Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

THE AI IMPLEMENTATION GAP: POLICY–AUDIT MISALIGNMENT IN THE UAE AND EGYPT

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DOI: https://doi.org/10.63544/jbii.v5i7.100

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Article History:
Received: 20.06.2026
Accepted: 07.07.2026
Published: 18.07.2026

Abstract
Following the International Auditing and Assurance Standards Board's (IAASB) findings, artificial intelligence (AI) developments over human governance in the February 2026 Technology Quality Management roundtables outcome statement, this study aims to disclose the disconnect between the policy and practice of external audit functions in AI adoption. The research employs a qualitative multi-method design that compares the narratives of Big Four organizations' transparency reports and audit practitioners in the United Arab Emirates (UAE) and Egypt. The study's context was determined by the identified gaps in prior empirical research on the differences between the attitudes of corporate management and auditors towards AI usage in external audits. The lead research question focuses on the distinctions in Big Four strategies and individual auditors' practices in AI applications. The findings are based on content analysis of the narrative of Big Four organizations' 2021–2025 transparency reports and thematic analysis (TA) of the semi-structured interviews with the auditors in the UAE and Egypt in 2026. The study discovers that auditor practices are currently disconnected from the strategic level propositions. While corporate reports depict a vision in which AI is regarded as a normal component of audit processes, auditors' experiences suggest it is limited and token adoption in practice. The authors conclude that governance and transparency issues, regional disparities in implementation, and algorithmic complexity contribute to the difficulties in auditor practices in adopting AI tools. These challenges drive the need to establish policy-practice configurations for the effective implementation of audit technologies based on AI.

Keywords: Artificial Intelligence, Big Four, External Audit, Institutional Theory, United Arab Emirates, Egypt.

1. Introduction

Artificial intelligence (AI) is disruptively changing how financial reporting and external audit engagements are performed by evolving from static task automation to autonomous operation. This paradigm shift toward agentic AI architectures built on generative AI (GenAI) and large language models (LLMs) augments autonomy and reasoning to be goal-oriented and adaptive, especially when big data analytics (BDA) are involved, further departing from the traditional view on automated work (Bandi et al., 2025; Bose et al., 2022). This paper refers to "AI" as a collective term for these agentic AI architectures and BDA; furthermore, the term "AI-enabled" is preferred over "AI-driven" to reinforce the importance of the auditor's role, judgment, and professional skepticism in modern assurance engagements. Additionally, any mention of "firms" refers to the Big Four, Deloitte, PwC, EY, KPMG.

Recently, the International Auditing and Assurance Standards Board (IAASB, 2026) note that there is a rising interest in emergent technologies, such as AI, integration into audit methodologies. Additionally, alongside aggressive national AI strategies and corporate investment surrounding AI, there persists a gap between institutional rhetoric and localized workflows amongst auditors. This implementation gap draws on established theories of policy–practice discrepancies and institutional decoupling (Akpughe & Raphael, 2026; Meyer & Rowan, 1977; Pressman & Wildavsky, 1973). By comparing regional transparency reports from Big Four firms (Deloitte, 2022, 2023, 2024, 2025a, 2025b; EY, 2021, 2022, 2023, 2024, 2025; KPMG, 2021, 2022, 2023, 2024, 2025; PwC, 2021, 2022, 2023, 2024, 2025) against practitioner interviews in the United Arab Emirates (UAE) and Egypt, two distinct emerging and developing economies (EMDEs) in the Middle East and North Africa (MENA) (International Monetary Fund, 2025), this study examines how this disconnect is perceived, why it may exist, and what it means for the audit profession.

1.1 Big Four Middle East and the AI Implementation Gap

The Big Four function as regulatory pioneers, demonstrating the leverage that global professional services networks have in shaping audit practices in a region. These firms engage in what is called "regulatory entrepreneurship" (Herman, 2019) through standardized practices that form cohesion within jurisdictions with fragmented or underdeveloped state policies. Through this practice, the deployment of proprietary AI-enabled audit platforms across global networks occurs and, as a consequence, extends into the MENA region. Although these firms frame these technologies as a means to preserve audit quality during global digital transformation, especially when BDA visualization and AI-automated testing alter the traditional mechanics of audit processes—evidence interpretation, documentation, and reporting (Li & Goel, 2025). Consequently, these emerging technologies and their recent developments reconfigure how practitioners interface with their work, in particular through the formation and preservation of professional judgment (Salijeni et al., 2021). Institutional theory helps inform the difference between the substantive and symbolic dimensions surrounding technology adoption in the region. Organizations tend to adopt formalities to signal compliance with expectations, thereby separating progressive implementation from operational realities (Meyer & Rowan, 1977; Power, 1997). This phenomenon accelerates under coercive, mimetic, and normative pressures, especially when corporate directives are ambiguous when faced with local regulatory and infrastructural constraints (DiMaggio & Powell, 1983; Kostova & Roth, 2002).

The implementation gap, or the "gap", turns out to be a sociometrical concept. By examining how human agency, technological materiality, and organizational norms intersect through the lens of Orlikowski (2007) and Leonardi (2011), this study investigates AI and audit practice. In particular, it focuses on how people used AI for substantive improvement of audit quality and its symbolic adoption to fulfil conformity requirements. The tension between these two themes emerges due to the dual nature of the technology as non-deterministic but at the same time limited by the opacity of algorithms, information asymmetry, and design choices (Burrell, 2016).

1.2 Problem Statement

AI adoption in the MENA region may well accelerate technology implementation but creates structural and compliance asymmetry (Finch & Butt, 2025). National strategies, including the United Arab Emirates National Program for Artificial Intelligence (2018) and the Egyptian framework to promote regional integration (National Council for Artificial Intelligence, 2025), define the start of the implementation gap between policy and practice. This discrepancy emerges due to the former's imposing corporate adoption of AI-driven solutions before effective governance mechanisms are in place. IAASB notes that International Standards on Quality Management (ISQM 1) and International Standards on Auditing (ISA 200 Revised) are "adequate" in the current business environment but acknowledges the absence of guidance on responding to the unique risks associated with non-deterministic systems (IAASB, 2026). Such a regulatory inconsistency results in institutional de-coupling or tokenistic adaptation (Pressman & Wildavsky, 1973; Meyer & Rowan, 1977; Finch & Butt, 2025). Therefore, this paper explores how practitioners in the UAE and Egypt navigate this compliance gap to maintain professional skepticism.

1.3 Scope of Research

This research focuses on Big Four external audit practices in the UAE and Egypt. The UAE acts as the primary focus because of its unique position as an EMDE and AI infrastructure hub, supported by sovereign investments in computing and regulatory initiatives facilitating its national AI strategy (Albous et al., 2025; Hassan et al., 2025). On the other hand, Egypt serves as a comparative study characterized by its significant supply of human capital alongside limitations defined by its data maturity and gaps in regulatory enforcement (Badawy, 2025; Alkhoudi et al., 2025). The methodology utilizes qualitative triangulation between regional transparency reports from 2021 to 2025 across Big Four firms, supplemented by interviews conducted in 2026 with practitioners from PwC (UAE and Egypt) and Deloitte (UAE). Institutional isomorphism (DiMaggio & Powell, 1983) allows these firms' organizational behaviors to function as proxies representing the Big Four group. The focus is on external audit engagements adopting AI in their substantive testing and risk assessment procedures.

1.4 Significance of Research

Audit practice is rarely aligned with the narrative disclosed by corporations. Given the recent concerns raised by IAASB (2026), this study focuses on the practice of quality management in uncertain settings, providing an alternative approach to distinguish between substantive and symbolic practices. The analysis demonstrates that the lack of technical expertise and associated technological determinism leads to questioning the role of professional skepticism as an essential aspect of auditing, where practitioners attempt to replace professional judgment with artificial intelligence (Birhane et al., 2024). By linking the practice to institutional theory, the article extends the understanding of decoupling to embrace auditing practice and the impact of AI therein.

1.5 Research Questions and Objectives

Research Question (RQ): To what extent do the AI-integration claims in Big Four Middle East reports align with the operational experiences of auditors in the UAE and Egypt?

- **RO1:** Critically analyze the AI-integration and quality management claims within Big Four regional Transparency Reports (2021–2025).
- **RO2:** Evaluate the degree of "practical clarity" perceived by practitioners in the UAE and Egypt when reconciling global mandates with localized regional reporting frameworks.
- **RO3:** Synthesize corporate disclosures and practitioner experiences to evaluate the extent of decoupling between global AI mandates and operational audit quality.

2. Literature Review

2.1 The Technological Evolution of Audit

Audit practice has evolved from the automation of relatively simple tasks to the development of dynamic autonomous systems. Early studies recognized the potential role of AI in complex auditing procedures within specific constraints as technology advanced (Baldwin et al., 2006; Issa et al., 2016; Kokina & Davenport, 2017; Sutton et al., 2016). However, the capabilities of new developments in AI, notably GenAI and LLMs, have proven to be much broader. They allow for implementing agentic AI, executing multifaceted processes with analytical steps outside direct human control and intervention (Bandi et al., 2025; Hosseini & Seilani, 2025; Powell et al., 2026; Schreyer et al., 2024). Contemporary audit practice involves using BDA to identify irregularities in extensive data sets (Bose et al., 2022). While AI can significantly contribute to collecting evidence necessary to express a reasonable assurance opinion, its application is dependent on the quality of the underlying data architecture, such as the use of blockchain technology, which is fundamental to input auditability (Han et al., 2023). Nevertheless, the "black-box" nature of AI's decision-making process poses a challenge to achieving the required level of control and independent verification (Li & Goel, 2025).

Despite technological advances, non-transparent and non-deterministic features generate challenges, in particular, in knowledge-intensive domains, through conflicting with well-established governance and regulatory frameworks (Bohni Nielsen et al., 2024; IAASB, 2026). According to Burrell (2016), the "black-box" problem is primarily explained by three factors, including the intentional secrecy, technical illiteracy, and intrinsic complexity. Indeed, these features diminish accountability and engagements, increase the risks of inconsistent assurance, automation bias, and inadequate professional skepticism (Birhane et al., 2024; Detzen & Gold, 2021; Kokina et al., 2025; Seethamraju & Hecimovic, 2022). Specialized governance, AI-specific auditing, and technical literacies are among the primary ways to address the identified issues, given the insufficiency of existing accounting standards to regulate non-deterministic phenomena (Birhane et al., 2024; Islam et al., 2025).

