Literature

Review". *International Journal Of Accounting Information Systems*, *48*, 100598. Https://Doi.Org/10.1016/J.Accinf.2023.100598

Hassan, S., Aksar, M. A., Khan, S., Ahmed, T., & Zahoor, M. (2023). "Impact of Audit Quality on Real Earnings Management: Moderating Role of Corporate Governance". *Reviews Of Management Sciences*, *5*(1), 1-12.

Haßler, B., Adam, T., Brugha, M., Damani, K., Allier-Gagneur, Z., Hennessy, S., Murphy, M. (2019). *Literature Reviews of Educational Technology Research in Low and Middle-Income Countries: An Audit of the Field*. Retrieved From

Janvrin, D., Bierstaker, J., & Lowe, D. J. (2008). "An Examination of Audit Information Technology Use and Perceived Importance". *Accounting Horizons, 22*(1), 1-21.

Jarrahi, M. H. (2018). "Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making". *Business Horizons*, *61*(4), 577-586.

K. Johl, S., Kaur Johl, S., Subramaniam, N., & Cooper, B. (2013). "Internal Audit Function, Board Quality and Financial Reporting Quality: Evidence from Malaysia". *Managerial Auditing Journal, 28*(9), 780-814.

Klein, A. (2002). "Audit Committee, Board of Director Characteristics, and Earnings Management". *Journal of Accounting and Economics, 33*(3), 375-400.

Kokina, J., & Davenport, T. H. (2017). "The Emergence of Artificial Intelligence: How Automation is Changing Auditing". *Journal of Emerging Technologies in Accounting*, *14*(1), 115-122.

Krahel, J. P., & Titera, W. R. (2015). "Consequences of Big Data and Formalization on Accounting and Auditing Standards". *Accounting Horizons, 29*(2), 409-422.

Krieger, F., Drews, P., & Velte, P. (2021). "Explaining the (Non-) Adoption of Advanced Data Analytics in Auditing: A Process Theory". *International Journal of Accounting Information Systems, 41*, 100511.

Lai, K.-W. (2009). "Does Audit Quality Matter More for Firms With High Investment Opportunities?". *Journal of Accounting and Public Policy*, *28*(1), 33-50.

Lehner, O. M., Ittonen, K., Silvola, H., Ström, E., & Wührleitner, A. (2022). "Artificial Intelligence Based Decision-Making in Accounting and Auditing: Ethical Challenges and Normative Thinking". *Accounting, Auditing & Accountability Journal, 35*(9), 109-135.

Li, L., Qi, B., Robin, A., & Yang, R. (2022). "The Effect Of Enforcement Action On Audit Fees And The Audit Reporting Lag". *Accounting and Business Research, 52*(1), 38-66.

Lin, P., & Hazelbaker, T. (2019). "Meeting The Challenge of Artificial Intelligence: What Cpas Need To Know. *The Cpa Journal, 89*(6), 48-52.

Lowe, D. J., Bierstaker, J. L., Janvrin, D. J., & Jenkins, J. G. (2018). "Information Technology in an Audit Context: Have the Big 4 Lost Their Advantage?". *Journal of Information Systems, 32*(1), 87-107.

Mahzan, N., & Lymer, A. (2014). "Examining the Adoption of Computer-Assisted Audit Tools and Techniques: Cases of Generalized Audit Software Use By Internal Auditors". *Managerial Auditing Journal, 29*(4), 327-349.

Manita, R., Elommal, N., Baudier, P., & Hikkerova, L. (2020). "The Digital Transformation of External Audit and Its Impact on Corporate Governance". *Technological Forecasting and Social Change, 150*, 119751.

Mohammadrezaei, F., Mohd-Saleh, N., Jaffar, R., & Hassan, M. S. (2016). "The Effects of Audit Market Liberalisation and Auditor Type on Audit Opinions: The Iranian Experience". *International Journal of Auditing, 20*(1), 87-100.

Nalukenge, I., Tauringana, V., & Mpeera Ntayi, J. (2017). Corporate Governance and Internal Controls Over Financial Reporting in Ugandan Mfis. *Journal of Accounting in Emerging Economies, 7*(3), 294-317.

Noordin, N. A., Hussainey, K., & Hayek, A. F. (2022). "The Use of Artificial Intelligence and Audit Quality: An Analysis from the Perspectives of External Auditors in the UAE". *Journal of Risk And Financial Management, 15*(8), 339.

Orr, G. (2003). "Diffusion of Innovations", By Everett Rogers (1995). *Retrieved January, 21*, 2005.

Parasuraman, A., & Colby, C. L. (2015). "An Updated and Streamlined Technology Readiness Index: TRI 2.0". *Journal Of Service Research, 18*(1), 59-74.

Pedrosa, I., Costa, C. J., & Aparicio, M. (2020). "Determinants Adoption of Computer-Assisted Auditing Tools (Caats)". *Cognition, Technology & Work, 22*, 565-583.

Porter, C., & Sherwood, M. (2023). "The Effect of Increases in Board Independence on Financial Reporting Quality". *Accounting Research Journal*, 36(2/3), 109-128.

