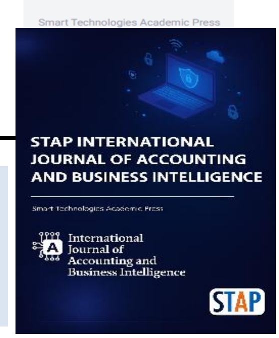

Smart Technologies Academic Press

STAP International Journal of Accounting and Business Intelligence

https://www.ijabi.thestap.com/

Artificial Intelligence in Auditing: Transforming Processes for Enhanced Effectiveness

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ARTICLE INFO

Article History

Received: 29-01-2025
Revised: 02-03-2025
Accepted: 02-04-2025
Published: 20-04-2025

Vol.2025, No.1

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ABSTRACT

The digital transformation, driven by exponentially increasing data and complex business operations, necessitates a paradigm shift in the auditing profession. This qualitative study explores how the integration of Artificial Intelligence (AI) systems enhances the effectiveness of the auditing process. Through semi-structured interviews with nine auditors in Saudi Arabia, the research investigates AI's role across pre-planning, planning, execution, and reporting stages. Findings reveal that AI significantly improves audit accuracy, speed, and efficiency by automating repetitive tasks, enabling full-population data analysis, and facilitating continuous auditing. While cost, skill intensity, and potential algorithmic bias are challenges, the benefits, including enhanced professional judgment and compliance with standards, are seen to outweigh the drawbacks. The study proposes a modified research model emphasizing auditor competence and skepticism as crucial factors for maximizing AI's positive impact on audit effectiveness. This work contributes to the nascent literature on AI in auditing and offers practical insights for auditors and corporate governance.

Keywords: Artificial Intelligence, Auditing, Effectiveness, Saudi Arabia.

How to cite the article

1. Introduction

The contemporary business landscape is characterized by rapid technological advancement, leading to increasingly complex operations and an unprecedented surge in data generation (Gepp et al., 2018). The auditing profession, traditionally a cornerstone of financial integrity, is compelled to adapt by investing in advanced technology, particularly Artificial Intelligence (AI), to effectively analyze these vast data volumes and assess business risks (KPMG, 2016). AI, initially conceptualized by John McCarthy in 1955-56 as "the science and engineering of making intelligent machines," involves computerized systems mimicking human problem-solving skills (Hernández-Orallo, 2017). While early AI projects were limited by computational power, recent breakthroughs, exemplified by IBM Watson and AlphaGo, have brought sophisticated AI systems into practical application (Ilachinski, 2017; Firat, 2025).

The application of AI in auditing is not entirely novel, having previously served as a decision support tool (Hansen & Messier Jr., 1986). However, the convergence of technological progress, the availability of "big data," and enhanced processing power positions AI to profoundly impact the field now and in the future (Kokina & Davenport, 2017; Bakinsky, 2025). The imperative for auditors is to augment their processing capabilities to uphold audit effectiveness and reliability. AI-based technology offers a strategic avenue to automate labor-intensive tasks, from automatic analysis of accounting entries to fraud detection through deep learning, thereby reducing human error and identifying anomalies at speed (Baldwin et al., 2006; Zhang, 2019; ASOSAI Journal, 2024). The World Economic Forum (2015) even predicted that 75% of corporate audits would be performed by AI by 2025, underscoring its transformative potential.

2. Problem statement

The escalating use of information technology (IT) tools in modern businesses has fundamentally altered how financial information is recorded and disclosed (Mansour, 2016). This increased complexity challenges auditors to remain technologically informed and equipped to effectively examine and understand entities' financial transactions (Issa et al., 2016). AI-based technology directly addresses this challenge by automating audit procedures across various stages (Moffitt et al., 2018; Bakinsky, 2025). Leading audit firms, such as KPMG with IBM Watson, PwC with Halo, and Deloitte with Argus for AI, are already leveraging these capabilities to enhance audit effectiveness (Kokina & Davenport, 2017).

Traditional auditing methods, which often rely on sampling data, inherently carry risks of omission and commission (Bailey et al., 2018). While Computer Assisted Auditing Techniques (CAATs) have allowed for broader data analysis, they still demand substantial human effort. AI systems offer the capacity to review entire populations of records and extract critical information rapidly (Omoteso, 2012; ASOSAI Journal, 2024). However, the implementation of AI also introduces challenges, including the need for robust data management and governance, and the acquisition of adequate skills in handling AI tools (Issa et al., 2016; Firat, 2025; Alhumoudi & Juayr, 2025). Despite the growing interest in AI in auditing, limited studies have extensively explored its ongoing transformational effect on the audit process and its impact on effectiveness. Existing literature often focuses on potential biases (Brown-Liburd et al., 2015) or characteristics of big data analytics (Kokina & Davenport, 2017; Omoteso, 2012), but less on the practical interactions and effectiveness from the users' perspective. This study aims to bridge this gap.