2.2 Audit Quality and the Integration of Emerging Technologies

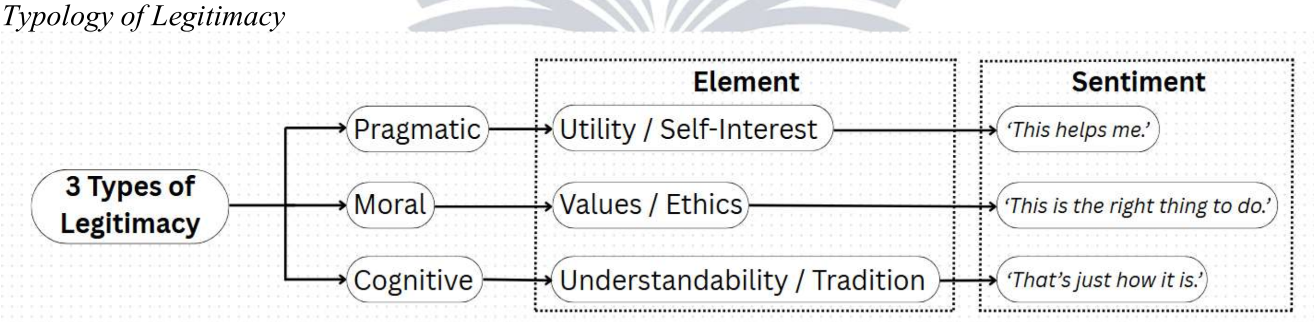
Audit quality is determined by an auditor's ability to uncover and report material misstatements that influence the reliability of corporate disclosure (DeAngelo, 1981; DeFond & Zhang, 2014); emerging technologies intervene in both stages of the process. Workflows benefit from automation, thus reducing human error (Pedrosa et al., 2020); in turn, AI applications are scalable and appropriate for complex analytics (Mitan, 2024). Furthermore, BDA enable greater capacity in evaluating complex financial datasets amidst volatile regulatory conditions (Bose et al., 2022). Yet, these benefits are constrained by the compliance asymmetries between local institutional capacity and top-down regulatory ambition (Finch & Butt, 2025). AI adoption is frequently linked with greater formal compliance but not with improved perceived benefits among practitioners (Thottoli et al., 2022). The success of AI depends on the technology's compatibility between the firm and the client (Rahman et al., 2024). Moreover, accountability is still more influenced by the institutional environment than by technology alone (Birhane et al., 2024). So, while AI may boost productivity, uneven adoption and limited structural change continue to reshape competition among the Big Four (Vitali & Giuliani, 2024). This suggests that mere adoption of technology does not guarantee improved audit quality and may serve to strengthen symbolic institutional dynamics.

2.3 Theoretical Framework

2.3.1 Institutional Theory. The implementation Gap is a concept from early policy literature that shows how complex, multi-actor chains of implementation systematically undermine initial strategic intentions (Pressman & Wildavsky, 1973). This divergence can be explained by institutional theory which suggests that organizations adopt "rationalized myths" (formal structures designed to signal that they are in line with social and regulatory expectations) to achieve legitimacy, resources and stability (Meyer & Rowan, 1977).

Figure 1

Typology of Legitimacy



Note. Author's illustration based on Suchman's (1995) typology of legitimacy.

Legitimacy is defined as a generalized perception of appropriateness within socially constructed norms (Suchman, 1995). It is divided into three forms (see Figure 1), namely pragmatic, moral, and cognitive. Although the underlying motivations for legitimacy differ, the homogeneity of the field is mainly attributable to institutional isomorphism where a high degree of environmental uncertainty such as the swift rise of agentic AI compels organizations to converge on similar structures (DiMaggio & Powell, 1983).

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
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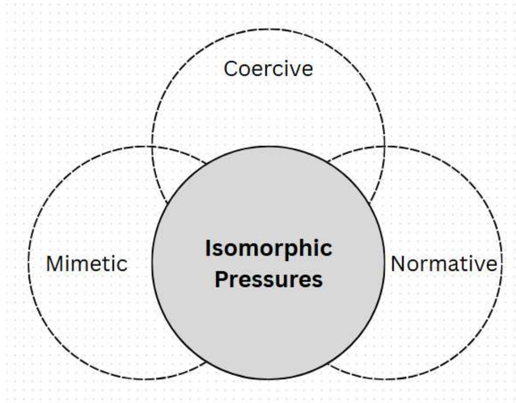
Figure 2: *Isomorphic Pressures*



Note. Author's illustration based on DiMaggio and Powell's (1983) isomorphic pressures.

Three isomorphic mechanisms are converging (see Figure 2): coercive, mimetic and normative pressures. These explain the structural similarity in Big Four AI disclosures where copying technology branding is used to support competitive and legitimate appearances (DiMaggio & Powell, 1983; Huda, 2022). However, institutional isomorphism does not ensure the alignment of mandates and practice. Bromley and Powell (2012) draw a distinction between policy–practice decoupling (divergence in implementation) and means–ends decoupling (disconnection of outcomes). In the AI context, the means deployed by firms may be sophisticated, with the ends opaque. The latter are often a matter of symbolic reporting rather than substantive professional judgment. Multinational professional service firms are subject to institutional duality, in which global organizational mandates intersect with very fragmented local institutional environments (Kostova & Roth, 2002). This often leads to a ceremonial adoption, where AI meets global network targets but is not meaningfully embedded in practice. This is typical of the "audit society" of Power (1997) where formal "auditability" is valued more highly than substantive transparency.

The global deployment of AI platforms by these firms functions symbolically rather than substantively, serving to gain institutional confidence and demonstrating performative alignment more than substantive improvement in audit quality. Evaluating these dynamics requires a sociomaterial lens to fully understand the codependent relationship between technological advances and human judgment.

2.3.2 Sociomateriality. Sociomateriality theory extends institutional theory by expanding the understanding of the relationship between technology and human action, defining them as inseparable dimensions of organizational operation. Accordingly, organizational practice emerges organically through ongoing interactions between people (social) and technology (material) (Orlikowski, 2007). Leonardi (2011) refers to this relationship as "imbrication," whereby human practices influence the use of technology alongside its capabilities and limitations, in turn transforming organizational routines. The most substantive constraints of AI-enabled auditing are the opacity of algorithmic systems. Using Burrell's (2016) taxonomy of algorithmic opacity and Seethamraju and Hecimovic's (2022) work, it is clear that reduced transparency affects auditors' access, interpretation and validation of evidence. This could result in auditors having less insight into AI-generated outputs, leading to a re-evaluation of how professional skepticism can best be applied in a more digitized audit environment (Li & Goel, 2025).

2.4 The Regulatory and Regional Landscape: MENA Asymmetries

The use of emerging technology is highly dependent on regional institutional environments. The IAASB (2026) through ISQM 1 and ISA 220 sets global baseline quality management expectations, but national AI trajectories have a significant effect on the regional implementation. Cave and Dihal (2023) compare the technocratic approach of the UAE, which involves huge capital investments and foreign workforces, with Egypt's approach, where human capital has to cope with the pre-existing socio-economic constraints. The Big Four firms' ability to align global network investments with localized mandates accelerates these aspirations (Bruno & Skoglund, 2024).

2.4.1 Strategic Leapfrogging and Hyper-Digitalization in the UAE. The UAE National Strategy for AI 2031's goal is to position the UAE as a global leader in AI through economic statecraft (United Arab Emirates National Program for Artificial Intelligence, 2018), using a combination of large capital investments in infrastructure, talent upskilling, and "soft regulation"—defined as ethical frameworks that enable flexible strategy instead of rigid statutory law—while bypassing traditional pathways to industrial development (Alkhoudi et al., 2025; Albous et al., 2025; Mishrif & Al Balushi, 2018). As sovereign funding in computing capacity and data centers supports the national AI agenda (Hassan et al., 2025), overreliance on out-of-country technology risks "Dutch knowledge disease," identified by Soete (2005), which stunts domestic growth, especially in the technology sector (Alyani, 2018). Knowing this ecosystem, Big Four accounting firms face coercive and mimetic pressures to conform by implementing AI platforms across their global network (DiMaggio & Powell, 1983). These platforms often operate as rationalized myths so these firms may secure pragmatic and cognitive legitimacy, allowing global alignment with regional requirements (Meyer & Rowan, 1977; Suchman, 1995; Kostova & Roth, 2002). Consequently, AI adoption can lead to means–ends decoupling, where technological deployment serves to fulfill legitimacy rather than produce empirical improvements in audit quality (Bromley & Powell, 2012). This process is enabled by sociomaterial imbrication (Leonardi, 2011); standardized and overly structured measures for procedural compliance and auditability may improve transparency but erode critical thinking integral to professional skepticism (Power, 1997; Seethamraju & Hecimovic, 2022).

2.4.2 Institutional Capacity and Regulatory Fragmentation in Egypt. Egypt's Second Edition AI Strategy is ambitious but aspirational, as it lacks specific guidance on how to actualize the goals in various sectors (Badawy, 2025; National Council for Artificial Intelligence, 2025). The strategy is designed to send a signal to the international community that Egypt is ready to embrace AI, but it does not provide concrete policies for effective national governance, which shows the gap between design and implementation caused by limited administrative capacity (Akpughe & Raphael, 2026). Although the UAE has better digital infrastructure than Egypt (Hassan et al., 2025), the latter has social barriers to widespread adoption of technology (Alyani, 2018; Cave & Dihal, 2023). Additionally, policymakers and practitioners have different perspectives on the issue, which increases the implementation gap (Mishrif & Al Balushi, 2018).

Big Four firms in Egypt acutely experience institutional duality (Kostova & Roth, 2002), intensified by governance deficits (Badawy, 2025). As domestic regulations and ethical guidelines for AI are absent, practitioners in the region depend entirely on global methodologies, further contributing to the divide between global corporate policy and regional fieldwork. Local firms must then adapt standardized global platforms to local challenges, such as esoteric and complex client data and fragmented regulatory supervision (Alkhoudi et al., 2025). This institutional friction drives mimetic isomorphism (DiMaggio & Powell, 1983), compelling firms to adopt AI to maintain technological parity with their international peers despite the risks and limitations of the emergent technology. As a result, this widespread adoption is vulnerable to policy–practice decoupling (Bromley & Powell, 2012), whereby narratives of AI integration mask the realities in the field and reinforce symbolic compliance (Akpughe & Raphael, 2026). From a sociomaterial lens, deficiencies in infrastructure impose material constraints affecting professional agency (Leonardi, 2011). When local client data fails to fit the template of global AI platforms, the result effects sociomateriality by restricting smooth human–technology interaction (Orlikowski, 2007). This misalignment between human and technology increases black-box opacity—especially during the carrying out of audit engagements with fragmented systems—negatively impacting professional skepticism and institutional trust (Burrell, 2016; Seethamraju & Hecimovic, 2022).

2.5 Research Gap

2.5.1 Empirical Gap: Lack of Practitioner-Level Evidence. Most of the existing research concentrates on the role of artificial intelligence (AI) in audit by analysing the number of delayed auditor reports and restatements of financial statements (Rahman et al., 2024). Although such an evidence base is

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

crucial, it is not sufficient for understanding the adjustments and restrictions that the industry experiences on a day-to-day basis. There are few studies that document how different firms resolve the problems of implementing a single, proprietary system from one company while addressing local issues, especially in the context of the uneven spread of AI audit technologies (Birhane et al., 2024). The latter omission undermines the ability to comprehend how dissimilar such influences are for firms in the UAE and Egypt. The former has a well-established and capital-intensive government with a substantial number of sovereign-sponsored projects (Alkhoudi et al., 2025). As a result, there is a tendency to adopt emerging technologies rapidly, which creates a gap between auditors' expertise, AI's abilities, and explainability practices typical of large corporations (Li & Goel, 2025). By contrast, the policy environment in Egypt lacks the necessary maturity, does not have binding regulations, and does not provide detailed guidance, resulting in a disconnect between official strategies and practitioners' approaches (Badawy, 2025). Thus, it is evident that existing research provides an incomplete picture of how AI is incorporated into the audit process because it fails to consider relevant local factors and improvisations.

