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The Effect of Using Artificial Intelligence Tools on the Professional Skepticism Traits of Auditors: A Field Study

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ABSTRACT

The primary objective of this research is to investigate the impact of using artificial intelligence (AI) tools on the professional skepticism traits of auditors in Egypt. To achieve this aim, a field study was conducted, analyzing 191 valid questionnaires. The Kruskal-Wallis test was employed to identify differences in auditors' opinions regarding the positive effects of AI tools on professional skepticism during the audit process, based on years of experience. The findings reveal agreement among Egyptian auditors regarding the positive impact of AI tools on certain professional skepticism traits, specifically the search for Knowledge and understanding of personal relationships. However, variations were observed in other aspects, including questioning mind, suspension of judgment, autonomy, and self-confidence. This study contributes to the existing literature by illuminating the complex relationship between technology adoption and professional skepticism in auditing. It offers a detailed perspective within the Egyptian context, emphasizing the role of years of experience in shaping auditors' attitudes towards technological advancements and their effects on professional skepticism traits. This enhances the academic understanding of how technological adoption influences core audit competencies, and they offer guidance for audit firms seeking to strike a balance between AI and auditor judgment. Additionally, it emphasizes the need for training programs that bridge the practical experience gap for auditors when integrating artificial intelligence into the audit process.

KEYWORDS

Artificial Intelligence – Advanced technology in auditing - Professional skepticism - Auditor's traits

1. INTRODUCTION

The rapid integration of artificial intelligence (AI) into auditing processes is fundamentally reshaping the auditing profession. AI is not only automating data analysis, but it is also ushering in new possibilities for enhancing audit efficiency, effectiveness, and risk management by enabling auditors to process complex financial information with unparalleled speed and accuracy, so AI can be seen as an umbrella term in this global mega-trend that includes big data analytics and sophisticated machine learning algorithms to learn from the data and model the future (Lehner et al., 2022).

AI technologies such as machine learning, natural language processing, robotic process automation, and advanced data analytics are now pivotal in audit workflows. it facilitate the identification of anomalies, trends, and patterns, thereby equipping auditors with powerful tools for detecting hidden risks and potential fraud schemes (Abdullah et al., 2024; Hasan, 2022; Argyres et al., 2020). These innovations hold the promise of transforming the auditing landscape and are expected to contribute to an estimated economic impact of $15 billion by 2030 (Palomares et al., 2021). However, the adaptation of AI tools in audit processes also introduces new complexities in auditing process. Challenges related to data quality, integrity, and accessibility are critical, as insufficient or inaccurate data may result in biased models and compromised outcomes (Argyres et al., 2020). Furthermore, ethical considerations such as algorithmic bias, privacy, and transparency necessitate rigorous oversight to maintain public trust in the audit function (Murikah et al., 2024 ; Tiron-Tudor and Deliu, 2022; Lehner et al., 2022). As adopting AI in auditing provides many opportunities and challenges, it raises fundamental questions about how it affects the foundational traits that enhance audit quality, specifically professional skepticism.

Professional skepticism is defined as an attitude that includes a questioning mind and a critical assessment of audit evidence. Skepticism is often associated with behaviors such as inquiry, critical observation, careful contemplation, and the temporary withholding of belief (Muhammad et al., 2024). Professional skepticism is considered as an essential part of audit quality (Nelson, 2009). The appropriate exercise of professional skepticism is important for detecting and addressing indications of material misstatements, thereby reducing the risks of overlooking unusual circumstances, drawing overgeneralized conclusions from audit findings, and employing incorrect assumptions in audit procedures and result evaluation (IAASB, 2021). While AI tools can enhance judgment accuracy, streamline audit procedures, and improve data quality (Abdullah & Almaqtari, 2024; Abdulameer et al., 2022), there is concern that excessive reliance on automated systems may erode an auditor's professional skepticism (Kokina et al., 2025; Chaker, 2024; Appelbaum et al., 2017).

The adopting of AI tools into auditing procedures poses a significant challenge to maintaining professional skepticism. Traditionally, auditors depend on their skills, experience, and analytical judgment when assessing financial statements and internal controls. However, AI systems, despite providing efficiency and speed, can impose biases or constraints that may not be readily obvious. This necessitates a transformation in auditors' methodologies, changing from simply accepting AI-generated results to determine whether data is inadequate, biased, or altered (Kokina et al., 2025; Deliu, 2013; chaker, 2024; Deliu, 2024).

Research on professional skepticism distinguishes between "states" and "traits. While states are temporary conditions influenced by contextual circumstances, traits are more influenced by individual differences in thoughts, feelings, and behaviors and are considered more stable than states (Hurtt, 2010; Hurtt et al., 2013; Nolder and Kadous, 2018). Therefore, understanding how these auditors' professional skepticism traits interact with AI capabilities is essential not only for audit quality but also for training, regulation, and public trust in the use of AI tools in auditing.

Despite prior researches have focused on it the positive influence of AI on professional skepticism and it is impact on detecting of fraud and errors in financial statements, there is a notable lack in the literature specifically investigating how using AI tools affects the underlying traits of professional skepticism in auditors. The primary purpose of this study is to address this critical gap by investigating the effect of artificial intelligence tools on the traits of professional skepticism among auditors using the Hurtt (2010) Professional Skepticism Scale. This scale comprises six distinct traits, each with components that can impact the auditor’s degree of professional skepticism. This research aims to provide fresh insights into how technological advancements are transforming the foundational attributes of auditors, particularly in relation to professional skepticism.

The remainder of the research is organized as follows: Section 2 presents reviews the literature and highlights the underlying study rationale, including hypotheses development. Section 3 outlines the research methodology. Section 4 presents a comprehensive discussion of the results. Section 5 presents the conclusion and outlines future studies.

2. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

2.1 Literature Review

Study of (Puthukulam et al.,2021) Examine the impact of artificial intelligence (AI) and Machine Learning (ML) on professional skepticism and judgment among auditors in Oman. By exploring the role of AI and ML in auditing practices, the study aims to enhance audit efficiency by enabling the analysis of entire financial transactions, subsequently influencing professional skepticism and judgment. The study found that a strong positive correlation between the application of AI and ML-assisted professional skepticism and judgment, and the improved detection of errors and misstatements. This is due to the ability of AI and ML to verify complete data, a capability not present in manual auditing. While advocating for the integration of AI and ML in auditing processes, the study also emphasizes the importance of human intervention in conjunction with these technologies.

Study of (Nairi et al., 2021) explores how the use of AI and Machine Learning (ML) in auditing influences the professional skepticism and judgment of internal auditors in Oman. The research concluded that a high positive correlation exists between internal auditor responses regarding AI and ML in auditing, which leads to an enhanced professional skepticism and judgment of internal auditors. This means that AI and ML can assist auditors in making more informed professional judgments and exercising greater skepticism during the audit process. The use of AI and ML in auditing contributes to improved professional skepticism and judgment in selected companies in Oman. Hence, AI and ML assist auditors in making more informed judgments, which are less prone to human errors when conducted manually. Additionally, the research results indicate that the most significant factors influencing the application of artificial intelligence and machine learning are professional skepticism and judgment, management and employee attitudes, as well as the availability of accurate data and the cost of implementation. These Various factors have helped professionals develop skepticism and judgment.

Li (2022) examined the behavioral challenges auditors encounter when exercising professional skepticism while using Audit Data Analytics (ADA). The study highlighted five main perspectives: auditors' attitudes toward ADA, data characteristics, anomalies detected by ADA, auditors' mindsets, and the broader social and organizational context. Although ADA offers substantial benefits to audit practice, it also creates difficulties that may hinder appropriate levels of professional skepticism. Inappropriate attitudes toward ADA can bias auditors' evaluation of evidence, while unreliable or irrelevant data inputs require careful screening to avoid weakening skeptical judgment. The presence of numerous anomalies, false positives, and false negatives further complicates auditors' judgments. Additionally, cultivating the right mindset is essential to effectively apply skepticism in ADA contexts. Finally, social and organizational factors—such as leadership tone, collaboration with data specialists, audit committee stance, client IT sophistication, and regulatory environment—significantly shape how skepticism is exercised. The study concluded that awareness and preparedness for these behavioral challenges are critical to leveraging ADA's benefits for strengthening professional skepticism and improving audit quality.

Study of (Chaker, 2024) explores the impact of auditors' reliance on AI on their professional skepticism within the French audit profession. The study contributes to the existing literature by shedding light on the complex relationship between technological adoption and individual judgment in auditing. It offers insights into the importance of understanding how AI affects professional skepticism among auditors. The findings reveal a significant positive association between AI reliance and professional skepticism, moderated by trait skepticism. The positive effect of artificial intelligence on professional skepticism is particularly evident among auditors with high trait skepticism. Additionally, the findings underscore the crucial role of individual auditor traits, such as skepticism levels, in shaping their responses to technological advancements in auditing practices.

Deliu (2024) explored the interaction between AI and Human Intelligence (HI) in auditing, with particular focus on their influence on professional judgment and skepticism. The study compared AI's cognitive abilities with those of human auditors and emphasized their complementary roles. Human auditors demonstrate strengths in professional judgment, skepticism, ethical reasoning, emotional intelligence, and contextual understanding, all of which are essential for detecting errors or fraud and ensuring audit reliability. In contrast, AI excels in data processing, speed, and pattern recognition, enabling the efficient handling of large datasets, yet it lacks ethical discretion, intuitive reasoning, and the nuanced skepticism required in auditing. While AI can support auditors by detecting anomalies and automating repetitive tasks, it cannot replace the critical human capacity for judgment and ethical decision-making. The study concluded that a cautious and balanced integration of AI is necessary, where auditors continue to play a central role in safeguarding ethical standards and maintaining the integrity of financial reporting.

Saleh and Abdullah (2025) investigated the impact of AI on enhancing professional skepticism and its effect on fraud detection in financial reporting. The study found a statistically significant relationship between AI techniques and the development of professional skepticism among external auditors, as well as between professional skepticism and fraud detection effectiveness. It emphasized the dynamic nature of this relationship, where professional skepticism plays a key role in maintaining audit quality by guarding against excessive reliance on AI. This cautious stance creates a constructive professional resistance that compels auditors to verify AI outputs rigorously. Conversely, when AI is applied judiciously, it supports and enhances skepticism by efficiently analyzing large datasets to identify anomalies and unusual patterns better than traditional approaches. The study underscored that AI should be viewed not as a replacement but as a complementary tool that strengthens professional skepticism. It recommends that auditors consistently apply skepticism in evidence evaluation and in validating accounting estimates within financial statements.

Upon analyzing the previous research, the researcher observed that there is consensus that AI tools can enhance the level of professional skepticism exhibited by auditors, improving audit effectiveness in detecting anomalies and irregularities. Despite these benefits, the studies generally do not explore in depth how AI influences the stable, underlying traits of professional skepticism, focusing more on situational or context-dependent effects. The relationship between AI use and professional skepticism is complex and multifaceted, influenced by various factors including auditors' personal traits, experience, costs associated with AI adoption, and the degree of reliance on AI tools. While AI excels at identifying data irregularities and automating routine processes, it cannot fully substitute the nuanced judgment and inherent skepticism that human auditors apply in audits. The studies recommend a balanced integration of AI and human auditors, emphasizing the need to understand AI's impact on auditors' skeptical mindset to optimize audit quality.

There remains a significant lack of research specifically focused on how AI impacts the traits of professional skepticism in auditors. This gap leaves important questions unanswered about whether the adoption of AI technology alters the traits and behavioral characteristics that define auditors' professional skepticism. The objective of this study is to fill this gap by systematically examining how the integration of AI tools influences auditors' professional skepticism traits, including their disposition and critical evaluative abilities.

Additionally, the study aims to provide insights into the previously unexplored mechanisms by which AI may affect these skepticism traits within the context of auditing in Egypt.