Qader, K. S., & Cek, K. (2024). "Influence of Blockchain and Artificial Intelligence on Audit Quality: Evidence from Turkey". *Heliyon, 10*, E30166. Https://Doi.Org/10.1016/J.Heliyon.2024.E30166

Ramen, M., Jugurnath, B., & Ramhit, P. (2015). UTR-CTOE: "A New Paradigm Explaining Caats Adoption". *Journal of Modern Accounting and Auditing, 11*(12), 615-631.

Rosli, K., Yeow, P. H., & Siew, E.-G. (2012). "Factors Influencing Audit Technology Acceptance by Audit Firms: A New I-TOE Adoption Framework". *Journal of Accounting and Auditing, 2012*, 1.

Roussy, M., & Brivot, M. (2016). "Internal Audit Quality: A Polysemous Notion?" *Accounting, Auditing & Accountability Journal, 29*(5), 714-738.

Seethamraju, R., & Hecimovic, A. (2023). "Adoption of Artificial Intelligence in Auditing: An Exploratory Study". *Australian Journal of Management, 48*(4), 780-800. Hhtps://Doi.Org/10.1177/03128962221108440

Salijeni, G., Samsonova-Taddei, A., & Turley, S. (2019). "Big Data and Changes in Audit Technology: Contemplating a Research Agenda". *Accounting and Business Research, 49*(1), 95-119.

Siew, E.-G., Rosli, K., & Yeow, P. H. (2020). "Organizational and Environmental Influences in the Adoption of Computer-Assisted Audit Tools and Techniques (Caatts) by Audit Firms in Malaysia". *International Journal of Accounting Information Systems, 36*, 100445.

Tiberius, V., & Hirth, S. (2019). "Impacts of Digitization on Auditing: A Delphi Study for Germany". *Journal of International Accounting, Auditing and Taxation, 37*, 100288.

Thottoli, M. M. (2024). "Leveraging Information Communication Technology (ICT) and Artificial Intelligence (AI) to Enhance Auditing Practices". *Accounting Research Journal*, *37*(2), 134-149. https://doi.org/10.1108/ARJ-09-2023-0269

Vafeas, N. (2005). "Audit Committees, Boards, and The Quality of Reported Earnings". *Contemporary Accounting Research*, *22*(4), 1093-1122.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). "User Acceptance of Information Technology: Toward A Unified View". *MIS Quarterly*, 425-478.

Widuri, R., O'Connell, B., & Yapa, P. W. (2016). "Adopting Generalized Audit Software: An Indonesian Perspective. *Managerial Auditing Journal, 31*(8/9), 821-847.

Xie, X., Zou, H., & Qi, G. (2018). Knowledge Absorptive Capacity and Innovation Performance in High-Tech Companies: A Multi-Mediating Analysis". *Journal of Business Research, 88*, 289-297.

APPENDIX

Survey Questions

Demographic Questions

Age___________________

Gender_______________

Years of Experience ____

Likert Scale Questions

1-7 (Strongly Disagree to Strongly Agree)

Corporate Governance

1-The board regularly calls for annual general meeting every year to discuss the institution's performance

2-Board members advise senior management on way forward on pertinent issues

3-The board represents the institution's interests in the community

4-The board sets resources for special projects and goals of the institution

5-Our board committees have chaired such committees elsewhere

Financial Reporting Quality

1-Our financial statements are presented in a format similar to the industry

2-All books of accounts are comparable across previous periods

3-Our source documents format is comparable with those of other firms in the same industry

4-Our annual report format does not change over periods

5-Our financial report figures can be compared to assets/ activities done

6-Semi-annual reports are ready after first half of the accounting period like with other firms in the same industry

7-Recommended language and procedures in reporting is used consistently
8-Our financial statements contain the necessary detail

Audit Quality

1-Our audit staff have performed accountancy work in other organizations before joining this institution
2-audit staff have accounting professional qualifications such as ACCA
3-audit staff get regular training and refresher courses through Continuous Professional Development programs
4-Our audit staff are not always under pressure by management to make adjustments in their findings.
5-We always refer to the IFRS and International Standards on Auditing for our activities

Technology Acceptance Model

1-Using AI in my job would enable me to accomplish tasks more quickly.

2-Using AI would improve my job performance.

3-Using AI in my job would increase my productivity.

4-Using AI would enhance my effectiveness on the job.

5-Using AI would make it easier to do my job.

6-I would find AI useful in my job. Learning to operate AI would be easy for me.

Technology Readiness Index

1-I prefer to use Artificial Intelligence because previously all processes were done manually.
2-Artificial Intelligence is more comfortable to use because it is a new technology
3-Usually, I use the latest technology to help with my work.
4-I feel that I don't have many problems using Artificial Intelligence compared to

other colleagues.

5-I feel that Artificial Intelligence complicates my work.

6-The guide to using Artificial Intelligence is difficult to understand.

7-I prefer to interact with humans compared to Artificial Intelligence.

8-I always double-check the data entered so that there is no error

Artificial Intelligence Adoption

1-I will use AI technologies when performing accounting or auditing tasks as an entry-level accountant or auditor

2-I consider using AI technologies as an entry-level accountant or auditor