3. Purpose of the Study

The purpose of this study is to explore the effects of AI-based systems in enhancing the effectiveness of the auditing process by investigating the interaction of auditing processes with AI tools. By identifying these benefits, the study seeks to contribute to the emerging knowledge base in this area and encourage corporate governance to advocate for the broader integration of AI systems within accounting and auditing departments (Hussain et al., 2018). Ultimately, the goal is to enhance audit quality through more effective audit processes, improved by accurate AI systems (Bakinsky, 2025; Alhazmi & Islam, 2025).

4. Research Question

The central research question guiding this study is:

How is AI enhancing the effectiveness of audit processes?

5. Research Objective

To examine the impact of AI enhancing the effectiveness of audit processes.

6. Theoretical Framework

This study is underpinned by four core auditing theories that contextualize the integration and impact of AI in the auditing profession (See figure 1).

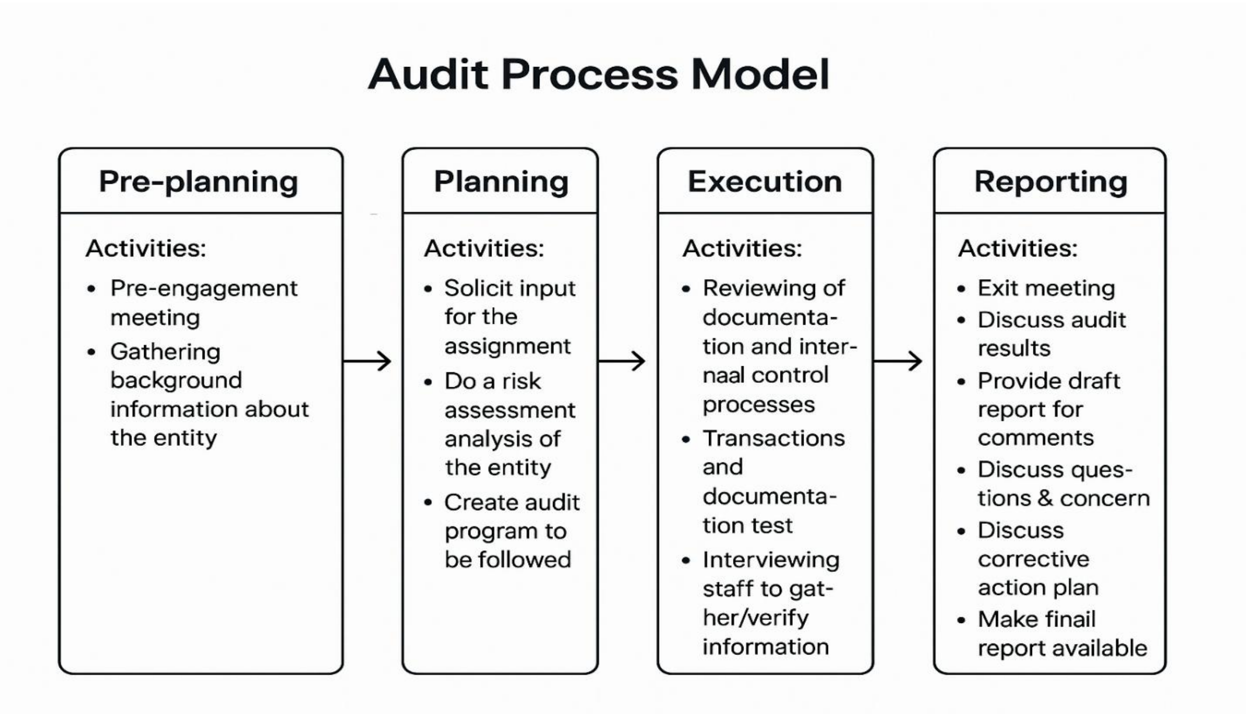

Figure 1: Audit Process Model

6.1 The Agency Theory

The Agency Theory describes the relationship between principals (investors) and agents (managers), where managers are appointed to act on behalf of investors. Auditing plays a crucial role in assuring investors that managers are upholding their interests by providing verified financial reports (Bosse & Phillips, 2016; Commerford et al., 2019). The increasing size of companies and corresponding data volumes necessitate timely and reliable information. AI systems offer a strategic advantage by enabling remote analysis of financial statements and reducing the complexity of operations, thereby facilitating the provision of high-value assurance to investors. By streamlining the audit process and eliminating conflicts of interest, AI helps deliver accurate financial performance reports, which is central to agency theory (Blair & Stout, 2017).

6.2 The Stakeholder Theory

Developed by Edward Freeman (1984), the Stakeholder Theory emphasizes that organizational management should create value for all stakeholders, including employees, suppliers, and communities, not just investors. In auditing, this translates to providing reliable and timely financial information to all interested parties. The integration of AI significantly enhances the value created for stakeholders by improving the reliability of information through extensive data processing and reduced human error. By producing higher quality and more reliable audit reports, AI increases client confidence and security, moving away from speculation towards data-driven conclusions (Jachi & Yona, 2019).