2.2 Professional skepticism

Professional skepticism is considered one of the fundamental principles underlying the auditor's work, helping them resist bias, professional pressure, and excessive trust in management. The International Standard on Auditing (ISA 200) defines professional skepticism as "an attitude of questioning and a critical assessment of audit evidence, including a critical eye towards conditions that may indicate a material misstatement" (IAASB, 2009). The International Standard on Auditing (ISA, 240) also addressed professional skepticism as "a mindset of critical assessment and a questioning mind towards audit evidence, to alert to the possibility of errors that may arise from fraud or human error."Many researchers have also focused on studying professional skepticism and defining its concept. Professional Skepticism is often associated with attitudes such as inquiry, critical observation, thoughtful contemplation, and temporary suspension of belief (Muhammad et al., 2024). Nelseon (2009) indicated that professional skepticism is related to the judgments and decisions made by the auditor based on the available information, reflecting a high assessment of the risk of misstatements in management's assertions. As Hurtt et al. (2013) explained, it can be understood as the auditor's ability to apply professional judgment, which is intrinsically linked to the concept of audit quality. (Quadackers et al., 2014) added that the concept of professional skepticism is based on the presumption of dishonesty, where the auditor assumes a degree of dishonesty on the part of management unless the evidence indicates otherwise.

Several researchers have clarified that professional skepticism is not just a technical skill, but a blend of knowledge and personal (physiological) traits. Knowledge is related to the means that the auditor must use during the evidence-gathering process, while personal traits are related to the auditor's behaviors that raise questions during the audit process and primarily deal with measuring the depth and impact of the auditor's mental interrogation (Nolder and Kadous, 2018; Hurtt et al., 2013).

There are two primary and slightly different views of professional skepticism that have arisen. The first is the neutral view. This view of professional skepticism suggests that auditors do not assume any bias ex ante and therefore neither assume guilt nor innocence in the absence of conflicting evidence. The second view, presumptive doubt view, is more consistent with that of forensic auditors (Nelson, 2009; Hurtt et al., 2013). The majority of academic literature takes a presumptive doubt view of professional skepticism and classifies a skeptic as one “whose behavior indicates relatively more doubt about the validity of some assertion” (Nelson, 2009, p. 4). Consequently, the skeptic can be viewed as someone who has more doubt about what is true than the average person, and auditors who exhibit high professional skepticism need relatively more persuasive evidence to be convinced that an assertion is correct (Dickey et al., 2022).

2.2.1 Professional skepticism traits of auditors

The study by Hurtt (2010) is one of the most prominent studies that addressed the professional skepticism scale among auditors, as it clarified the existence of six characteristics that play an important role in determining the level of professional skepticism practices among auditors. This scale was developed to measure trait professional skepticism. Each attribute comprises components that have the potential to impact the investigator’s degree of professional skepticism. The Hurtt professional skepticism scale consists of six that can be divided into three dimensions as follows (Hurtt , 2010; Hurtt et al., 2013; Hussin & Iskandar, 2015; Dickey et al., 2022).

The first dimension: is the evidence based "trust but verify" that relates to how the auditor evaluates the evidence and the methods used in evaluating that evidence and includes:

- Questioning Mind: This refers to the auditor's ability to continuously question the validity of the evidence or information obtained during the audit process. It relates to the tangible proof that is sought for verification when statements or assertions are made.
- Suspension of judgment: This refers to the auditor needing to be convinced of the information or evidence obtained from the management of the economic unit before making decisions. The auditor should not make decisions before obtaining sufficient information.
- Search for Knowledge: it depends on the level of curiosity the auditor possesses during the audit process; it refers to the curiosity necessary to investigate beyond what may seem obvious. Consequently, this curiosity leads the auditor to further investigate the accuracy of information or evidence, which reduces uncertainty factors and helps in detecting misstatement.

The second dimension: is the behavioral-based "presumptive doubt" that aligns with the "presumptive doubt" view of professional skepticism that, the auditor's evaluation of the source of evidence and information and includes:

- Interpersonal understanding: The characteristic of understanding interpersonal relationships refers to the importance of the auditor studying the human aspects behind the implications of the evidence they receive, with the aim of understanding the incentives, pressures, opportunities, and justifications that drive the audit client to commit manipulation and violations.

The third dimension: is the self-reliance that relates to the auditor's personal ability to handle the available evidence and information and includes:

- Self-determination (Autonomy)**:** is related to independent thinking and the propensity to think autonomously. The auditor must make decisions courageously and impartially regarding the evaluation of audit evidence or the information obtained, and when presenting their unbiased technical opinion on the fairness and presentation of the financial statements.
- Self-Confidence**:** Self-confidence means the extent to which auditors believe in themselves and their abilities. This confidence leads to the formation of attitudes and behaviors related to understanding what can be done and what has been achieved, and setting the objectives of the review process.

2.2.2 Increasing interest in professional skepticism in the audit environment

The concept of professional skepticism has gained significant attention in recent decades (Ho et al., 2021). It is no longer seen merely as a personal trait or a skill that auditors can acquire; instead, it has become a fundamental pillar of audit quality (Chaker, 2024). This shift is particularly relevant in today's complex and evolving environment within the accounting and auditing profession. The Securities and Exchange Commission has emphasized that a lack of professional skepticism was a primary factor in the high-profile Satyam fraud case in India, which has drawn considerable attention in the U.S. over the past decade (Dickey et al., 2022). Sayed Hussin and Iskandar (2013) argue that auditors must maintain a high degree of professional skepticism throughout the audit process to implement effective audit procedures. Additionally, auditors may employ a continuum of professional skepticism, contingent upon the particular circumstances, in order to achieve an optimal balance between efficiency and efficacy in the execution of their duties (Muhammad et al., 2024). Several factors have contributed to the growing interest in the factors that influence auditors' professional skepticism, including:

- **The global financial crisis and financial scandals:** Since the collapse of major companies like Enron and WorldCom, practices of professional skepticism have come under societal and regulatory scrutiny. Many researchers stated that potential reason behind auditors' failure to identify instances of fraud and corruption through the auditing auditing process is a deficiency in professional skepticism (Muhammad et al., 2024). Auditors were criticized for not applying sufficient professional skepticism at that time, particularly regarding the review of fair values, related party transactions, and going concern assessments. This prompted regulatory and professional bodies to reinforce and emphasize the standards of professional skepticism in international auditing standards such as (ISA 200 & ISA 240) (Chaker, 2024). These financial scandals continue to affect the present day, including "the Wirecard scandal" in Germany, which declared bankruptcy in June 2020; Ernst & Young (EY), considered one of the largest auditing firms in the world, faced severe criticism for failing to detect this fraud.
- **The increasing complexity of the accounting and financial environment:** Professional skepticism has become an essential priority within the audit profession, especially as accounting procedures get more complicated and necessitate higher estimation, subjectivity, and judgment. Auditing standards consistently emphasize professional skepticism, asserting that audits must be designed and executed with a mindset of professional skepticism (Dickey et al., 2022). In light of the big data environment and rapid technological advancements, accounting evidence is no longer paper-based or traditional. Auditors no longer deal with standard accounting records; instead, they are digital, encompassing big data and transactions processed through complex systems such as Enterprise Resource Planning (ERP) systems (Jacky and Sulaiman, 2022). This transformation requires the auditor to exercise professional skepticism based on a deep understanding of the audit environment, which has become characterized by complexity and speed.
- **Adopting artificial intelligence tools in the auditing process:** The rapid development of artificial intelligence technologies has led to fundamental transformations in auditing practices, whether in terms of the nature of evidence, evaluation methods, or risk assessment. Although artificial intelligence tools provide significant support in data analysis and fraud detection, they cast a shadow over professional skepticism practices. The auditor is now required not only to question the data or procedures followed in the audit process but also to examine the results of algorithms and the decision-making analysis resulting from the use of artificial intelligence tools (Nolder and Kadous, 2018). So, auditors should be increasingly tasked with applying professional skepticism to information generated by automated systems (Appelbaum et al., 2017).

2.3 Artificial intelligence

The definition of artificial intelligence is constantly evolving, with different perspectives highlighting different aspects of the concept. Grewal (2014) suggested AI to be the mechanical simulation system of gathering knowledge and information that also processes intelligence of the universe. It involves collating and interpreting and finally disseminating the knowledge, information and intelligence to the eligible parties in the form of actionable intelligence. Lee & Tajudeen (2020) argued that AI allows machines to learn from their mistakes, adapt to new input, and perform human-like tasks, while also enabling data analysis and pattern recognition. Zhang et al. (2020) define AI a bit differently by saying that AI is the result of successful uses of big data and machine learning (ML) technology to comprehend the past and forecast the future using massive amounts of data. Artificial intelligence, according to most definitions, is hardware and software that can learn reason, adapt, analyze, make judgments, and execute complicated and judgment-based activities in the same way as the human brain can. Consequently, AI is a self-sustaining and developing technology. The more advanced its performance, the more intelligent it becomes, to the extent that machines are now instructing other machines and acquiring knowledge through experience (Hasan, 2022)

2.3.1 Application of artificial intelligence tools in auditing

Based on studying the existing literature, the most frequently mentioned areas of application include, but are not limited to, the following, as the tools of artificial intelligence used in the auditing environment vary according to purpose and function:

- Big Data Analytics: These tools rely on analyzing vast amounts of financial and non-financial data, including unstructured data such as emails and meeting reports. These tools help in discovering illogical patterns and relationships, enhancing the auditor's ability to identify risk areas and develop a risk-based audit strategy (Salijeni et al., 2019). Big data analytics also enable auditors to examine extensive audit evidence in ways that were previously not technically possible (Zhang et al., 2018).
- Machine Learning: Machine learning algorithms can be used to develop models capable of predicting fraud, classifying transactions by risk level, or learning from past review outcomes to improve decisions (Hasan, 2022). These models are used to evaluate historical data and predict future behaviors related to risks (Isa & Subramanian, 2024). Machine learning also allows for continuous model adjustments with each new review cycle, adding flexibility and self-evolution to the review tool (Appelbaum et al., 2017).
- Natural Language Processing (NLP): NLP techniques are used to analyze unstructured texts such as contracts, emails, and administrative reports, and to identify words or phrases that may indicate potential distortion or manipulation. These tools enable the auditor to handle data that were not traditionally examinable (Hezam et al., 2023). Natural language processing also helps in detecting inconsistencies or fraud indicators in internal documents without direct manual intervention (Herath et al., 2023).
- Fuzzy Logic: It is a technique of reasoning that resembles human thinking since its methodology mimics how humans make decisions. The truth value of variables in fuzzy logic can be any real number between 0 and 1, making it a type of many-valued logic. It’s used to deal with the concept of “partial truth” or “degrees of truth”, where the truth value can be somewhere between absolute true and absolute false (Hasan, 2022).
- Robotic Process Automation (RPA): Robotic Process Automation (RPA) represents the ideal tool for repetitive tasks that used to consume the auditor's time without adding any intellectual value. They are used to automate routine and repetitive tasks in auditing, such as data retrieval, updating work schedules, and automatic data matching from multiple sources. This reduces the time spent in the auditing process and allows the auditor to focus on analytical tasks (Moffitt et al., 2018).

- Intelligent Decision Support Systems: These systems provide data-driven recommendations to guide auditors in making specific decisions, such as assessing the sufficiency of evidence or the need to expand the scope of actions, and often rely on cognitive models and probability assessment algorithms (Issa et al., 2016).
- Fraud Detection Systems: Advanced algorithms such as Random Forest and neural networks are used to detect suspicious transactions or abnormal patterns, and these systems are often integrated with previous fraud databases by employing practical, efficient, accurate, and comprehensive methods to furnish reliable audit evidence and support the decision-making process (Tang & Karim, 2019).
- Hybrid Systems**:** Hybrid Systems may involve combination of any of the above discussed AI technologies. All the audit tasks are not of the same nature i.e. some involve quantitative analysis; some involve qualitative judgment whereas some may involve both (Hasan, 2022).