2.5.2 Conceptual Gap: Decoupling in AI-Enabled Auditing. The synthesis of institutional theory and sociomateriality to explain the non-linear relationship between AI adoption and audit quality has not yet been conceptualized in the literature. Most studies view technology as a passive tool that does not recognize the constitutive entanglement through which the black-box materiality of AI influences the reshaping of professional skepticism (Orlikowski, 2007; Seethamraju & Hecimovic, 2022). Research has also yet to address the compliance asymmetry (Finch & Butt, 2025) that arises when technological mandates outpace the maturity of regional governance frameworks, or to apply the distinction between policy-practice and means-ends decoupling (Bromley & Powell, 2012) to AI adoption in multinational contexts. Thus, existing frameworks do not explain why organizations may substantially adopt AI (the means) but fail to achieve the desired improvements in audit quality (the ends), particularly in the context of institutional duality (Kostova & Roth, 2002). This gap is further exacerbated by the combination of Burrell's (2016) intentional secrecy and the organizational distrust acknowledged by Seethamraju and Hecimovic (2022) that facilitates means-ends decoupling (Bromley & Powell, 2012). This study fills these gaps by examining how global isomorphic pressures and local material constraints may lead to a performative rather than substantive integration of AI in the UAE and Egypt.

2.5.3 Proposed Conceptual Framework. This study approaches the identified gaps in empirical and conceptual research by developing a multilevel model which assumes that implementation problems are manifested in tensions between ideal prescriptions and actual practice (Pressman & Wildavsky, 1973). The proposed conceptualization aims to provide a dynamic understanding of the implementation lag in the adoption of AI in auditing by postulating that tensions shape policy design at three levels: macro, meso, and micro processes associated with the audit profession.

Figure 3
Conceptual Framework

Note. Conceptual Framework of the AI Implementation Gap in Audit.

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
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The implementation gap operates across three institutional levels (macro, meso, and micro) and five overall layers (see Figure 3). At the national level, AI strategies rely on soft regulation (Albous et al., 2025) and exhibit compliance asymmetry (Finch & Butt, 2025), framing technological innovation as rationalized myths. At the organizational layer, firms deploy proprietary AI platforms across its global network to secure legitimacy in state-governed environments (RO1); however, regional institutional and material constraints—such as the sovereign-funded infrastructure in the UAE and the limited administrative capacity in Egypt—dictate whether adoption is symbolic or substantial (Hassan et al., 2025; Akpughe & Raphael, 2026). At the operational level, auditors navigate non-deterministic systems in the field within a disorganized ecosystem (Birhane et al., 2024), where preserving auditability relies on professional competencies and model explainability (Li & Goel, 2025) (RO2). This misalignment forms the basis for means–ends decoupling (Bromley & Powell, 2012) and exposes the disconnect between AI adoption (the means) and professional skepticism or substantive audit quality (the ends) (RO3).

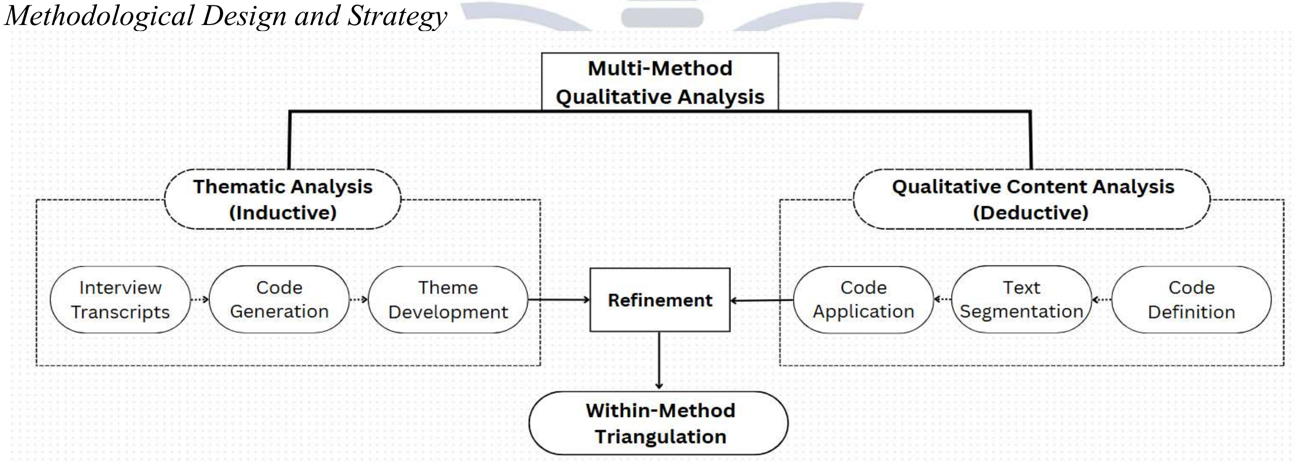
3. Research Methodology

3.1 Research Philosophy

This study follows an interpretivist philosophy, analyzing and viewing AI integration in audit as a social phenomenon shaped by organizational context, professional judgment, and human interpretation (Weber, 1978; Saunders et al., 2023). This approach examines auditor experiences directly, contrasting them with the formal narratives found in transparency reports (Chowdhury, 2014; Saunders et al., 2023). An abductive qualitative approach allowed empirical evidence and theoretical frameworks to inform each other iteratively during the analysis of implementation gaps (van Hulst & Visser, 2025), which is useful when investigating emerging technologies that challenge existing theoretical frameworks (Lim, 2025; Kosow & Gaßner, 2008). Methodological rigor was maintained through a multi-method qualitative design utilizing within-method triangulation (Bekhet & Zauszniewski, 2012). Figure 4 outlines the integration of inductive thematic analysis (TA) derived from semi-structured interviews with a deductive qualitative content analysis of Big Four Transparency Reports published between 2021 and 2025.

Figure 4

Methodological Design and Strategy



Note. Developed by the author based on the methodological frameworks of Philipp Mayring (2014, 2019), Lorelli S. Nowell et al. (2017), and Abir K. Bekhet and Jaclene A. Zauszniewski (2012).

TA followed the systematic framework established by Nowell et al. (2017) to identify patterns in practitioner experiences during AI implementation. For the evaluation of AI-related disclosures within Transparency Reports, a qualitative content analysis was executed using the rule-based coding structures defined by Mayring (2014, 2019), building upon the methodological criteria of Kuckartz (2014) and Schreier (2012). Methodologically, these two data sources intertwine through within-method triangulation (Bekhet & Zauszniewski, 2012) to compare corporate narratives against daily field realities. Theoretically, these findings

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
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relied on Burrell's (2016) conceptualization of opacity and the technological, organizational, and environmental (TOE) framework, which was kept relevant by Seethamraju and Hecimovic's (2022) up-to-date research.

The research design is made up of both longitudinal and cross-sectional dimensions (Saunders et al., 2023). Transparency reports of the years 2021 through 2025 establish over time the longitudinal timeline, whereas practitioner interviews conducted in 2026 provide the point-in-time cross-sectional data of AI-enabled experiences in audit.

3.2 Data Collection Method

Primary data was gathered using a purposive sampling strategy to ensure that participants who have worked with AI-enabled auditing frameworks were recruited (Creswell, 2013). Interviews were conducted remotely via Google Meet with early-career external audit practitioners from the selected firms, Deloitte (UAE) and PwC (UAE and Egypt). The interview questions were indirectly worded to minimize the possibility of social desirability bias and elicit more honest professional perspectives from participants (Kvale & Brinkmann, 2009; Tourangeau & Yan, 2007). Additionally, reports from Big Four firms that pertain from 2021 to 2025 from the UAE or MENA regions were used as secondary data sources. In cases where reports could not be found in either region or written in English, transparency reports from similar Big Four entities were considered instead to maintain the consistency of the timeframe and geographic scope of the study.

3.3 Research Ethics

This study adhered to ethical guidelines of informed consents, confidentiality, and data protection for the participants as described in the provided participant information sheets reviewed and signed by the participants. The present study was conducted in accordance with the regulations under the EU's General Data Protection Regulation (GDPR) (Regulation (EU) 2016/679), the UAE Federal Decree-Law No. 45 of 2021 concerning Data Protection, and Egypt's Law No. 151 of 2020 on Information Technology. In particular, all participants were asked to sign the informed consent forms, and their responses were stored in encrypted digital files by using AES-256 encryption. Additionally, to ensure confidentiality, the participants were code-named based on their positions using the labels provided in Table 1 below.

Table 1

Anonymity Strategy

Position	Example Label(s)	Anonymity Level
Associate / Senior Associate	e.g. Associate A or Senior Associate B	High. Thousands of individuals fit this profile in the MENA region.
Manager / Senior Manager	e.g. Manager C or Senior Manager D	Moderate. Relatively safe in larger offices, but may be generalized in smaller offices.
Director / Partner	e.g. Senior Leadership Participant E	Low. Should be generalized to avoid direct identification via public firm directories.

Note. Mitigation Strategy to Prevent Risk of Deductive Identification of Professionals. Own Work.

4. Results and Findings

4.1 Interviewee Profiles

Table 2

Auditor Participant Profiles

Identifier	Job Label	Current Firm	Country	Years of Experience
P1	Associate A	PwC	Egypt	1-2 year(s)
P2	Associate B	Deloitte (ex-EY)	UAE	3-4 years
P3	Associate C	PwC	Egypt	2-3 years
P4	Senior A	PwC (ex-Deloitte)	UAE	4-5 years
P5	Associate D	Deloitte	UAE	2 years

Note. Organized List of Anonymized Big Four External Auditors. Own Work.

The interviewee profiles (see Table 2) present information about five Big Four early-career auditors working in the UAE and Egypt. Four of the participants are at the level of associates, and one is at the level of a senior associate. Each participant has between two and five years of experience in external audit, which is relevant to this paper's research question, as the professionals have been exposed to the industry's changes throughout the 2021-2026 timeframe (Leonardi, 2011). For confidentiality and consistency reasons, the participants are identified by codes P1–P5 in this paper.

4.2 Data Analysis

4.2.1 Qualitative Content Analysis. Big Four transparency reports from 2021 through 2025 were analyzed using a deductive framework based on Mayring's (2014, 2019) qualitative content analysis guidelines. The coding process distinguished between operational claims (Category 1) and the strategic framing of audit quality (Category 2). Disclosure depth was evaluated based on implementation specificity (Categories 3A–3C), ranging from high-clarity procedural descriptions (Category 3A) to low-clarity rhetorical mentions (Category 3C). Moreover, the framework has captured global–regional alignment (Category 4), strategic-operational decoupling (Category 5) and institutional legitimacy framing (Category 6), permitting a comparative assessment of substantive content and strategic positioning.