6.3 The Theory of Inspired Confidence

Limberg's Theory of Inspired Confidence posits that the demand for audit services stems from external stakeholders' need for accountability from management. The overarching purpose of an audit is to meet the expectations of an average interested party. With modern companies handling vast operations and immense amounts of data, human auditors may struggle to provide timely and comprehensive coverage (Mathias & Kwasira, 2019). AI systems strategically address this by facilitating fast and accurate data collection and analysis, which enhances the timeliness and quality of audit results. Automation allows for continuous auditing, enabling auditors to acquire up-to-date data and detect anomalies promptly, thereby fulfilling the expectations of informed stakeholders (Elewa & El-Haddad, 2019).

6.4 The Credibility Theory

The Credibility Theory asserts that the primary function of auditing is to bolster the credibility of financial statements, thereby increasing investor faith by reducing information asymmetry (Chen et al., 2018; Al-Shaer & Zaman, 2018). Conflicts of interest can diminish this credibility, making independent auditors essential. The speed and quality improvements brought by AI systems are crucial in achieving higher levels of credibility. By standardizing the auditing process and enabling full population testing rather than sampling, AI reduces human errors and allows for more precise measurement of data correctness. This automation enhances audit quality, making audit reports more reliable and credible for all users (Matonti, 2018).

7. Literature Review

7.1 The Process of Auditing

The audit process involves a series of activities to obtain evidence and form an opinion on an entity's financial statements. While procedures vary based on risk factors and internal controls (Kearney, 2013), AI is adaptable to enhancing effectiveness at each step. These steps are interconnected, with the output of one step often becoming the input for the next (Issa et al., 2016; Kokina & Davenport, 2017).

● Pre-planning (Pre-engagement): Auditors assess new clients by reviewing internal policies, management integrity, compliance, and potential threats to determine acceptance (Knechel & Salterio, 2016; Cannon & Bedard, 2017).

● Planning: This stage involves developing the overall audit strategy, defining scope, timing, and risk handling to ensure an effective and efficient audit (Cannon, 2017; Kearns et al., 2017; European Court of Auditors, 2024).

● Execution: This phase includes understanding the entity's control environment to foresee material errors, gathering audit evidence, and performing tests of controls and substantive procedures (Bailey et al., 2018; Cannon, 2017; Collins & Quinlan, 2020).

● Reporting: The final step involves evaluating evidence, ensuring proper documentation, and ultimately preparing the final audit report (Żytniewski, 2017; Sikka et al., 2018).

7.2 Artificial Intelligence (AI) and AI in Auditing

AI, often synonymous with machine intelligence or cognitive computing, refers to the integration of human-like intelligence into machines to enable them to understand context and make intelligent decisions (Ransbotham et al., 2018; Kokina & Davenport, 2016). For auditing, AI is a "hybrid set of technologies supplementing and changing the audit" (Issa et al., 2016; O'Leary, 1987; Firat, 2025). Its integration removes repetitive tasks, facilitates in-depth understanding of large data volumes, and enables auditors to focus on value-adding activities (Kokina & Davenport, 2017; Luo et al., 2018; ASOSAI Journal, 2024). AI tools make it easier to detect high-risk transactions through full-population testing, a significant improvement over manual sampling (Shaikh, 2005). The advent of AI introduces cognition into automation, allowing tools to mimic human activities in audit processes and perform tasks more effectively, leading to quality and effective audit assignments within reasonable timeframes and costs (Deloitte, 2015; Brazilian Journals Publicações, 2025). Sulaiman et al. (2018) note Gartner's (2017) prediction that AI would be prevalent in almost all new software products by 2020.

7.3 Audit Effectiveness

Audit effectiveness signifies the degree to which an audit achieves its primary objectives (Beckmerhagen et al., 2004; Audit Committee Chair Forum ACCF, 2006). This study defines AI-based systems in auditing as tools that ease the assignment while ensuring compliance with standards, thereby enhancing effectiveness. AI boosts effectiveness and efficiency by helping auditors navigate large information pools rapidly (Commerford et al., 2019; Noraini et al., 2018; Scientific Research Publishing, 2025). It streamlines information exchange, prioritizes critical messages using machine learning (Noor & Mansor, 2019), and eliminates redundant tasks, notably through blockchain technology which can revolutionize bookkeeping by providing instantaneous and immutable records (Omoteso, 2016; Raschke et al., 2018). AI also transforms auditing by enabling real-time data analysis and continuous auditing, a shift from historical data verification to proactive anomaly detection (Elliot, 1994; Van Liempd et al., 2019; Alles et al., 2008; PwC, 2006; Rikharddson & Dull, 2016; University of Malta, 2025). This enhances the speed and accuracy of audit evidence collection, making internal control monitoring continuous and improving the integrity of information flow (Cascarino, 2012; Yoon et al., 2015).

7.4 Professional Approach to the Adoption of AI

The adoption of AI is reshaping professions, much like industrialization transformed craftsmanship (Susskind & Susskind, 2015). Auditing, a knowledge-intensive profession requiring legal, accounting, and governance expertise, along with integrity and judgment (Saxena & Srinivas, 2010; Eilifsen et al., 2014), must integrate advanced technology to remain effective. Modern audit firms are increasingly adopting sophisticated, high-tech audit support systems to enhance efficiency and gain competitive advantages (Dowling & Leech, 2014; Carson & Dowling, 2012; University of Twente, 2024; Othman, 2025). While some skeptics argue that humans possess unique contextual analysis abilities that machines lack (Adler et al., 2018; Tiron-Tudor et al., 2024), others contend that AI excels in collecting, analyzing, and classifying massive data volumes (Marcello et al., 2017). The evolving role of auditors suggests a symbiotic relationship, where AI handles data extraction and auditors focus on data analysis, decision-making, and client consultation (Momodu et al., 2018). Yi et al. (2006) also discuss factors influencing professionals' technology acceptance decisions.