2.4 Using artificial intelligence tools and professional skepticism traits

AI tools have become a crucial component in enhancing the efficiency and effectiveness of auditing processes. However, the emergence of these tools has raised important questions about their impact on the professional skepticism traits of auditors. Literature has provided mixed results were using AI tools decreases and in other cases elevates the skepticism trait; we can express this through the three key trends as follows:

2.4.1 The first perspective:

The first viewpoint suggests that the use of AI tools positively enhances professional skepticism. This positive effect arises from several advantages that AI tools can provide, which can be summarized in the following points:

- Enhancing the ability to analyze evidence: AI tools improve an auditor's capability to analyze vast amounts of data with greater accuracy. They help identify complex patterns and detect anomalies more precisely than traditional methods. This enhancement supports the principles of logical skepticism and critical evaluation of evidence, reducing reliance on sampling and increasing the chances of uncovering material misstatements (Abdullah & Almaqtari, 2024). In other words artificial intelligence tools have emerged as powerful by automating evidence gathering, anomaly detection, and risk assessment, thereby enhancing effectiveness of audit evidence (Salijeni et al., 2019).
- Continuous inquiry: Artificial intelligence tools enhance the auditing process by providing advanced analyses and pinpointing areas of risk. This encourages auditors to ask deeper questions and persist in verifying information, thereby fostering a culture of continuous inquiry (Richins et al., 2017). Additionally, AI and machine learning enable auditors to focus on more critical aspects, such as estimations, risk assessment, and anomaly detection, rather than being bogged down with routine and repetitive tasks (Moffitt et al., 2018).
- Supporting impartiality: AI tools can help mitigate personal biases by delivering results and analyses based on accurate and independent algorithms, which enhances the objectivity of auditors (Dowling & Leech, 2014). Proponents argue that automating routine tasks minimizes human bias and emotion, leading to more objective and impartial audit judgments. Additionally, by reducing direct interactions between auditors and clients in sensitive situations, AI may lower the risk of familiarity threats and unconscious bias (lehner et al., 2022)
- Raising the level of cognitive processing: Cognitive processing is crucial for auditors to exercise appropriate skeptical judgment, particularly when tasks require a more in-

depth analysis (Nolder & Kadous, 2018). A study by Teye (2023) examined the influence of framing and optimism bias on professional skepticism. The findings revealed that optimism bias was associated with an increase in cognitive load, which was in turn associated with decreased professional skepticism. Thus, a higher cognitive load may be lead to a less skeptical mindset. Conversely, using AI tools can uncover unusual patterns and correlations, encouraging auditors to adopt more vigilant and analytical approaches (fundamental aspects of cognitive vigilance). According to Appelbaum et al. (2017), artificial intelligence enhances an auditor's ability to identify red flags through in-depth and real-time analysis of both structured and unstructured data. This improvement boosts their professional vigilance and allows for a more accurate and objective application of professional skepticism.

2.4.2 The second perspective:

Conversely, another perspective expresses concerns that the excessive and uncritical application of artificial intelligence tools may negatively affect professional skepticism traits if auditors depend on the systems' results without sufficient evaluation. These concerns can be summarized in the following points:

- Transparency and explainability: A central concern relates to the "black-box" nature of many AI systems used in auditing, where most artificial intelligence tools rely on complex structures known as "black-box", where it is difficult to interpret how the system arrives at its decisions or predictions (Arrieta et al., 2020). This ambiguity may affect the auditor's ability to evaluate the logic of the results, thereby weakening the elements of "critical appraisal" and "continuous inquiry" in professional skepticism. so recent studies with major audit firms find that, while AI can assist with procedural tasks, it is not yet considered reliable enough as a stand-alone tool, precisely due to its restricted transparency (Kokina et al., 2025)
- Algorithmic Bias: One of the significant challenges in maintaining professional skepticism with AI is addressing algorithmic bias. AI models learn from the data they are trained on, and if this data reflects existing societal or organizational biases, the AI system will perpetuate those biases. In the context of auditing, such discrimination could result in overlooking or misjudging certain transactions or activities, leading to inaccurate audit findings (Murikah et al., 2024). Despite the expectation that artificial intelligence systems are neutral, the data input into these models may contain implicit biases stemming from human design or the sources of the data themselves. These biases can lead to inaccurate or unfair results, which may mislead reviewers when making decisions based on those results (Groves et al., 2024). As Martin (2019) pointed out, algorithmic bias undermines the traits of professional skepticism, potentially leading to unjust auditor decisions and threatening the principles of integrity and professionalism. According to Gartner’s 2018 CIO Agenda Survey, 85 percent of AI projects are likely to yield misleading results due to bias in the data, computations, or team selection (Puthukulam et al., 2021).
- Loss of Professional Judgment: One of the primary concerns is that an excessive reliance on AI tools could undermine the auditor’s professional judgment, especially if the output from these systems is regarded as "undebatable facts”. This perspective contradicts the essence of professional skepticism, which relies on human evaluation

and individual accountability. Samiolo et al. (2024) stated that significant elements of deliberation and sense-making, arguably critical for professional skepticism, may be lost when excessive use of AI tools. There, over-reliance on technical tools may diminish the analytical and critical skills essential for auditors (Ahmad, 2019). Maintaining skepticism is crucial, and it's essential to ensure that AI is not seen as an infallible tool. Instead, AI should be considered a means to an end rather than the ultimate solution.

- Reliance on Third Parties: AI tools are often purchased or contracted from external providers, raising doubts about the quality and reliability of these tools, as well as the auditor's actual control over their operation and updates. Such reliance may weaken the auditor's ability to exercise professional skepticism effectively if they lack sufficient knowledge of these tools (Moffitt et al., 2018).