Table 3

Cross-Firm Qualitative Content Analysis (Deductive)

Category	Deloitte	EY	KPMG	PwC	Key Observations
1: AI Adoption Claims	Procedural enhancement and client disclosure evaluation (Appendix C).	Globally scaled AI release and compliance integration (Appendix D).	AI-driven data mining and trust-focused narratives (Appendix E).	AI as specialist capability and stakeholder driver (see Appendix F).	Universal pivot to GenAI strategies across all firms by 2024/25.
2: Quality & Assurance Framing	Associates AI with human problem-solving and process acceleration (Appendix C).	Links digital tools to skepticism, independence, and risk guidance (Appendix D).	Connects technological evolution to deeper, richer audit insights (Appendix E).	Ties investment to digital age challenges and enhanced quality (see Appendix F).	Consistent framing of AI as a fundamental driver of audit quality and standards.
3A: High Clarity	Branded platforms (Omnia, Levvia) and fraud detection models (Appendix C).	Specificity in Canvas, Helix, and Atlas workflows (Appendix D).	Heavy reliance on KPMG Clara and AI agents (Appendix E).	Focus on Aura and Halo for risk and population testing (Appendix F).	Substantive implementation clusters around branded global audit platforms.
3B: Medium Clarity	Functional description of internal AI platform CURA Learning (Appendix C).	Minimal representation; clustering at high-clarity or low-clarity extremes (Appendix D).	Minimal representation; focus remains on 3A platform capabilities (Appendix E).	"Powerful platforms" descriptions without detailed procedural workflows (Appendix F).	Infrequent use of mid-level functional descriptions across the dataset.
3C: Low Clarity	Abstract focus on "incorporating technological	Rhetorical emphasis on "modernizing" via "cutting-	Minimal representation; substantive	Vague descriptors such as "panoramic	Abstract narratives typically serve as introductory or

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ISSN-p: 3006-2284, ISSN-e: 3006-0982
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Category	Deloitte	EY	KPMG	PwC	Key Observations
	capabilities" (Appendix C).	edge" tools (Appendix D).	focus prioritized (Appendix E).	views" (Appendix F).	visionary text in recent reports.
4: Global–Regional Alignment	Global leadership participation and structural links to NSE (Appendix C).	Driving regional consistency through global methodology (Appendix D).	Linking global scale to regional audit consistency (Appendix E).	Implied through regional adoption of global tools (Aura, Halo) (Appendix F).	Top-down implementation of global strategy to ensure regional consistency.
5: Evidence of Decoupling	Exploratory/assessment phases for GenAI (Appendix C).	Partial adoption and future-dated deployment timelines (Appendix D).	"Staged implementation" of technological milestones (Appendix E).	Ongoing "building" of next-gen ecosystems (Appendix F).	Widespread gap between strategic vision (GenAI) and operational maturity.
6: Institutional Legitimacy Framing	Innovation awards (Silver Stevie) and aspirational support (Appendix C).	"Audit of the future" and $1b investment claims (Appendix D).	Strategy for talent retention and service excellence (Appendix E).	Vision of "human and machine intelligence" blend (Appendix F).	Use of reputational assets (awards, investment) to signal innovation leadership.

Note. Author's analysis based on Mayring (2014, 2019). The coding framework was developed by the author using Mayring's qualitative content analysis methodology. Supporting evidence for each firm is provided in Appendices C–F.

The difference between current digital workflows and the addition of new AI technologies is shown in Table 3. AI functions are incorporated into procedures such as automated population analysis and real-time monitoring on global platforms such as Deloitte Omnia, EY Canvas, KPMG Clara and PwC Aura, which are Substantive Adoption (Category 3A). In contrast, we find a discrepancy with respect to GenAI. Firms use AI-centric narratives (Category 1) whereas disclosures mostly report exploratory or "building" phases (Category 5). Regional disclosures in the MENA region follow suit with these global strategies where the emphasis is on the adoption of network-wide tools rather than localized technical deviations. Overall, these findings indicate that core digital auditing is functionally integrated, whereas GenAI's narrative is visionary, often supported by references to industry awards and investment numbers (Category 6).

4.2.2 Thematic Analysis

Table 4

Trustworthiness Criteria of Thematic Analysis (Inductive)

Phase of Thematic Analysis	Means of Establishing Trustworthiness
Phase 1: Familiarization with data (Appendix G)	Involved prolonged engagement with interview transcripts and the documentation of theoretical and reflective thoughts within well-organized archives.
Phase 2: Generating initial codes (Appendix H)	Was supported by reflexive journaling and a detailed audit trail to record the evolution of code generation.
Phase 3: Searching for themes (Appendix I)	Utilized diagramming to clarify thematic connections and maintain detailed notes regarding the development of concept hierarchies.
Phase 4: Reviewing themes (Appendix J)	Required testing for referential adequacy by consistently returning to the raw data to ensure emerging themes accurately reflected the source material.

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ISSN-p: 3006-2284, ISSN-e: 3006-0982
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Phase 5: Defining and naming themes (Appendix K)	Involved documenting the specific naming logic and final interpretive consensus to ensure analytical consistency.
Phase 6: Producing the report (Table 5)	Provides a "thick description" of the context, disclosing the explicit reasons for the theoretical, methodological, and analytical choices made throughout the study.

Note. Adapted from Nowell et al. (2017).

The inductive TA was conducted according to the trustworthiness criteria (Table 4) of Nowell et al. (2017) and was guided by a systematic framework to provide an auditable decision trail. Interpretive work involved long engagement and recording reflective insights while familiarizing with the data (Phase 1) and reflexive journaling to trace the development of coding (Phase 2). Analytical clarity was addressed by mapping thematic relationships (Phase 3) and checking referential adequacy against extracts from the raw data (Phase 4). Finally, the documentation of the rationale for theme naming (Phase 5) allowed for a final report that provided a "thick description" of the research context supported by traceable analytical steps (Phase 6).

Table 5

Inductive Analysis Phase 6 – Report on Interview Transcripts

Theme	Sub-theme	Supporting Codes and Extracts	Source(s)
1. Ceremonial vs. Functional Gap	A. Technological Posturing vs. Procedural Continuity	**i. Refinement over Transformation:** "Aura is working on it… but, in my opinion, Aura is—it feels very developed it's quite refined" (P4); "I don't see how we are exactly replicating or how exactly are we creating a next-generation audit… it's not something that has like any use of AI or something to lessen the human intervention" (P3). **ii. Ceremonial Integration:** P1 stated that they did not think the tool was "as strong or as helpful as they make it seem to be." When asked whether this could be described as "ceremonial," P1 agreed, stating: "Yeah, yeah, I would." **iii. Procedural Focus:** "The next-generation audit is essentially just an updated set of procedures for the same work" (P3).	Appendix I; K
	B. Sense-Check as Functional Guardrail	**i. Triple-Layer Defense:** "Even if both [IT and AI] give a green light… we still do some kind of testing from our part… ultimately the decision depends on us" (P5); "I still have to kind of look through, let's say, maybe like 60% to 70% of the data set. But I'm just skimming—I'm scanning, right?" (P1). **ii. Judgment Preservation:** "Whatever needs actual judgment, this is where we still don't use AI and we just do it ourselves manually" (P3); "When it comes to professional judgment, nothing can be done by AI yet… it comes upon experience" (P5). **iii. Out-of-the-Box Thinking:** "It [AI] isn't necessarily smarter… you could have two different clients… but one has a specific thing that's a bit different or like a quirk… It can't really discern it" (P1); "We just don't follow the expectations… we go outside expectations. That's where the difference is" (P5).	Appendix H; J; K

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Theme	Sub-theme	Supporting Codes and Extracts	Source(s)
	C. Operational Workaround Reality	**i. Personal Macros:** "We do use personal macros… designed for us to do very specific things… if there are certain entries that are knocking off… we have macros that can show us which entries relate to another one" (P4); "We run the macros we find out it is a… built-in excel tool where we find out our reversing entries… we remove the netting of items and then we run the sampling" (P5). **ii. Manual Documentation:** "For huge clients…we still work on Excel Microsoft… all the remaining work papers need to be done in Excel" (P5).	Appendix J; K
2. Regional / Local Shortcomings	A. Standard Mismatch (IFRS vs. EAS)	**i. Similarity Conflict:** "Whenever I would ask a question it would give me for example the IFRS standard not the EAS standard… those small like instances or like differences would create a bigger issue later on" (P1). **ii. Manual Verification Layer:** "Whenever we get something out of an AI tool you need to still check the like authenticity of it… because at the end of the day it is an AI system" (P3).	Appendix H; I
	B. Informal Practices & Relational Nuance	**i. Contextual Blindness:** "If that company's owner had links to a different country's president… AI is never going to pick it up" (P5); "…Is there any government influence on the entity?… For these transactions the AI is not much developed yet" (P5). **ii. Behavioral Cues:** "Working on the field is really helpful to understand how the controls are effective… AI cannot do [this]… there is a human touch needed in this" (P5).	Appendix H; I
3. Early-Stage Immaturity	A. Technological Immaturity	**i. Immature AI:** "AI is just a baby… it's just the beginning stage where you just put the data and then the AI just tells you" (P5). **ii. Historical Data Deficiency: "**The AI doesn't compare the company's past. They just focus on the current issue and the current day… it is never going to happen [yet]" (P5).	Appendix I; J
	B. Managerial Skepticism & Stability	**i. Manual Mandates:** "The managers would personally tell you not to do that [automated costing] and do the costing and comparing of the financials manually… even though there is a system" (P5). **ii. Stability over Innovation:** "Deloitte's a bit slow [relative to other Big Four]… they want to prioritize stability over innovation… we understand that we are slightly behind, but the reason why we're behind is because we want to perfect it" (P2).	Appendix H; I

Note. Author's analysis using the framework described by Nowell et al. (2017). Quotations are from interview transcripts. Appendix references are provided.

The TA (Table 5) below demonstrates the gap between the goals of AI technology set by the leadership and the actual practice experienced by the participants. Since AI technologies are currently in the early stages of development, participants compensate for the shortcomings of new computer technologies with their own judgment. The practitioners in the UAE and Egypt pointed out that the human auditor is the ultimate guarantor

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of the accuracy of data processing since even getting an unconditional positive result from IT audit software is not enough, as P5 pointed out: "even if both [IT and AI] give a green light… ultimately the decision depends on us." Auditors process confidential information and perform complex procedures, which means that AI software optimizes the ability to work but does not replace human judgment altogether. Moreover, it was found that the AI software lacked features that took into account specific problems, thus creating a conflict with the IFRS. This problem was highlighted by P1, who noted that "those small… differences would create a bigger issue later on," resulting in the need for workarounds such as personal macros or a manual audit to process further transactions.