8. Methodology

8.1 Research Design

This study employs a qualitative research methodology, aimed at understanding the complexities of AI's impact through participants' lived experiences. It adopts an abductive approach, allowing for iterative movement between theoretical models and empirical data to refine understanding (Reichertz, 2004; Awuzie & McDermott, 2017; Malterud, 2001). The epistemological position is interpretivism-constructivism, viewing reality as socially constructed through human interaction and interpretation (Maxwell, 2006; Bogdan & Biklen, 1992; Tuli, 2010). The ontological position is constructionism, recognizing that reality is a product of social processes and individual perceptions (Neuman, 2003). This framework allows for in-depth exploration of how AI enhances audit process effectiveness, drawing insights directly from auditors' experiences.

8.2 Data Collection

Data were collected through semi-structured interviews conducted with auditors from auditing firms in Saudi Arabia that have adopted AI-based tools. This method was chosen for its flexibility, allowing for deep exploration of responses while maintaining a guiding structure (Drever, 1995). Purposive sampling, a non-probability method, was utilized to select participants who possessed specific expertise and experience with AI in auditing (Etikan et al., 2016). Initial interview requests were sent to 18 managers, resulting in nine positive responses. The interviewees comprised three entry-level, three middle-level, and three senior/managerial auditors, ensuring a diverse representation of the audit team hierarchy (Bamber, 1983; Muczyk et al., 1986). Their professional experience ranged from two to fifteen years, with most being CPA certified and having backgrounds in accounting, economics, or business (Altındağ & Kösedağı, 2015; Bach, 2017). Due to the COVID-19 pandemic, all interviews were conducted online via video call (Zoom or Skype), ensuring continued face-to-face interaction. Sessions were audio-recorded and later transcribed verbatim to enhance reliability and facilitate accurate analysis.

Table 1: Interview Session Analysis

Interview Dates	Participants	Position at the Firm	Gender	Interview means	Length of interview
6 May	Auditor 1	Middle level auditor	Male	Skype	44 mins
7 May	Auditor 2	Senior auditor/managerial level	Female	Zoom	48 mins
7 May	Auditor 3	Entry level auditor	Male	Zoom	40 mins

8 May	Auditor 4	Middle level auditor	Male	Skype	49 mins
11 May	Auditor 5	Independent Senior auditor	Male	Skype	55 mins
14 May	Auditor 6	Entry level auditor	Male	Skype	40 mins
15 May	Auditor 7	Middle level auditor	Female	Skype	45 mins
18 May	Auditor 8	Entry level auditor	Male	Zoom	44 mins
15 May	Auditor 9	Entry Level Auditor	Male	Google meet	35 mins

8.3 Data Analysis

The transcribed data underwent thematic analysis, a process involving segmenting information into common phrases, expressions, or ideas, referred to as themes or codes (Creswell, 2007; Miles & Huberman, 1994; Hardan, & Al-Najjar, 2021). The analysis followed a structured approach, aligning with the sections of the interview guide and the study's initial research model. Interviewee responses were quoted directly to present their viewpoints authentically and enhance credibility (Kvale, 2007; Turner, III, 2010; Wolcott, H. F., 1994). Interpretation was performed at each stage, linking common themes in responses to relevant theoretical concepts. The researchers maintained a "healthy skepticism" to ensure all pertinent information, even that which diverged from initial frameworks, was included to bolster the abductive approach (Malterud, 2001).

8.4 Bias and Trustworthiness

The study acknowledges inherent selection bias due to the purposive sampling method, as the aim was to target a specific population of auditors already using AI (Pannucci & Wilkins, 2010). However, measures were taken to ensure trustworthiness and credibility. Credibility was enhanced by audio-recording and transcribing interviews verbatim, and by having both researchers involved in the interview process and data analysis to minimize individual bias (Gill et al., 2008). Authenticity was addressed by ensuring that the participants represented various levels of auditors within an audit team, providing a fair representation of viewpoints within the study's context (Smallbone & Quinton, 2004).

9. Results

The data collected from nine professional auditors in Saudi Arabia illuminate the multifaceted impact of AI on the auditing process. This section presents key findings structured according to the interview guide.