2.4.3 The third perspective:

Many scholars propose that the relationship between artificial intelligence (AI) tools and professional skepticism transcends a mere paradox of enhancement versus contradiction. Instead, it should be regarded as a dynamic and complementary interaction that holds the potential to enhance Professional skepticism. While AI systems are increasingly effective in detecting anomalies, irregular patterns, and possible fraudulent transactions, their analytical capacity is limited to observable data and algorithmic outputs. They cannot interpret the broader context of managerial intent, strategic motivations, or ethical implications underlying such transactions—dimensions that remain central to the auditor's judgment (Deliu, 2024). In the same context, Abdullah et al. (2025) stated that Auditors bring a level of expertise and skepticism that machines cannot replicate, especially in uncertain scenarios where clear answers are not available. Professional skepticism of an auditor depends on experience, intuition, and the capacity to evaluate dangers that may not be readily discernible from depending on AI tools. In this sense, the auditor retains a distinctive role in exercising critical inquiry, validating the credibility of management's explanations, and applying ethical reasoning to ensure that conclusions extend beyond the scope of AI-driven detection.

Almaqtari (2024) emphasizes that AI should be understood as an augmentative resource rather than a substitute for auditor decision-making in auditing. This requires auditors not only to familiarize themselves with the technical functionalities of AI tools but also to develop the capacity to interpret their outputs with a questioning mindset. Critically engaging with algorithmic results—challenging assumptions, cross-verifying evidence, and recognizing potential biases in data models—deepens rather than diminishes the need for professional skepticism. Chaker (2024) further highlights that this interaction is mediated by individual auditor traits such as analytical ability, ethical sensitivity, and openness to technology. Consequently, AI does not replace auditor judgment but acts as a catalyst, expanding the auditor's capacity to detect risks and address complex audit issues. The relationship is therefore dialectical: technology enhances the reach of audit procedures, while auditors ensure integrity, contextual understanding, and ethical accountability that AI cannot replicate.

Based on the above debate, we postulate the following hypotheses:

$H0_1$: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the question mind.

$H0_2$: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the suspension of judgment.

$H0_3$: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the search for Knowledge.
$H0_4$: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the understanding interpersonal relationship.
$H0_5$: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the autonomy.
$H0_6$: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the Self-Confidence.

3. METHODOLOGY

This study aims to investigate whether differences exist among Egyptian auditors in their perceptions of the positive impact of using artificial intelligence tools on their professional skepticism traits. So we use the contingency theory to deduce the results of using AI tools in the auditing process and the analytical approach for measuring the perception differences and their impact on professional skepticism traits of the auditors.

3.1 Sample and data collection

The study population consisted of Egyptian external auditors. The researcher distributed the questionnaires electronically, and the response rate was (191) auditors. The sample reflects various experiences and educational backgrounds. The researcher used data sources and types to gather the necessary information from representative survey respondents and related sources. Data were analyzed from respondents using closed-ended questionnaires with 5-point Likert scales (ranging from 5 strong agreements to 1 strong disagreement).

3.2 Analyzing characteristics of the sample

Table 1. The Distribution of sample items

Criteria		Frequency	Percent
Qualification	Bachelor	165	86.39%
	Diploma	14	7.33%
	Master	9	4.71%
	PhD	3	1.57%
	Total	**191**	**100%**
Years of experience	less than 5 years	50	26.18%
	from 5 years to 10 years	45	23.56%
	from 10 years to 15 years	38	19.90%
	more than 15 years	58	30.37%
	Total	**191**	**100%**

Source: From the results of the SPSS program outputs

3.3 Validity and reliability test

To determine the efficiency of the questionnaire, the study relied on the reliability and Validity of the questionnaire, which means that the same results would be obtained if the measurements were redistributed at any time and under the same conditions. To test the reliability of the questionnaire, the study used the Cronbach's Alpha test. According to statistical standards, the value is accepted if the desired limits are equal to or greater than 60%, allowing the results to be applied to the study population. The validity was confirmed through the reliability coefficient, which is equal to the square root of the alpha Cronbach coefficient; it must be within the needed limit, equal to or greater than 60%, which is shown in the Table 2:

Table 2. Results of the reliability and validity test

Number of phrases for the survey list as a whole	Number of questions	Reliability	validity
First axis	**3**	**0.953**	**0.976**
Second axis	**4**	**0.958**	**0.978**
Third axis	**3**	**0.850**	**0.921**
Fourth axis	**3**	**0.752**	**0.867**
Fifth axis	**4**	**0.778**	**0.882**
Sixth axis	**3**	**0.860**	**0.927**
Total	**20**	**0.858**	**0.926**

Source: From the results of the SPSS program outputs

The results revealed that the value of the reliability coefficient for all study variables is (85.8%), and the value of the validity coefficient for all study variables is (92.6%). Therefore, the questionnaire has a high degree of internal reliability and validity, and the study can rely on it to achieve the objectives and popularize the results.

3.4 The normal distribution tests

The study employed the Kolmogorov-Smirnov and Shapiro-Wilk tests to determine whether the study variables followed a normal distribution. The variables follow the normal distribution if the significance value (Sig.) is more than 0.05. which is shown in the Table 3:

Table 3. Results of the normal distribution test

Axes	Test of Normality					
	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
First axis	**.231**	**191**	**.000**	**.843**	**191**	**.000**
Second axis	**.216**	**191**	**.000**	**.822**	**191**	**.000**
Third axis	**.247**	**191**	**.000**	**.798**	**191**	**.000**
Fourth axis	**.245**	**191**	**.000**	**.803**	**191**	**.000**
Fifth axis	**.245**	**191**	**.000**	**.789**	**191**	**.000**
Sixth axis	**.281**	**191**	**.000**	**.778**	**191**	**.000**

Source: From the results of the SPSS program outputs

The results indicated that the significance values for the Kolmogorov-Smirnov and Shapiro-Wilk tests were less than 0.05, which reflects that the study variables did not follow the normal distribution. Therefore, the study employed nonparametric tests to validate the hypotheses and achieve more accurate results. The Kruskal-Wallis Test was used to measure the differences between the sample’s opinions about the effect of using artificial intelligence tools on the auditor’s professional skepticism traits according to experience.