4.2.3 Synthesis of Qualitative Analyses

Table 6

Abductive Synthesis of the Policy–Audit Misalignment

Institutional Expectation (Deductive QCA)	Operational Reality (Inductive TA)	Policy–Audit Gap (Abductive Synthesis)
Claim: AI facilitates a "human and machine intelligence" (PwC, 2021) blend to drive audit quality (Category 2; 6).	**Observation:** AI is described as a "ceremonial" search engine or grammar tool, while core judgment remains strictly human (Theme 1.A.ii.; 1.B.).	**Symbolic Adoption for Legitimacy:** Firms adopt AI narratives to signal innovation and institutional legitimacy (Category 6), but maintain manual practices to protect audit quality against technologically "immature" limitations (Theme 1A; 3.A.i.).
Claim: Top-down implementation of global platforms (Aura, Omnia, Clara) ensures regional consistency (Category 3A; 4).	**Observation:** Global tools default to IFRS, creating a "Standard Mismatch" with local frameworks like EAS and ignoring regional "Informal Practices" (Theme 2.A.; 2.B.).	**De-contextualized Standardization:** Global strategies prioritize network-wide consistency (Category 4) over local accuracy. This forces practitioners to act as a "Manual Verification Layer" to fix mismatches between rigid global standards and regional realities (Theme 2.A.ii.).
Claim: Integration of proprietary AI accelerates the technical core and enhances efficiency (Category 1; 2).	**Observation:** The "Triple-Layer Defense" and reliance on "Personal Macros" to clean data actually increase the manual verification workload (Theme 1.B.i.; 1.C.i.).	**Pragmatic Skepticism:** Because the tool has "Historical Data Deficiency" and "Contextual Blindness" (Theme 2.B.i.; 3.A.ii.), AI fails to act as an efficiency driver. Instead, it is a "risk object" that forces auditors to perform "sense-checks" to validate its outputs (Theme 1.B.).
Claim: Ongoing "staged implementation" of next-gen ecosystems indicates a transition toward GenAI maturity (Category 5).	**Observation:** Managers mandate manual costing/comparison despite the availability of tools like DataSnipper to ensure stability (Theme 3B).	**Stability over Innovation:** There is a conflict between the firm's desire for innovation and the managerial requirement for "bug-free" data, resulting in "Tool Shadowing" and intentional decoupling to protect daily work (Category 5; Theme 3B).

Note. Expectations were taken from the deductive QCA (Table 3). Realities were taken from inductive TA (Table 4). This table is an abductive synthesis of tables 3 and 4.

Abductive analysis (see Table 6) revealed that the contradiction between the policies at the macro level and practitioners' activities at the micro level could be explained by implementation theory proposed by Pressman and Wildavsky (1973). The similar contradictions were prevalent within the scope of globalization. While firms claimed to embrace the technology that puts human beings and artificial intelligence in synergy, the results demonstrated otherwise. Practitioners emphasized that automation did not mean the eradication of humans from the process, as the systems required extra adjustment to meet the needs of different countries in

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Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
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terms of regulation and other factors. Overall, while companies tried to adapt new technologies to fit the existing institutional framework, they still relied on their previous practices to ensure effective operations. Therefore, the efforts to maintain the audit procedures in the context of informatization resulted in software shadowing as practitioners used macros and other tools to facilitate the process while conforming to the policies of their firms.

5. Discussion

5.1 Interpretation of Findings and Theoretical Integration

5.1.1 Big Four Corporate Disclosures as Rationalized Myths (RO1). The Big Four rely on AI adoptions as legitimizing devices, which advance institutional legitimacy (Meyer & Rowan, 1977). Although disclosures generally conform to the UAE National Strategy 2031 (United Arab Emirates National Program for Artificial Intelligence, 2018) and Egypt's developmental goals (National Council for Artificial Intelligence, 2025), the prevalence of vague and aspirational language suggests limited substantive guidance on actualizing these objectives (Power, 1997). This reflects mimetic isomorphism as regional subsidiaries and practices are used to position the parent entities as competitive within uncertain markets (DiMaggio & Powell, 1983). Collectively, these insights add to isomorphic processes by indicating that symbolic adoption precedes substantive transformation in emerging markets (Finch & Butt, 2025).

5.1.2 Lived Operational Realities and the Ceremonial Gap (RO2). Operational realities are different from what is presented by the corporation about the implementation of AI-enabled systems are decoupled from day-to-day auditing practices (Meyer & Rowan, 1977). While corporate disclosures depict processes where AI technologies are leveraged efficiently, practitioners reveal that such tools are not mature enough to perform independently and require continuous human input to produce accurate results. The very nature of such models, which is based on non-deterministic systems, decreases the levels of trust among professionals (Burrell, 2016; Orlikowski, 2007). As a result, accountants tend to rely on impromptu testing and utilize various manual workarounds (Leonardi, 2011). Similar findings are reported by Seethamraju and Hecimovic (2022) who witness that advanced AI tools obscure field practices and require human involvement to correct errors. Ultimately, the role of humans is critical in ensuring data reliability within the accounting field. However, such a systemic lack of transparency can lead to immediate susceptibility to automation bias if human monitoring is reduced (Detzen & Gold, 2021).

5.1.3 Means–Ends Decoupling in Regional Quality Management (RO3). The quality management systems differ significantly in different regions, thus highlighting the disconnect between corporate discourse and practice. The Big Four's agencies use the global auditing platforms, including Aura, Omnia, and Clara, to meet the requirements of networks. At the same time, the practitioners use manual interventions to address the conflicts between the software and the local regulatory frameworks, such as IFRS-configured procedures and EAS (Bromley & Powell, 2012; Kostova & Roth, 2002). In this regard, artificial intelligence is an isolated administrative tool that is not integrated into the broader auditing processes, thus creating a reliance on manual interventions for assurance. Therefore, the transition to the new auditing tools is dependent on the regulatory environment and the role of human intervention (Power, 1997; Birhane et al., 2024).

5.2 Implications of the Study

5.2.1 Theoretical Implications. This study extends the understanding of the relationship between institutional theory and sociomateriality by examining the ways in which diverse and often conflicting uses of AI systems characterize professional service organizations. By building on the theoretical foundation proposed by Bromley and Powell (2012), the findings presented below aim to contribute to ongoing debates on AI governance and control. Indeed, the analysis below sought to address the ways in which multinational corporate networks addressing different institutional logics reconcile the tension between policy–practice decoupling (Bromley & Powell, 2012). The analysis revealed that the emergence of institutional duality characteristic of AI governance in multinational professional service organizations shifts the type of decoupling from policy–practice to means–ends (Bromley & Powell, 2012). In addition, the study demonstrated that black-box opacity (Burrell, 2016) functions as a material barrier to institutionalization and

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

strategic response capacity in human-agent relations (Leonardi, 2011). This accounts for the observed lag in corporate AI narratives in emerging markets.

5.2.2 Practical Implications. The data indicates that implementing AI does not guarantee obtaining a quality audit. Leadership should consider how time-consuming the process of checking the work done by AI is and address the issue of automation bias accordingly. The guidelines should require auditors to conduct manual checks and exercises to confirm the accuracy of the work done by AI. Thus, the process of training and educating employees who will interact with these systems should go deeper into understanding limitations, structures, and data governance rather than learning how to navigate new programs.

5.2.3 Policy Implications. These findings can indicate that innovation signaling produces symbolic compliance, not actual improvement in the delivery of high-quality engagements. The recent IAASB roundtables outcome recommends the replacement of strategy-based ethical frameworks with verifiable AI disclosure practices (e.g., scope and limitations of individual models) by regulatory policy makers. Additionally, regulatory supervisory bodies (RSBs) should embed data-centric competencies within professional accounting qualification programs to better prepare accounting practitioners for the increased reliance on automated auditing processes.

6. Limitations of the Study

The primary limitation of this study stems from the restricted timeframe for data collection, which coincided with the statutory audit busy season. This time constraint inherently limited participant availability and the potential for prolonged engagement with more practitioners. Consequently, the interview sample is mainly composed of early-career practitioners; future research should expand this scope to incorporate the strategic perspectives of senior leadership, such as managers and partners. Furthermore, this narrow window restricted the use of broader sampling techniques and limited opportunities for deeper iterative analysis. Finally, the occasional absence of region-specific transparency reports necessitated a reliance on global network disclosures as proxy data, potentially introducing a degree of network-level bias into the evaluation of localized operational claims.

7. Conclusion

This study aims to investigate the incongruence between the corporate narratives about adopting AI in auditing tasks and the real-life practices of auditors. The research compares the statements of the Big Four companies' transparency reports and the regional practices of the firms in the UAE and Egypt. The study's design is based on the interpretivist paradigm and abductive methodology. It uses qualitative research methods and techniques of content and TA. In this study, the QCA of the selected Big Four companies' transparency reports is integrated with a qualitative TA of the semi-structured interviews with the auditors conducted in 2026. The findings demonstrate that the companies' statements about using AI are designed to promote symbolic communication to establish institutional legitimacy since firms' actual practices do not support such claims.

The study's results reveal that the discrepancies between organizational narratives and operational practices are explained by the tendency to meet national requirements related to the need to embrace technology-driven solutions and follow national AI strategies. At the same time, real-life auditing activities are hindered by a number of factors, including the complexity of AI technologies, their insufficient development, and audit-specific challenges. Therefore, auditors address the issues of adopting AI by relying on human expertise and using their own macro processes.

Thus, the study concludes that auditing practices do not support the narrative of embracing AI as a way to achieve legitimacy and ensure the quality of audits. This conclusion is based on the idea that human expertise is the only way to ensure professional skepticism and adequate auditing quality control. By integrating empirical research evidence and professional judgment, this study contributes to addressing technology governance concerns in the context of emerging technologies by demonstrating the necessity to rely on human expertise and evidence-based auditing practices. The research adds value by providing empirical support for theories and paradigms about technology governance and legitimacy and promoting appropriate technology adoption strategies for organizations operating in the MENA region.

Acknowledgments

The authors would like to thank the participants for their support and cooperation in conducting this study.

Contribution of Authors

All the authors participated in the ideation, development, and final approval of the manuscript, making significant contributions to the work reported.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Informed Consent

Informed consent was obtained from all individual participants included in the study.

Ethical Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of 1964 Helsinki declaration and its later amendments.

Data Availability

The datasets generated during and analyzed during the current study are available from the corresponding author on reasonable request.

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Appendix A
Semi-Structured Interview Protocol, Objective Mapping, and Justification

Table A1

Interview Protocol, Objective Mapping, and Justification

Identifier	Question	Main Target	Sub Target	Justification
Q1.	Global strategy for [PwC/Deloitte] often emphasizes a next-generation audit where AI facilitates a more human-led approach. In your daily experience with [Aura/Omnia] here in [UAE/Egypt], how does the reality of the workflow align with this vision of transformation, and in what ways does it alter—or perhaps replicate—traditional manual procedures?	Research Objective 2	Research Question	Directly interrogates the practical clarity of the vision of a human-led audit versus the reality of daily routines in the UAE/Egypt.
Q2.	In scenarios where both the IT team's movement checks and the AI tool's outputs provide a green light on journal entries, walk me through your process for investigating the potential for management override of controls. How do you ensure professional skepticism is maintained throughout this process?	Research Objective 3	Research Question	Evaluates the decoupling between the mandated exercise of skepticism and the material agency of the AI's green light outputs.
Q3.	Proprietary AI platforms often utilize standardized risk parameters established at a global network level. How do you reconcile these global rules with your localized knowledge of the business environment in the [UAE/Egypt]? Can you describe an instance where local market nuances required you to adjust or supplement the AI's findings?	Research Objective 2	Research Question	Explores the regional asymmetry and the clarity—or lack thereof—found when reconciling global network rules with MENA market nuances.
Q4.	When proprietary platforms struggle with disorganized client data, practitioners often have to find creative ways to maintain momentum. In your experience, how common is the use of supplementary or outside tools—such as personal Excel macros or publicly available AI tools—to assist with data cleaning or organization in practice? Where do you feel these workarounds sit in relation to the firm's formal quality management protocols?	Research Objective 3	Research Objective 1	Provides empirical proof of Implementation Gaps (e.g., using Excel macros) which can be synthesized against the formal AI-integrated claims of reports (Research Objective 1).
Q5.	The integration of AI is often positioned as a mechanism to enhance audit efficiency by accelerating the technical core of the process. In practice, as these tools produce increasingly sophisticated outputs, how do you manage the tension between the firm's performance metrics	Research Objective 3	Research Objective 2	Investigates the tension between institutional performance metrics (Meso-level) and professional audit quality requirements (Micro-level).