9.1 Competence in the Use of IT Tools

Auditors demonstrated varying levels of tech-savviness, from "moderately good" to "extremely good," with none reporting poor technological proficiency. All respondents were familiar with at least one accounting software, with Sage being frequently mentioned (Mansour, 2016). However, some noted that traditional software like Sage required significant human effort, leading to the adoption of newer AI solutions like "Apache Mahout." While auditors generally expressed comfort with IT tools, comfort levels with AI-specific auditing software varied. Experienced auditors tended to be "extremely comfortable," while junior auditors, or those from firms newer to AI, were "moderately comfortable" or "not comfortable" due to the newness of the system and required skills. This indicates a skills gap that necessitates additional training for auditors to maximize AI's benefits, aligning with AICPA's (2018) emphasis on adaptable competencies (Noraini et al., 2018; Gonzalez-Padron, 2016; Journal of Multidisciplinary Business and Economics, 2025).

Table 2: Background Information of the Participants

Participants	Auditor 1	Auditor 2	Auditor 3	Auditor 4	Auditor 5	Auditor 6	Auditor 7	Auditor 8	Auditor 9
Role at the firm	Middle level	Senior auditor/managerial level	Entry Level	Middle level	Senior auditor/managerial level	Senior auditor/managerial level	Entry level auditor	Entry level auditor	Middle-level auditor
Years of Experience	5 years	15 years	2 years	6 years	15 years	10 years	3 years	2.5 years	4 years
Duties	Implement audit schedule	Make audit policies and Oversee audit process	Assist middle-level and senior-level auditors in audit schedule implementation	Implement audit schedule	Supervise audit process	Oversee audit process	Assist in audit process	Assist in implementing audit program	Participate in entire audit process as outline by the senior auditor
Professional certification	CPA Certified	CPA Certified	CPA certified	CPA Certified	CPA Certified	CPA Certified		CPA certified	CPA certified
Educational Background	Business Studies	Accounting	Economics	Economics	Economics	Accounting	Business	Accounting	Accounting
Gender	Male	Male	Male	Female	Female	Male	Male	Male	Male

9.2 Personal Views on the Importance of Automation

Auditors consistently defined audit automation as the use of software to streamline auditing processes, reducing reliance on intensive human engagement. They confirmed active use of AI tools in their firms, citing examples like "AI-one," "DeepLearning4J," "Apache Mahout," "MindBridge AI," and "Cygna Audit." The pervasive adoption signifies that AI is becoming a critical competitive advantage (Carson & Dowling, 2012; Banker et al., 2002; University of Twente, 2024). The consensus was that AI enhances the professional and widespread auditing required by agency theory (Blair & Stout, 2017), as firms increasingly depend on AI for implementing auditing frameworks. Even entry-level auditors showed exposure to modern accounting and auditing software, underscoring the industry-wide shift.

9.3 AI's Role in Audit Process Stages

The study extensively explored AI's specific contributions to each stage of the auditing process:

● Pre-engagement: The majority of auditors agreed on AI's significant role in client evaluation. AI analyzes historical information, predicts risks, and processes documents with speed and accuracy, reducing human effort (Rahimi & Gunlu, 2016). This allows auditors to make quicker acceptance decisions and reallocate time to critical human interactions with corporate officers. This aligns with the theory of inspired confidence (Mathias & Kwasira, 2019), where efficiency in preliminary stages fosters confidence. For instance, an AI system could rapidly scan a potential client's past financial statements and public records to flag unusual transaction patterns or compliance issues, enabling a faster and more informed pre-engagement decision.

● Planning Stage: All auditors concurred that AI greatly aids this stage, primarily in classifying materiality and identifying patterns. AI rapidly sifts through multiple files, flagging "highly material" items with high variability and "raising red warnings" for sudden changes in transaction patterns. This is crucial for accurate risk assessment and developing effective audit strategies, directly contributing to audit effectiveness (Ramamoorti et al., 1999; Cannon, 2017; Kinney & Burgstahler, 1990; Chewning et al., 1998; European Court of Auditors, 2024). For example, AI can analyze a company's entire ledger to identify unusual fluctuations in specific accounts, guiding auditors to allocate more resources to those high-risk areas.

● Execution Stage: AI was uniformly acknowledged for bringing swiftness, effectiveness, and ease to control tests. Auditors reported that AI enables "sweeping exercises," reviewing multiple financial entries instantaneously and performing full-population testing instead of sampling. This reduces the burden of compliance and substantive tests, allowing auditors to concentrate on critical control accounts and areas prone to weaknesses, thereby increasing confidence in the system's credibility (Shen et al., 2017; Noor & Mansor, 2019; Brazilian Journals Publicações, 2025; EnPress Journals, 2025; Scientific Research Publishing, 2025). An AI tool like IBM Watson, for instance, can rapidly review thousands of lease contracts to ensure compliance with IFRS 16, a task that would be highly time-consuming and prone to human error if done manually.

● Reporting Stage: Most participants agreed on AI's important role in this concluding stage. AI integrates findings from previous stages, leading to higher quality reports. Its speed and accuracy in perusing files and generating reports enhance the overall effectiveness of the process (Hardan, 2024; ASOSAI Journal, 2024). This aligns with the agency, stakeholder, inspired confidence, and credibility theories, all of which require verifiable, timely, and credible financial reports for stakeholders. AI can, for example, automate the generation of preliminary audit reports based on analyzed data, allowing auditors to focus on refining the narrative and adding professional judgment.