3.5 Descriptive statistics

Table 4 shows the results of the descriptive analysis of the positive effect of using artificial intelligence tools on the professional skepticism traits**.**

Table 4. Descriptive statistics of the sample responses

Axis	No.	Statement	Mean	Std. deviation	Importance
the first axis	1	Using AI tools drives me to ask more questions about the available data.	3.24	1.366	1
	2	Using AI tools raises continuous questions about the validity of the evidence obtained through these tools.	3.11	1.347	3
	3	Reliance on AI increases professional skepticism towards the results of the auditing process.	3.21	1.261	2
	Total		**3.19**	**1.324**	
the second axis	1	Using AI tools makes me more cautious before making final judgments.	3.19	1.277	2
	2	I completely verify AI results before making any professional decision.	3.15	1.353	3
	3	I consider AI results to be decisive and final	3.14	1.316	4
	4	AI tools help me make faster decisions.	3.23	1.285	1
	Total		**3.17**	**1.307**	
the third axis	1	AI tools allow me to analyze different types of data.	4.46	0.604	2
	2	AI tools help me explore multiple alternatives and hypotheses during the auditing process.	4.45	0.558	3
	3	I use AI to enhance my understanding of complex issues during the auditing process.	4.48	0.623	1
	Total		**4.46**	**0.595**	
the fourth axis	1	Using AI tools helps me detect early signs of misstatement or manipulation.	4.53	0.631	1
	2	Using AI enhances my understanding of the incentives, pressures, opportunities, and justifications that drive the audit client to commit fraud or other violations.	4.39	0.541	3
	3	AI tools support my ability to interpret the behaviors of related parties.	4.45	0.604	2
	Total		**4.45**	**0.592**	
the fifth axis	1	Relying on AI tools does not affect my independence in making professional decisions	3.07	1.286	1
	2	I make sure to review AI results before adopting these results.	3.05	1.352	2
	3	I believe that AI is an assisting tool and not a substitute for independent professional judgment.	2.97	1.615	4
	4	I am able to make decisions that may differ from AI tool results.	3.01	1.342	3
	Total		**3.02**	**1.401**	
the sixth axis	1	Using AI tools enhances my confidence in the results of my work	3.28	1.382	1
	2	I feel more reassured when AI results support my decisions.	2.95	1.356	3
	3	AI tools increase my confidence in handling complex cases.	3.23	1.435	2
	Total		**3.15**	**1.391**	

Source: From the results of the SPSS program outputs

3.6 Statistical hypothesis testing

First hypothesis: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the question mind.

Table 5. Kruskal-Wallis test to demonstrate the difference between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the question mind

Axis	Categories	Frequency	Chi-Square	Sign.
First axis: the positive effect of using artificial intelligence tools on the question mind	less than 5 years	50	147.701	0.000
	from 5 years to 10 years	45		
	from 10 years to 15 years	38		
	More than 15 years	58		

Source: From the results of the SPSS program outputs

It is clear from the previous table that the p-value is less than 0.05; therefore, the alternative hypothesis is accepted, and the null hypothesis is rejected. It means there are statistically significant differences between the opinions on the positive effect of using artificial intelligence tools on the question of mind.

Second hypothesis: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the suspension of judgment.

Table 6. Kruskal-Wallis test to demonstrate the differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the suspension of judgment

Axis	Categories	Frequency	Chi-Square	Sign.
Second axis: the positive effect of using artificial intelligence tools on the suspension of judgment	less than 5 years	50	154.068	0.000
	from 5 years to 10 years	45		
	from 10 years to 15 years	38		
	More than 15 years	58		

Source: From the results of the SPSS program outputs

The previous table clearly demonstrates table that the p-value is less than 0.05; therefore, the alternative hypothesis is accepted, and the null hypothesis is rejected. It means there are statistically significant differences between the opinions on the positive effect of using artificial intelligence tools on the suspension of judgment.

Third hypothesis: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the search for Knowledge.

Table 7. Kruskal-Wallis test to demonstrate the differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the search for Knowledge

Axis	Categories	Frequency	Chi-Square	Sign.
Third axis: the positive effect of using artificial intelligence tools on the search for Knowledge	less than 5 years	50	32.106	0.350
	from 5 years to 10 years	45		
	from 10 years to 15 years	38		
	More than 15 years	58		

Source: From the results of the SPSS program outputs

The previous table clearly demonstrates table that the p-value is greater than 0.05; therefore, the null hypothesis is accepted. It means there are no statistically significant differences between the opinions on the positive effect of using artificial intelligence tools on the search for Knowledge.

Fourth hypothesis: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the understanding interpersonal relationship.

Table 7. Kruskal-Wallis test to demonstrate the differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the understanding interpersonal relationship

Axis	Categories	Frequency	Chi-Square	Sign.
Fourth axis: the positive effect of using artificial intelligence tools on the search for Knowledge	less than 5 years	50	40.820	0.365
	from 5 years to 10 years	45		
	from 10 years to 15 years	38		
	More than 15 years	58		

Source: From the results of the SPSS program outputs

The previous table clearly demonstrates that the p-value is greater than 0.05; therefore, the null hypothesis is accepted. It means there are no statistically significant differences between the opinions on the positive effect of using artificial intelligence tools on the understanding interpersonal relationship.

Fifth hypothesis: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the autonomy.

Table 7. Kruskal-Wallis test to demonstrate the differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the autonomy

Axis	Categories	Frequency	Chi-Square	Sign.
Fifth axis: the positive effect of using artificial intelligence tools on the autonomy.	less than 5 years	50	149.332	0.000
	from 5 years to 10 years	45		
	from 10 years to 15 years	38		
	More than 15 years	58		

Source: From the results of the SPSS program outputs

The previous table clearly demonstrates that the p-value is less than 0.05; therefore, the alternative hypothesis is accepted, and the null hypothesis is rejected. It means there are statistically significant differences between the opinions on the positive effect of using artificial intelligence tools on the autonomy.

Sixth hypothesis: There are no statistically significant differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the self-confidence.