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Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
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Identifier	Question	Main Target	Sub Target	Justification
	(e.g. speed/efficiency) and the professional requirement for deep, manual scrutiny?			

Note. The interview protocol was developed by the author to align each interview question with the study's research objectives and overarching research question.

Appendix B

Deductive Coding Framework (Qualitative Content Analysis Codebook)

Table B1

Qualitative Content Analysis Codebook

Category	Subcategory	Definition	Inclusion Rule	Exclusion Rule
1. AI-Integration Claims	N/A	Statements that describe or reference the utilization of artificial intelligence, machine learning, advanced analytics, or automation within the specific context of audit processes.	The coder shall include any textual segments that explicitly mention artificial intelligence, machine learning, advanced analytics, or automation in auditing; reference digital audit tools, platforms, or data-driven systems; or describe the technological transformation of audit processes.	The coder shall exclude general statements of innovation or technology, which are not directly related to the audit function, generic statements of information technology infrastructure with no specific application to auditing, and technologies that are not applied to audit practice.
2. Audit Quality & Assurance Framing	N/A	Statements linking the application of artificial intelligence or digital technologies to the enhancement of audit quality, assurance, operational efficiency, or risk management.	The coder shall include any text indicating artificial intelligence as a means of improved audit quality or assurance; connections between AI and risk identification, detection, or mitigation; or AI's association with efficiency, consistency, and reliability in audit engagements.	The coder will eliminate generic statements about quality that do not specifically mention AI or other digital technologies, as well as generic statements about compliance and governance that do not specifically mention technology.
3. Implementation Specificity	3A: High Clarity	The level of operational detail provided regarding the specific mechanisms of AI implementation within professional audit practice.	The coder shall include segments where particular tools, platforms, or named systems are specified, concrete audit procedures are explained, such as journal testing or anomaly detection, and workflows or uses cases are specified.	The coder shall exclude general, abstract, or non-functional descriptions of technology.
	3B: Medium Clarity		The coding shall include segments where the text explains the functions without going into detail about the processes that achieve them, and that describe artificial intelligence in general terms, for instance, the application of analyzing information data in general.	The coder shall exclude fully detailed operational descriptions (High Clarity) as well as vague or purely rhetorical statements (Low Clarity).
	3C: Low Clarity		The coder shall include statements that are vague, abstract, or simply rhetorical in nature, or references to	The coder shall exclude any statements that provide clear functional or procedural detail regarding technology use.

Category	Subcategory	Definition	Inclusion Rule	Exclusion Rule
			artificial intelligence without elaboration on its function.	
4. Global-Regional Alignment	N/A	Statements indicating how global corporate AI strategies are implemented, adapted, or constrained at regional levels, specifically within the UAE and MENA jurisdictions.	The coder shall include any text that references global audit platforms or systems; describes regional implementation or adaptation of these systems; or mentions regulatory and jurisdictional constraints affecting AI deployment.	The coder shall exclude purely global statements that carry no regional implication, and local statements that have no connection to broader global structures.
5. Evidence of Decoupling	N/A	Statements indicating a functional gap, inconsistency, or institutional tension between strategic AI claims and actual implementation or clarity of execution.	The coder shall include any text referring to pilot programs or partially implemented initiatives, indicating implementation on a limited or experimental basis, containing vague statements not specifying activities or operations to be performed, or suggesting areas of strategy that are aspirational or inconsistent with demonstrated actions.	The coder shall exclude implemented and fully specified AI use cases, as well as general descriptive statements that do not imply any institutional tensions.
6. Institutional / Legitimacy Framing	N/A	Statements presenting artificial intelligence as a component of strategic positioning, innovation leadership, or legitimacy-building rather than providing operational detail.	The coder shall include any text referring to or suggesting leadership by the AI, innovation, or transformation; using inspirational or aspirational language; and positioning the AI as a strategic or reputational asset to the firm.	The coder shall exclude concrete implementation details and operational descriptions of how AI is used in specific audit tasks.

Note. Codebook developed by the author for the deductive QCA

Appendix C
Deductive Coding Output – Deloitte Transparency Reports (2021–2025)

Table C1

Deductive Coding of Deloitte Transparency Reports (2021–2025)

Excerpt with Source	Year	Category	Subcategory	Justification	Source Type
"Deloitte Bulgaria auditors are enhancing procedures by making more use of data-driven analytics, as well as cognitive and cloud-based technologies like Artificial Intelligence (AI)" (Deloitte, 2022, p. 7).	2021	Category 1: AI-Integration Claims	N/A	Explicitly identifies AI as a tool for enhancing procedural execution.	Proxy (EU)
"Deloitte Bulgaria has released Deloitte Omnia, our next-generation cloud-based audit delivery platform, as well as Deloitte Levvia, a tailored solution to support our very small audits" (Deloitte, 2022, p. 7).	2021	Category 3A: High Clarity	Implementation Specificity	Identifies specific, named digital audit platforms utilized in practice.	Proxy (EU)
"With automation that improves routine tasks, analytics that yield a deeper and more insightful view into the data, and artificial intelligence that enhances human discovery and problem-solving" (Deloitte, 2022, p. 7).	2021	Category 2: Audit Quality & Assurance Framing	N/A	Associates AI with the qualitative enhancement of professional problem-solving.	Proxy (EU)

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ISSN-p: 3006-2284, ISSN-e: 3006-0982
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Excerpt with Source	Year	Category	Subcategory	Justification	Source Type
"Further development, enhancement, and broad deployment of both solutions will continue over the next several years" (Deloitte, 2022, p. 7).	2021	Category 5: Evidence of Decoupling	N/A	Indicates a gap between the current state and intended future broad deployment.	Proxy (EU)
"Through the use of fraud detection models using artificial intelligence (AI), we aim to conduct audits that can respond to fraud risks in a timely manner…" (Deloitte, 2023, p. 2).	2022	Category 3A: High Clarity	Implementation Specificity	Describes a concrete audit procedure (fraud risk response) using a specific model.	Proxy (EU)
"Deloitte OOD Audit & Assurance leaders participate in Deloitte network groups that set and monitor quality standards, and from which a number of audit quality initiatives emanate" (Deloitte, 2023, p. 5).	2022	Category 4: Global–Regional Alignment	N/A	Explicitly references the participation of regional leadership in global quality structures.	Proxy (EU)
"We are focused on incorporating advancing technological capabilities, such as artificial intelligence, into our business processes and methodologies" (Deloitte, 2024, p. 1).	2023	Category 3C: Low Clarity	Implementation Specificity	Mentions AI-integration in an abstract manner without functional or procedural detail.	Proxy (EU)
"This structure fosters shared investment in audit innovation and resources as well as the sharing of leading practices across geographies…" (Deloitte, 2024, p. 6).	2023	Category 4: Global–Regional Alignment	N/A	Outlines the mechanism for cross-geographic sharing of global innovation strategies.	Proxy (EU)
"By incorporating advanced technologies, such as Generative Al, we are able to accelerate processes and empower our people to focus on high-value activities that drive quality" (Deloitte, 2025a, p. 2).	2024	Category 2: Audit Quality & Assurance Framing	N/A	Directly links the adoption of GenAI to improvements in audit quality.	Proxy (EU)
"We are assessing how we can use Gen Al in our audits and remain focused on harnessing the power of cognitive technologies within our Deloitte Omnia and Deloitte Levvia platforms" (Deloitte, 2025a, p. 9).	2024	Category 5: Evidence of Decoupling	N/A	Indicates an exploratory or assessment phase rather than operational implementation.	Proxy (EU)
"Silver Stevie Award: Award for Innovation in Artificial Intelligence (Al) and Machine Learning (ML) - Financial Services…" (Deloitte, 2025b, p. 22).	2025	Category 6: Institutional / Legitimacy Framing	N/A	Uses industry awards as a signal of innovation leadership and reputational value.	Primary
"CURA Learning (a digital platform, using Artificial Intelligence technology, that provides curated learning resources based on the users knowledge, needs and interests)…" (Deloitte, 2025b, p. 20).	2025	Category 3B: Medium Clarity	Implementation Specificity	Provides a functional description of an AI platform used for internal development.	Primary
"NSE holds practice rights to provide professional services using the 'Deloitte' name which it extends to Deloitte entities within its territory (including the Middle East Countries and Deloitte UAE)" (Deloitte, 2025b, p. 5).	2025	Category 4: Global–Regional Alignment	N/A	Establishes the structural link between the global North and South Europe (NSE) entity and the UAE.	Primary
"We are evaluating the impact of Al and GenAl implementation on financial reporting and other	2025	Category 1: AI-	N/A	Describes the application of AI to	Primary

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
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Excerpt with Source	Year	Category	Subcategory	Justification	Source Type
disclosures within the entities Deloitte audits…" (Deloitte, 2025b, p. 15).		Integration Claims		the audit of client financial disclosures.	
"Going forward. [W]e believe Gen AI will further support our auditors in delivering high quality audits including supporting further risk-sensing, identification of potential issues, and automation of certain processes" (Deloitte, 2025b, p. 15).	2025	Category 6: Institutional / Legitimacy Framing	N/A	Employs aspirational language to frame AI's future impact on audit quality.	Primary

Note. The coding results presented below were obtained through the author's deductive QCA of Deloitte transparency reports (2021-2025). In this context, reports labelled "Primary" were prepared by Deloitte Middle East, while reports labelled "Proxy (EU)" were issued by Deloitte's European member firms acting as proxies for the Middle East region when local reports were unavailable.