9.4 Overall Impact and Effectiveness Rating

Auditors consistently affirmed AI's superiority over manual or traditional methods. AI allows for full data set analysis, identifying outliers and exceptions that human auditors might miss. It can extract information from unstructured data (emails, audio files) and enable continuous auditing, transforming a previous "mere dream" into reality (Omoteso, 2016; University of Malta, 2025). Auditors using AI reported a reduction in human reliance and a shift from labor-intensive tasks to more analytical roles (Hardan, 2024; University of Twente, 2024). When asked to rate AI's effectiveness on a scale of 1 to 10, the collective responses yielded an average score of 7.80, strongly indicating that AI significantly enhances both the effectiveness and efficiency of auditing. Studies in Saudi Arabia also support that AI positively impacts operational efficiency through task automation and predictive insights, reducing manual effort and enhancing productivity (Othman, 2025) (See figure 2).

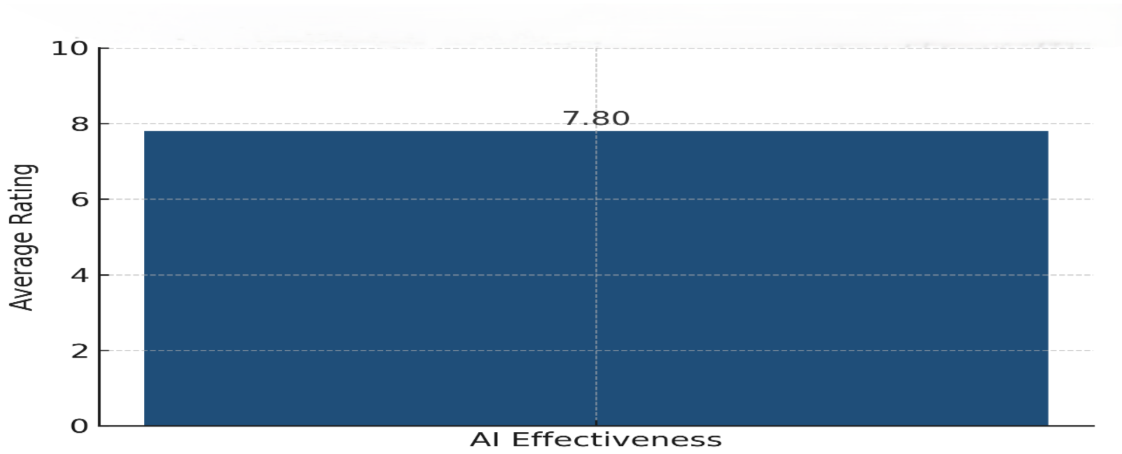

Figure 2: Average AI Effectiveness Rating (Scale of 1-10)

10. Discussion

The empirical findings of this study conclusively demonstrate that Artificial Intelligence profoundly enhances the effectiveness of the auditing process. The primary mechanism through which AI achieves this is by reducing errors and extensive human labor, which traditionally lead to rework and increase the risk of manipulation or omission. AI systems' capability to collect, peruse, and analyze financial records coherently and effectively, especially through full-population testing, addresses the limitations of manual sampling and significantly improves audit quality. This validates the study's central research question: AI is enhancing audit effectiveness by providing unparalleled accuracy, speed, and analytical depth across all audit stages.

These practical benefits directly reinforce the theoretical underpinnings discussed earlier. The Agency Theory is supported by AI's ability to provide timely and reliable information to investors, ensuring greater transparency and reducing information asymmetry (Blair & Stout, 2017). For instance, AI's continuous monitoring capabilities allow for real-time insights into financial health, providing principals with up-to-date assurance on agent performance. The Stakeholder Theory is fulfilled as AI-enhanced audits produce more trustworthy financial reports, building confidence among all interested parties (Jachi & Yona, 2019). By minimizing human error and increasing data reliability, AI ensures that all stakeholders receive accurate information, fostering trust. The Theory of Inspired Confidence is met by AI's capacity to process vast data volumes rapidly, delivering audit results that meet heightened stakeholder expectations for accuracy and immediacy (Mathias & Kwasira, 2019). AI's speed allows auditors to keep pace with the increasing complexity of modern business operations, maintaining public confidence. Finally, the Credibility Theory is strengthened by AI's role in standardizing audit procedures and enabling comprehensive data review, leading to highly credible financial statements (Matonti, 2018). The ability of AI to analyze 100% of transactions, rather than just a sample, fundamentally increases the verifiability and thus the credibility of financial reports. Research in Saudi Arabia also indicates that AI adoption improves audit quality by reducing errors and increasing consistency (Othman, 2025; ResearchGate, 2024c).

A crucial emergent finding, leading to a modified research model (Figure 3), is the indispensable role of auditor competence and professional skepticism. While AI tools provide optimal performance in each step of the auditing process, their effectiveness is amplified by the human element. The interaction between AI and the auditing process, coupled with the auditors' proficiency in handling IT tools and their capacity for professional skepticism, jointly leads to enhanced effectiveness. This highlights that AI is not a replacement but a powerful augmentation, requiring auditors to evolve their skills to leverage the technology optimally. The dual-directional arrows in the modified model signify the symbiotic relationship: AI informs the audit process, and the auditors' skills determine how effectively AI is applied and its outputs are interpreted.