Table 8. Kruskal-Wallis test to demonstrate the differences between the auditor's opinions according to years of experience about the positive effect of using artificial intelligence tools on the Self-Confidence

Axis	Categories	Frequency	Chi-Square	Sign.
Sixth axis: the positive effect of using artificial intelligence tools on the Self-Confidence.	less than 5 years	50	150.250	0.000
	from 5 years to 10 years	45		
	from 10 years to 15 years	38		
	More than 15 years	58		

Source: From the results of the SPSS program outputs

4. DICUSSION OF RESULTS

The study found that auditors in the Egyptian environment had different perceptions regarding the positive effects of artificial intelligence on professional skepticism traits. These differences are attributed to the variation in years of experience among auditors. Specifically, significant differences were observed among the auditors for the elements of questioning mind, suspension of judgment, autonomy, and self-confidence. For questioning mind, our results align with Chaker (2024) and Puthukulam et al. (2021), who stated that AI tools can reinforce auditors' tendency to question and investigate anomalies, but this effect is depends on the auditor's personality traits, experienced auditors or those with high trait skepticism see a greater positive effect of using AI tools on practices professional skepticism. Moreover, advanced AI can encourage a more probing, inquisitive mindset but may also reduce skepticism for some auditors if over-relied upon. Regarding suspension of judgment, the findings support Deliu (2024), who noted that AI fosters better judgment. However, this improvement depends upon the auditor's ability and experience in utilizing these tools effectively.

Our findings align with Li (2022) regarding autonomy, showing that automating routine tasks increases the perceived autonomy of experienced auditors, allowing them to exercise greater judgment. In contrast, less experienced auditors may feel a decrease in autonomy because they are more inclined to depend on AI tools too much. Similarly, self-confidence appears enhanced among experienced auditors with exposure to AI systems, as supported by Chaker (2024) who stated that exposure to and familiarity with AI systems can enhance auditor self-confidence, particularly for experienced auditors who integrate AI insights with their professional judgment. Less experienced auditors may either feel emboldened by AI support or uncertain due to a lack of trust in their own judgments versus automated outcomes. In contrast, for the dimensions of search for knowledge and understanding interpersonal relationships, no statistically significant differences were observed across experience levels. The literature suggests that AI facilitates the analysis of large datasets and highlights unusual patterns (Appelbaum et al., 2017); it notably strengthens the auditors' drive for knowledge or interpersonal understanding, both of which require more than technical tools to develop.

In summary, AI tools can enhance the professional skepticism traits for auditors by promoting the search for knowledge and understanding interpersonal relationships. On the other hand, the impact is conditional (between positive and negative) with traits such as the tendency to question, deliberation in judgment, independence, and self-confidence, depending on the auditor's experience and the degree of reliance on AI tools and how they interpret and analyze results critically.

5. CONCLUSION AND FUTURE RESERCHES

This study examined how the integration of artificial intelligence tools influences the professional skepticism traits of auditors. This dimension has been overlooked by prior research, which has focused predominantly on AI's role in fraud and error detection. While existing literature highlights AI's potential to enhance audit efficiency and effectiveness, the specific impact on auditors' enduring skeptical traits remains underexplored. Addressing this gap, our findings reveal that Egyptian auditors generally agree that AI tools positively affect certain professional skepticism traits, such as the search for knowledge and understanding of personal relationships. However, they exhibit divergent opinions regarding other critical traits, including a questioning mind, suspension of judgment, autonomy, and self-confidence. The results also highlight the significant moderating role of auditors' years of experience in shaping these perceptions. These insights contribute both theoretically and practically, they enrich the academic understanding of how technological adoption interacts with core audit competencies, and they provide actionable guidance for audit firms seeking to optimize the balance between AI and human judgment.

Future research should delve deeper into the following areas, offering potential benefits for the field of auditing and AI:

- How the auditor interprets the results of artificial intelligence tools,
- The necessity and challenges of verifying the data sources used in the review process in a big data environment,
- The professional responsibility of using artificial intelligence tools, and
- Developing a comprehensive model for professional skepticism practices in an intelligent auditing environment.

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أثر استخدام أدوات الذكاء الإصطناعي على سمات الشم المهني للمراجعين: دراسة ميدانية

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ملخص البحث

تمثل الهدف الرئيسي للبحث في دراسة تأثير استخدام أدوات الذكاء الاصطناعي على سمات الشك المهني لدى مراجعي الحسابات في البيئة المصرية. ولتحقيق هذا الهدف، أجريت دراسة ميدانية شملت تحليل 191 استمارة باستخدام اختبار كروسكال-واليس للتحقق من وجود فروق في آراء المراجعين بشأن التأثير الإيجابي لأدوات الذكاء الاصطناعي على سمات الشك المهني أثناء عملية المراجعة، بناءً على عدد سنوات الخبرة لدى المراجعين. أظهرت النتائج وجود اتفاق بين المراجعين حول التأثير الإيجابي لأدوات الذكاء الاصطناعي على بعض سمات الشك المهني المتمثلة في البحث عن المعرفة وفهم العلاقات الشخصية، بينما ظهرت اختلافات في التأثير فيما يتعلق ببعض سمات الشك المهني الأخرى المتمثلة في إصدار الاحكام، فهم العلاقات الشخصية، والاستقلالية، والثقة بالنفس. تساهم هذه الدراسة في الأدبيات العلمية الحالية من خلال تسليط الضوء على العلاقة المعقدة بين تبني أدوات الذكاء الاصطناعي وسمات الشك المهني في مجال المراجعة. وتقدم منظورًا مفصلاً في السياق المصري، مع التركيز على دور سنوات الخبرة في تشكيل استجابات المراجعين تجاه التطورات التكنولوجية وآثارها على سمات الشك المهني. يعزز هذا الفهم كيفية تأثير تبني التكنولوجيا على متطلبات المراجعة الأساسية، ويقدم إرشادات حول ضرورة تحقيق التوازن بين استخدام أدوات الذكاء الاصطناعي والحكم البشري للمراجع. كما يشدد على ضرورة وجود برامج تدريبية تهدف إلى تقليل فجوة الخبرة العملية للمراجعين عند دمج الذكاء الاصطناعي في عملية المراجعة.

الكلمات المفتاحية: الذكاء الإصطناعي، التقنيات المتقدمة في المراجعة، الشك المهني، سمات مراجع الحسابات.