Appendix D

Deductive Coding Output – EY Transparency Reports (2021–2025)

Table D1

Deductive Coding of EY Transparency Reports (2021–2025)

Excerpt with Source	Year	Category	Subcategory	Justification	Source Type
"Through a data-first approach enabled by analytics and digital tools, teams were able to deliver high-quality audits with independence, integrity, objectivity and professional skepticism" (EY, 2021, p. 9).	2021	Category 2: Audit Quality & Assurance Framing	N/A	Links analytics and digital tools to the achievement of core audit quality principles.	Primary
"Using EY Canvas and Milestones (se page X) [sic], as well as ever more sophisticated artificial intelligence (AI) tools, the QELs are able to build a picture of audit quality performance in real time" (EY, 2021, p. 9).	2021	Category 3A: High Clarity	Implementation Specificity	Identifies specific global platforms (Canvas) and the use of AI tools for real-time quality monitoring.	Primary
"EY member firms continue to develop the audit of the future, including ever more sophisticated data analytics, efficiently delivering greater insight and assurance…" (EY, 2021, p. 9).	2021	Category 6: Institutional / Legitimacy Framing	N/A	Uses aspirational language ("audit of the future") to frame technological development as a strategic asset.	Primary
"EY has deployed leading technological tools that enhance the quality and value of EY audits, including the EY Canvas online audit platform, EY Helix analytics platform and EY Atlas research platform" (EY, 2022, p. 14).	2022	Category 3A: High Clarity	Implementation Specificity	Explicitly names the firm's primary digital audit and analytics platforms (Canvas, Helix, Atlas).	Primary
"EY Smart Automation is the library of smart automation solutions that automate audit procedures and processes. EY Smart Automation is deployed through an automation hub directly integrated within EY Canvas" (EY, 2022, p. 21).	2022	Category 3A: High Clarity	Implementation Specificity	Describes a specific functional integration between automation capabilities and the main audit platform.	Primary
"A broader adoption of these data analytic tools is set to occur this year" (EY, 2022, p. 15).	2022	Category 5: Evidence of Decoupling	N/A	Indicates that full adoption of tools has not yet been achieved, revealing a partial implementation status.	Primary
"This commitment includes a US$1b investment in a next-generation Assurance technology	2023	Category 6: Institutional /	N/A	Frames technology through large-scale capital investment	Primary

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
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Excerpt with Source	Year	Category	Subcategory	Justification	Source Type
platform to facilitate trust, transparency and transformation" (EY, 2023, p. 4).		Legitimacy Framing		and high-level strategic objectives.	
"EY Helix enables EY teams to analyze over 775 billion lines of journal entry data annually" (EY, 2023, p. 20).	2023	Category 3A: High Clarity	Implementation Specificity	Provides concrete operational metrics (volume of data processed) for a named analytical tool.	Primary
"At the heart of our transformation is driving consistency in how we apply our audit methodology, how we manage our audits and how we use innovative technology" (EY, 2023, p. 4).	2023	Category 4: Global–Regional Alignment	N/A	Describes the use of technology to ensure methodological consistency across the global network.	Primary
"In 2023, EY released more than 20 new major Assurance technology capabilities… include globally scaled artificial intelligence (AI)" (EY, 2024, p. 22).	2024	Category 1: AI-Integration Claims	N/A	Explicitly identifies the release of globally scaled AI capabilities for assurance services.	Primary
"These Al-enabled capabilities… are directly, seamlessly integrated with EY Canvas to support EY Assurance professionals in assessing risk" (EY, 2024, p. 22).	2024	Category 3A: High Clarity	Implementation Specificity	Identifies specific Al integration within a named platform for the concrete audit procedure of risk assessment.	Primary
"EY is also introducing new Al-enabled capabilities in predictive analytics; content search and summarization; and document intelligence, including financial statement tie-out procedures" (EY, 2024, p. 22).	2024	Category 3A: High Clarity	Implementation Specificity	Describes concrete audit procedures (financial statement tie-out) and specific AI functions (predictive analytics).	Primary
"Al at scale and other intelligent capabilities help to drive quality by standardizing processes and leveraging data to provide risk guidance and relevant recommendations to EY teams" (EY, 2024, p. 22).	2024	Category 2: Audit Quality & Assurance Framing	N/A	Associates AI-driven standardization and data leverage with improved audit quality and risk guidance.	Primary
"Enhanced forensics metrics, which use data to identify indicators of elevated risk of fraud based on application of machine learning techniques to historical financial statement data sets…" (EY, 2024, p. 24).	2024	Category 3A: High Clarity	Implementation Specificity	Provides operational detail on the application of machine learning for specific fraud risk assessment.	Primary
"The topics currently in-scope of the Global Compliance Office are Artificial Intelligence (AI) compliance, data compliance, conflicts of interest…" (EY, 2025, p. 18).	2025	Category 1: AI-Integration Claims	N/A	Explicitly mentions AI within the functional scope of corporate compliance and governance.	Primary
"We are taking a number of actions to enhance audit quality, including… modernizing our approach with guided workflows and cutting-edge technology…" (EY, 2025, p. 3).	2025	Category 3C: Low Clarity	Implementation Specificity	Uses vague and rhetorical terms ('cutting-edge technology')	Primary

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Excerpt with Source	Year	Category	Subcategory	Justification	Source Type
				without identifying specific systems or procedures.	

Note. The coding results presented below were obtained through the author's deductive QCA of EY transparency reports (2021-2025). In this context, reports labelled "Primary" were prepared by EY MENA, while reports labelled "Proxy (EU)" were issued by EY's European member firms acting as proxies for the Middle East region when local reports were unavailable.

Appendix E
Deductive Coding Output – KPMG Transparency Reports (2021–2025)

Table E1
Deductive Coding of KPMG Transparency Reports (2021–2025)

Excerpt with Source	Year	Category	Subcategory	Justification	Source Type
"We have dedicated significant investment in best-in-class technology such as KPMG Clara (our smart and intuitive technology platform that is driving globally consistent audit execution) and tools for engagement teams" (KPMG, 2021, p. 5).	2021	Category 3A: High Clarity	Implementation Specificity	Identifies a specific, named smart audit platform (KPMG Clara) and its global role.	Primary
"The expanding role of innovation and technology in audit continues to evolve, providing greater clarity and generating deeper and richer insight" (KPMG, 2021, p. 6).	2021	Category 2: Audit Quality & Assurance Framing	N/A	Associates technological evolution with the qualitative outcome of deeper audit insights.	Primary
"KPMG Clara Steering Committee… responsible for overseeing the staged implementation of our KCw in accordance with the global milestones" (KPMG, 2021, p. 12).	2021	Category 5: Evidence of Decoupling	N/A	Mentions "staged implementation," indicating partial or ongoing rather than full adoption.	Primary
"KPMG Clara delivers smarter, data-driven outcomes and deeper insights by blending the best of technology with the best of our people" (KPMG, 2022, p. 3).	2022	Category 3A: High Clarity	Implementation Specificity	Describes the functional blending of technology and human expertise within a named platform.	Primary
"Globally, this market-leading technology helps our 90,000+ audit professionals in 144 countries, deliver consistent high-quality audits in a seamless way" (KPMG, 2022, p. 3).	2022	Category 4: Global–Regional Alignment	N/A	References the global network's technological scale and its impact on regional audit consistency.	Primary
"Review the outcome of global audit quality initiatives/programs including… Clara data mining…" (KPMG, 2022, p. 7).	2022	Category 1: AI-Integration Claims	N/A	Explicitly mentions a specific AI-related technique (data mining) within the audit platform.	Primary
"The firm has made significant investments in technology, training, and personnel to ensure that our teams attract and retain top talent and provide excellent service to our clients in the region" (KPMG, 2023, p. 4).	2023	Category 6: Institutional / Legitimacy Framing	N/A	Frames technology investment as a strategic asset for talent retention and regional service excellence.	Primary
"In 2024, changes driven by the rise of Artificial Intelligence (Al) and growing importance and regulation of Environmental, Social and Governance (ESG) reporting have led to an increasing demand for greater trust…" (KPMG, 2024, p. 4).	2024	Category 1: AI-Integration Claims	N/A	Mentions the "rise of AI" as a significant driver for changes in the reporting and trust landscape.	Primary

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Excerpt with Source	Year	Category	Subcategory	Justification	Source Type
"With KPMG Clara, our cloud-based audit platform, we are integrating trusted generative Al to make audits more efficient and accurate" (KPMG, 2024, p. 4).	2024	Category 3A: High Clarity	Implementation Specificity	Identifies the specific integration of "generative AI" into the named audit platform to improve accuracy.	Primary
"Digital Audit in KPMG LG integrates Tech Assurance and Data & Analytics (D&A) capabilities, bringing together resources who are experts in technology audits, data analytics and information security" (KPMG, 2024, p. 17).	2024	Category 1: AI-Integration Claims	N/A	Describes the internal organizational integration of digital audit and analytics capabilities.	Primary
"Our D&A technologies have spread across General Ledger analytics with Clara Advanced Analytics as well as various standard and tailored sub ledger analytics solutions" (KPMG, 2024, p. 17).	2024	Category 3A: High Clarity	Implementation Specificity	Provides operational detail on specific analytics solutions (Clara Advanced Analytics) used for ledger testing.	Primary
"…transforming our approach through continuous innovation, strategic integration of Artificial Intelligence (Al) and an unwavering commitment to quality and professional excellence" (KPMG, 2025, p. 4).	2025	Category 6: Institutional / Legitimacy Framing	N/A	Uses future-oriented and strategic language to frame AI-integration as part of a transformation journey.	Primary
"We are proud to be leading the transformation through our global smart audit and assurance platform, KPMG Clara, now enhanced with Al agents and generative Al capabilities" (KPMG, 2025, p. 4).	2025	Category 3A: High Clarity	Implementation Specificity	Identifies concrete enhancements to the platform, including "AI agents" and "generative AI."	Primary
"These leading technologies are embedded directly into the audit workflow to support risk assessment, testing procedures and documentation…" (KPMG, 2025, p. 4).	2025	Category 3A: High Clarity	Implementation Specificity	Specifies the exact stages of the audit workflow (risk assessment, testing) supported by the technology.	Primary

Note. The coding results presented below were obtained through the author's deductive QCA of KPMG transparency reports (2021-2025). In this context, reports labelled "Primary" were prepared by KPMG Lower Gulf, while reports labelled "Proxy (EU)" were issued by KPMG's European member firms acting as proxies for the Middle East region when local reports were unavailable.