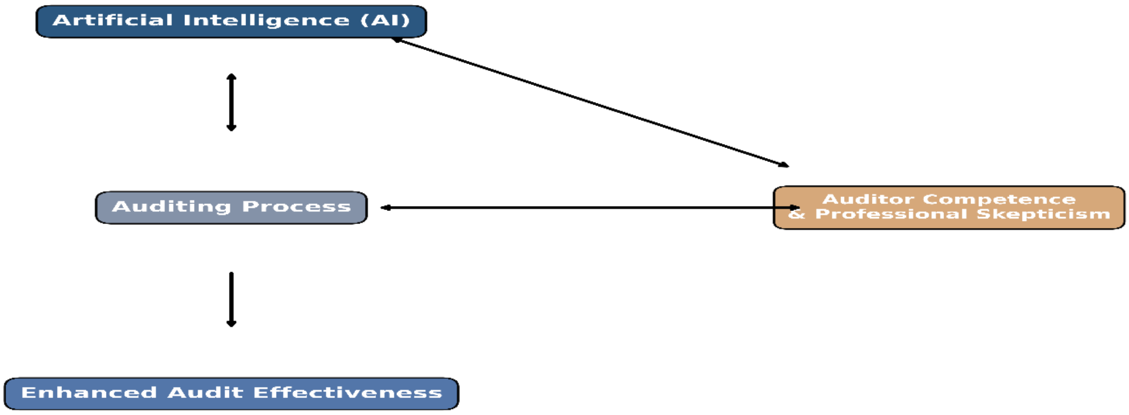

Figure 3: Modified Research Model

10.1. Ethical Concerns

The integration of AI in auditing presents a nuanced landscape of both significant advantages and considerable challenges, particularly concerning ethical considerations.

10.1.1. Pros:

Auditors uniformly highlighted several key benefits. AI significantly increases accuracy by having a low error rate compared to humans, especially when correctly coded (Interviewee 7). This translates to unbelievable precision and speed in perusing primary documents and identifying anomalies. AI systems are not influenced by adverse human situations, enabling them to complete risky or exhaustive assignments. They offer digital assistance in daily duties, act as rational decision-makers, and overcome the human limitation of getting fatigued (Interviewee 5). Furthermore, AI can optimize and automate accounting tasks, leading to increased productivity and efficiency (Interviewee 6). A key advantage identified was the capacity for increased innovation, fostering a culture open to new approaches in auditing. AI also facilitates the processing of large volumes of data that would be impractical for manual review, and through its learning capabilities, it can eliminate human errors by continually updating its methodology (Interviewee 2). Studies in Saudi Arabia also emphasize that AI enhances the quality of financial reports, efficiency, and accuracy of audits, and supports regulatory compliance (Alhazmi & Islam, 2025).

10.1.2. Cons:

Despite the advantages, significant drawbacks were noted. The most prominent concern is that AI is both capital-intensive and skills-intensive. The initial investment in AI software and the ongoing need for training auditors are substantial challenges (Interviewee 7, 4; Noraini et al., 2018; Brazilian Journals Publicações, 2025; Alhumoudi & Juayr, 2025; ResearchGate, 2025d). This can pressure companies to "skim necessary steps," potentially compromising regulatory standards. A critical ethical concern is the potential for algorithmic bias. As AI systems are only as good as the data they are trained on, "bad information is often laced with racial, gender, communal or ethnic biases" (Interviewee 8; The Brookings Institution, 2019; Emerald, 2025; ResearchGate, 2025b). If these biases remain undetected within algorithms, they can lead to unethical and unfair outcomes, potentially reducing the reliance and credibility of the AI system. This lack of transparency and the need for unbiased data and easily explainable algorithms pose a significant hurdle.

Furthermore, auditors expressed concerns about AI's current inability to fully replicate intricate human intelligence, emotions, and moral values (Interviewee 2, 5; Tiron-Tudor et al., 2024; ResearchGate, 2024b). While AI excels at repetitive tasks, it may lack the dynamic adaptability and nuanced judgment characteristic of human auditors in complex, unforeseen situations. The integration of AI with existing auditing systems can be challenging due to funding, training time, and the risk of data loss or inconsistencies with confidential data (Interviewee 1; Brazilian Journals Publicações, 2025). Some noted that AI models require vast amounts of training data, and the extent of machine learning can be hard to determine, leading to a "lack of transparency" (Interviewee 6; Brazilian Journals Publicações, 2025). Challenges specific to Saudi Arabia include resistance to change, technological infrastructure, skills gap, and regulatory compliance concerns, as highlighted by Alhumoudi & Juayr (2025) and ResearchGate (2025c). Addressing these challenges in Saudi Arabia often involves strategic initiatives under Vision 2030, which prioritizes digital transformation and upskilling the workforce (UNESCO Digital Library, 2025).