Appendix F
Deductive Coding Output – PwC Transparency Reports (2021–2025)

Table F1

Deductive Coding of PwC Transparency Reports (2021–2025)

Excerpt with Source	Year	Category	Subcategory	Justification	Source Type
"We continuously invest in innovation and new technology… to meet the changing challenges in a digital age and to enhance the quality of our audit services" (PwC, 2021, p. 4).	2021	Category 2: Audit Quality & Assurance Framing	N/A	Explicitly links investment in new technology to the enhancement of audit service quality.	Primary
"We aim to achieve a perfect blend of people and technology, reimagining the audit and how we bring the best of human and machine intelligence to our clients" (PwC, 2021, p. 5).	2021	Category 6: Institutional / Legitimacy Framing	N/A	Employs aspirational language regarding "machine intelligence" and "reimagining the audit" as a strategic vision.	Primary

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Excerpt with Source	Year	Category	Subcategory	Justification	Source Type
"This includes a US $1bn investment in a multi-year programme to deliver a new audit ecosystem, which is human-led, tech-powered and data-driven" (PwC, 2022, p. 4).	2022	Category 6: Institutional / Legitimacy Framing	N/A	Frames technological advancement through large-scale strategic investment and brand narratives.	Primary
"It will enable us to make continuous improvements to audit quality by further standardising, simplifying, centralising and automating our audit work…" (PwC, 2022, p. 4).	2022	Category 2: Audit Quality & Assurance Framing	N/A	Attributes automation and the new tech ecosystem with the specific outcome of improved audit quality.	Primary
"Today, we have powerful platforms and tools… as we consider how to enhance our use of technology and data in the future to communicate securely and provide better insights to our audit clients" (PwC, 2022, p. 5).	2022	Category 6: Institutional / Legitimacy Framing	N/A	Uses future-oriented language to frame technology as a tool for delivering superior client insights.	Primary
"In response to ISA 315R, the firm's global documentation platform, AURA, was updated to facilitate the engagement team's risk identification and risk assessment process" (PwC, 2023, p. 8).	2023	Category 3A: High Clarity	Implementation Specificity	Identifies a specific, named global platform (Aura) and its functional role in the risk assessment process.	Primary
"Through investing in emerging technologies and our upskilling programmes, we are supercharging citizen-led innovation, and sharing through the Digital Lab" (PwC, 2023, p. 19).	2023	Category 6: Institutional / Legitimacy Framing	N/A	Emphasizes "citizen-led innovation" and strategic internal platforms (Digital Lab) as reputational assets.	Primary
"It combines expertise in audit, tax and compliance activities with a drive to expand specialist capabilities in areas such as… Artificial Intelligence (AI)" (PwC, 2024, p. 4).	2024	Category 1: AI-Integration Claims	N/A	Explicitly identifies Artificial Intelligence (AI) as a core area for expanding specialist firm capabilities.	Primary
"Yet, from Gen AI to the climate, trust has never been harder to earn, nor easier to lose" (PwC, 2024, p. 5).	2024	Category 1: AI-Integration Claims	N/A	Mentions "Gen AI" as a relevant context for the current institutional challenge of establishing trust.	Primary
"With the power to transform data, apply predictive analytics and with automation at our fingertips, we will be able to provide clients and audit teams with a panoramic view of their audit landscape" (PwC, 2024, p. 5).	2024	Category 3C: Low Clarity	Implementation Specificity	Describes technological capabilities like predictive analytics in abstract terms without procedural detail.	Primary
"Halo, our data auditing tools, address large volumes of data, analysing whole populations to improve risk assessment, analysis and testing" (PwC, 2024, p. 26).	2024	Category 3A: High Clarity	Implementation Specificity	Names a specific data auditing tool (Halo) and provides a clear description of its functional application in testing.	Primary

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Excerpt with Source	Year	Category	Subcategory	Justification	Source Type
"We are building a revolutionary audit ecosystem and equipping our auditors with new digital capabilities to deliver a Next Generation Audit…" (PwC, 2024, p. 5; 2025, p. 5).	2024/2025	Category 5: Evidence of Decoupling	N/A	Mentions the ongoing "building" of an ecosystem, indicating a multi-year transition rather than full current adoption.	Primary
"As demand grows in areas like ESG, controls, and AI, we continue to engage with investors… to stay ahead of expectations" (PwC, 2025, p. 5).	2025	Category 1: AI-Integration Claims	N/A	Positions AI as a key area of growing demand for institutional transparency and stakeholder engagement.	Primary
"We combine our core strengths in audit, tax, and compliance with growing capabilities in cybersecurity, data privacy, ESG, and AI — all underpinned by a deep commitment to quality and governance" (PwC, 2025, p. 4).	2025	Category 1: AI-Integration Claims	N/A	Explicitly references AI as a growing capability that is integrated with the firm's quality and governance framework.	Primary

Note. The coding results presented below were obtained through the author's deductive QCA of PwC transparency reports (2021-2025). In this context, reports labelled "Primary" were prepared by PwC Middle East, while reports labelled "Proxy (EU)" were issued by PwC's European member firms acting as proxies for the Middle East region when local reports were unavailable.

Appendix G
Inductive Analysis Phase 1 – Familiarization with Data

Table G1

Participant Characteristics and Key Systems Identified During Familiarization

Identifier	Firm	Region	Key Systems Mentioned in Interview
Associate A = P1	PwC	Egypt	Aura, Halo, ChatPwC, Copilot (P1)
Associate B = P2	Deloitte	UAE	Omnia, PairD, DataSnipper, Deloitte Connect (P2)
Associate C = P3	PwC	Egypt	Aura, Halo, Alteryx, ChatPwC, Copilot (P3)
Senior A = P4	PwC	UAE	Aura, Halo, Copilot (P4)
Associate D = P5	Deloitte	UAE	Omnia, Levvia, PairD, DataSnipper (P5)

Note. This table presents the participant codes and the key systems (audit-focus) identified by the participants for their respective organizations.

Appendix H
Inductive Analysis Phase 2 – Initial Code Generation

Table H1

Initial Codes Generated During Phase 2 of the Inductive Thematic Analysis

Category A: Tool Functionality & Integration	Category B: Professional Skepticism & Human Agency
System Partitioning: Distinguishing between tools for large clients (e.g. Deloitte Omnia) vs. small clients (e.g. Deloitte Levvia) (P5; Deloitte, 2022; 2023; 2024; 2025a; 2023b)	**Automation Trust vs. Scrutiny:** A rift between those who felt that "green lights" reduced their workload, while those who increased their skepticism "tenfold" because they had to review the tool itself (P3) (P1).
Administrative Automation: Using AI for non-audit tasks like email drafting, translation, and document summarization (P5).	**The Triple-Layer Defense:** A recurring workflow: First, IT Check. Second, AI Output. Third, Human "Sense Check" (P1; P2; P4; P5).
The Similarity Conflict: Global tools using international standards (International Financial Reporting Standards) in the context of their local environment, where their application is required (Egyptian Accounting Standards) (P1; P3).	**Contextual Blindness:** The inability of AI to recognize "out-of-box" nuances, such as historical intercompany patterns or government links (P5).

Proprietary Constraints: Strict prohibition of public AI tools (e.g., OpenAI ChatGPT/Google Gemini) due to data sensitivity, replaced by sanctioned firm versions (e.g., ChatPwC/PairD) (P1; P3; P4; P5).	**Judgment Preservation:** The consensus that AI cannot supplement final "professional judgment" or handle "significant risk" areas like impairment assessments (P3; P5).

Note. Initial codes developed during the second stage of the inductive thematic analysis are presented below. The labels reflect the participants' transcripts (P1-P5).

Appendix I

Inductive Analysis Phase 3 – Searching for Coded Themes

Table I1

Candidate Themes and Subthemes Identified During Phase 3 of the Inductive Thematic Analysis

Theme	Description	Sub-themes
1. Ceremonial vs. Functional Gap	This theme explores the misalignment between firm marketing and practitioner utility.	- **Marketing as Ceremonial:** P1 uses this term to describe AI. - **Next-Gen Audit as Procedure Updates:** P3 says that the "Next Generation Audit" (PwC, 2023; 2024; 2025) was interpreted by them as an updated manual processes and regional risk repositories, rather than AI-driven interventions. - **System Refinement vs. Transformation:** P4 notes that Aura is a "refined" version of traditional systems rather than a transformative AI shift.
2. Regional / Local Shortcomings	This theme identifies the specific gaps where global software fails to address Middle Eastern nuances.	- **Standard Mismatch (IFRS vs. EAS):** P1 and P3 both mentions how ChatPwC creates an additional level of manual verification due to differing standards and that the AI does not account for local applications in its output. - **Informal Practices Nuance:** P5 discusses one of the main limitations of using AI in audits, including the inability to capture informal interactions, meetings, and behaviors.
3. Early-Stage Immaturity	This theme captures the current limitations and the developmental trajectory of audit AI.	- **Immature AI:** P5 repeatedly characterizes the current state of AI as being in a "baby" stage or starting phase. - **Historical Data Deficiency:** P5 explains that current systems struggle to compare multi-year historical data to predict current-year adjustments. - **Managerial Skepticism:** P5 notes that even when tools like DataSnipper are available, managers still mandate manual costing and comparison due to distrust in the tool's maturity.

Note. Candidate themes and subthemes identified during the searching phase of an inductive thematic analysis (Phase 3). P1–P5 refer to participants as indicated in the transcripts.

Appendix J

Inductive Analysis Phase 4 – Reviewing the Themes

Table J1

Review of Emerging Themes Against the Interview Data

Emerging Theme	Supporting Question (see Appendix A)	Supporting Evidence
Operational Reality vs. Marketing	Q1	"I don't see how this constitutes a 'next-generation audit'; it reflects more updated procedures aligned with current practices" (P3).
Trust Layering	Q2	"…when AI is introduced, professional skepticism must increase… as auditors must be skeptical not only of the client but also of the tool" (P1).
Contextual Shortcomings	Q3	"…currently, the AI does not compare the company's historical data; it focuses only on current-period issues" (P5).
Tool Shadowing	Q4	"Use of external tools is forbidden under firm policy. However, we do use personal macros designed for specific tasks. For example, when certain accounting entries are

Journal of Business Insight and Innovation
Volume 5 Issue 7, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

Emerging Theme	Supporting Question (see Appendix A)	Supporting Evidence
		assessed as low risk, macros help identify and link related entries to support filtering and review processes” (P4).
Judgment Bottleneck	Q5	“Tasks requiring judgment are still carried out manually rather than using AI. We mainly use it as a search tool, which significantly improves efficiency compared to manual searching” (P3).

Note. The emerging themes were evaluated using relevant extract of interview conducted during phase 4 (reviewing themes) of inductive thematic analysis. The supporting interview questions were provided in the semi-structured interview protocol (see Appendix A).

Appendix K
Inductive Analysis Phase 5 – Theme Definition

Table K1

Final Theme Definitions Developed During Phase 5 of the Inductive Thematic Analysis

Theme / Sub-theme	Definition	Key Points
Theme 1: Ceremonial vs. Functional Gap	Divergence between firm-level AI positioning as transformative—“next-generation audit” (PwC, 2023; 2024; 2025)—and practitioners’ lived experience of AI as incremental, supportive, and non-transformational.	AI is perceived as enhancing efficiency rather than transforming audit practice; core manual judgment remains central.
A. Technological Posturing vs. Procedural Continuity	Disjunction between strategic branding of AI and its operational reality in audit workflows.	**- Refinement over Transformation:** Such tools as Aura can be described as “refined” and “developed” methods to achieve better organization (linking/grouping), but they are not seen to change the auditor’s core functions (P4). **- The Ceremonial Label:** P1 clearly states that the integration is “ceremonial” and that while the firm promises a fundamental change, the tools are not “as powerful or as effective as they are made out to be.”
B. Sense-Check as Functional Guardrail	Human judgment remains a mandatory layer that constrains AI autonomy and ensures verification of outputs.	**- Professional Skepticism:** AI is relegated to a “search engine” or “documentation” assistant (P3; P4) because it lacks the “out-of-the-box” thinking (P1; P5) required for high-risk judgments (P3; P5). **- Verification Cycles:** Even if systems indicate the “go,” the practitioner must perform their own “green light” analyses (P1; P4; P5) to ensure that the system has not failed to account for subtleties, such as intercompany history (P5) and regional political ties (P5).
C. Operational Workaround Reality	When AI systems are insufficient for local or unstructured data, auditors rely on manual or informal tools.	**- Personal Macros:** Practitioners use “personal macros” in Excel to clean data because their “proprietary AI” fails to address the “unique formatting conventions of regional clients” (P4; P5).

Note. Final themes, subthemes, and definitions established during phase 5 (defining and naming themes) of the inductive thematic analysis. The P stand for the participants (P1–P5).