10.2. Compliance and Professional Judgment:

Auditors largely agreed that AI functionality enables compliance with international accounting and auditing standards, often providing superior solutions compared to traditional tools (Interviewee 6; Bustinza et al., 2015). However, some expressed uncertainty about full compliance, suggesting that the rapid evolution of technology has outpaced the development of clear standards for AI in auditing (Interviewee 7; Brazilian Journals Publicações, 2025). This implies a need for regulatory bodies to catch up.

Regarding professional judgment, the consensus was that AI promotes professional judgment rather than impairing it. AI augments auditors' capabilities by providing accurate, data-driven insights, which allows auditors to perform due diligence more effectively and make better-informed decisions (Interviewee 7; Lombardi & Dull, 2016; ResearchGate, 2024b; MDPI, 2025). The ability of AI to identify material misstatements using "unsupervised learning" by detecting outliers without bias or prior records allows "the statistics talk for itself," thereby enabling auditors to focus their judgment on more complex, subjective areas (Interviewee 5). This suggests a shift in the nature of professional judgment, where AI handles the routine, data-intensive aspects, freeing auditors to apply their expertise to strategic and ethical considerations. The materiality concept, as discussed by Jaradat, & Hardan, (2024), remains crucial.

11. Conclusion

The overarching purpose of this research was to explore how Artificial Intelligence (AI) enhances effectiveness in the auditing process. The comprehensive analysis of responses from nine professional auditors in Saudi Arabia provides compelling evidence that AI indeed has a widespread positive impact on the overall quality and efficiency of audits. AI significantly streamlines and improves the four main stages of the audit process—pre-planning, planning, execution, and reporting—primarily by reducing human errors and the arduous, repetitive labor historically associated with auditing.

A key deduction from this study is that AI's ability to collect, peruse, and analyze financial records with unparalleled speed and accuracy, particularly through full-population testing, fundamentally transforms audit effectiveness. This is a considerable advancement over manual methods that often rely on random sampling, increasing the reliability and depth of audit findings. Auditors consistently reported that AI tools reduce the physically and mentally exhausting aspects of their work, which historically increased the risk of errors, manipulation, and omissions. These findings satisfactorily address the research question by demonstrating how AI enhances effectiveness through increased precision, efficiency, and the capacity for continuous auditing. Research from Saudi Arabia supports that AI positively impacts operational efficiency and audit quality (Othman, 2025; ResearchGate, 2024c).

Furthermore, the respondents strongly agreed that AI systems elevate professionalism and ensure better compliance with international auditing standards. The overall sentiment strongly favored the adoption of AI-based auditing systems over traditional tools. The study's emphasis on the crucial role of auditor competence and sound professional skepticism led to a significant modification of the initial research model, highlighting these human factors as underlying elements that profoundly boost the interaction between AI tools and the audit process. This revised model underscores a synergistic relationship where technology and human expertise combine for optimal audit performance.

While the study acknowledges certain limitations—including the high cost of AI adoption, the intensive skill requirements, and the persistent challenge of potential algorithmic bias—the identified pros of AI integration substantially outweigh these cons. The increased accuracy, speed, enhanced effectiveness, and fostering of innovation are transformative benefits for the auditing profession. Addressing the cons through appropriate funding, continuous training, and a commitment to unbiased algorithm development will further solidify AI's positive impact. Ultimately, the focus on AI and auditing is set to continue, as it promises to deliver more sustainable and high-quality audits, thereby bolstering confidence in capital markets for the benefit of all stakeholders.

11.1 Theoretical and Practical Contribution

As AI in auditing is a rapidly evolving and underexplored area, this study makes a significant theoretical contribution by filling a gap in the existing literature. It provides an in-depth qualitative exploration of AI's transformative effects on audit processes. From a practical perspective, the study offers valuable insights for auditors and corporate governors, detailing the specific advantages AI brings to each audit stage. By presenting the viewpoints and experiences of auditors who are actively using these systems, the research provides actionable information that can encourage broader implementation of AI technology to enhance overall audit quality.

11.2 Limitation of the Study

Despite achieving its primary aim, this study faced several limitations. The short timeframe constrained the scope, leading to a limited sample size. Slow or no responses to interview requests also contributed to this, preventing the inclusion of potentially interested participants. The COVID-19 pandemic necessitated online interviews, which, while enabling continued interaction, deviated from the traditional in-person qualitative research approach. Lastly, the scarcity of prior studies specifically on AI in auditing posed a challenge in drawing wider comparative insights, reflecting the nascent stage of this research area.

11.3 Future Research Agenda

For future research, it is crucial to continue investigating the accuracy and evolution of AI algorithms as the software develops, with a particular focus on mitigating potential biases. Undetected biases within algorithms could compromise the professionalism and long-term reliability of AI systems. Specifically, future studies could explore the development of explainable AI (XAI) models for audit judgment in the Saudi Arabian context. Additionally, conducting this same study quantitatively within the same or different contexts could provide broader generalizability and allow for statistical comparisons of AI's impact on audit effectiveness. Further research into the optimal training methodologies for auditors in an AI-driven environment, perhaps through a longitudinal study on the long-term impact of AI adoption on audit firm structure and human capital development in Saudi Arabia, would also be beneficial.

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