The Impact of Hybrid Artificial Intelligence Decision-Making on Auditor Professional Judgment: A Field Study in The Egyptian Context

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Abstract

This study empirically examines the impact of Hybrid Artificial Intelligence (AI) systems on the professional judgment of Egyptian auditors, focusing on its impact across three core dimensions: risk assessment capabilities, professional skepticism, and complex problem-solving proficiency. using a quantitative survey methodology, the research was conducted via a structured questionnaire distributed to a sample of 137 auditing professionals, academics, and postgraduate students, with responses measured on a five-point Likert scale. The results demonstrated a significant and positive impact of Hybrid AI on auditor professional judgment, with a strong consensus among respondents indicated by consistently high mean scores exceeding 4.3. The findings confirmed that Hybrid AI significantly improve risk identification and assessment, strengthens professional skepticism by providing data-driven evidence, and improves the ability of auditors to solve complex problems by offering advanced analytical insights. In addition to these benefits, the research identified key implementation challenges, such as the need for continuous AI training for auditors, and the necessity of establishing clear regulatory standards for AI integration.

Keywords

Hybrid AI, Auditing, Professional Judgment, Risk Assessment, professional skepticism

الملخص:

تهدف هذه الدراسة إلى تقييم أثر أنظمة الذكاء الاصطناعي الهجين على الحكم المهني لمراجعي الحسابات في مصر، مع التركيز على ثلاثة أبعاد رئيسية :القدرة على تقدير المخاطر، الشك المهني، والقدرة على حل المشكلات المعقدة. اعتمدت الدراسة على تصميم استبيان وتوزيعه على عينة مكونة من 137 من مراجعي الحسابات والأكاديميين وطلاب الدراسات العليا.

اظهرت النتائج وجود تأثير إيجابي معنوي لأنظمة الذكاء الاصطناعي الهجين على الحكم المهني لمراجعي الحسابات، حيث أظهرت نسبة الاجابات معدلات مرتفعة تجاوزت 4.3 نقطة في المتوسط. وكما أكدت النتائج على وجود تأثير معنوي إيجابي على قدرات مراجعي الحسابات في تقدير الخطر، وتحسين الشك المهني، وتحسين القدرة على حل المشكلات المعقدة باستخدام التحليلات المتقدمة..

كما سلطت الدراسة الضوء على التحديات الرئيسية في التطبيق العملي، بما في ذلك الحاجة الى التدريب المستمر على تقنيات الذكاء الاصطناعي، وضرورة وضع معايير تنظيمية واضحة لدمج هذه التقنيات.

الكلمات المفتاحية :

الذكاء الاصطناعي الهجين، مراجعة الحسابات، الحكم المهني، تقدير الخطر، اشك المهني

1. Introduction

Hybrid Artificial Intelligence (AI) represents a significant advancement in the field, combining multiple AI approaches within a unified framework to enhance performance and address the limitations of individual techniques (GeeksforGeeks, 2024). By integrating rule-based systems with machine learning (ML), hybrid AI effectively handles tasks that require both structured reasoning and data-driven pattern recognition (Gerber, 2025). These systems are designed for efficiency, adaptability, and the ability to solve complex problems across various domains, often incorporating natural language processing (NLP) to improve human-computer interaction (Kokina & Davenport, 2017).

In the context of financial auditing, hybrid AI offers transformative potential by automating large-scale data analysis while maintaining essential human oversight (Gerber, 2025). Traditional auditing methods, which rely heavily on manual sampling and professional judgment, face challenges in managing increasing data volumes and regulatory complexity. Hybrid AI mitigates these issues by synergizing symbolic reasoning (rule-based systems) with subsymbolic learning (ML), enabling more robust and dynamic auditing processes (Kokina & Davenport, 2017; GeeksforGeeks, 2024).

2. Literature Review:

The rapid advancement of artificial intelligence (AI) technologies has significantly transformed the auditing profession, particularly through the development of human-machine hybrid decision-making systems. This literature review examines the current state of research on how these hybrid systems influence auditor professional judgment, focusing on three key areas: (1) technological implementations and frameworks, (2) benefits and enhancements to audit quality, and (3) challenges and limitations in adoption.

2.1 Technological Implementations and Frameworks

Recent studies have developed several architectural frameworks for AI integration in auditing systems. Gerber (2025) proposes a robust three-tiered architecture for deploying audit-proof hybrid intelligence systems, addressing critical legal requirements, technical specifications, and organizational prerequisites. This comprehensive framework guides implementation from initial project design through continuous model optimization, with empirical evidence demonstrating substantial efficiency improvements in practical applications.

In a complementary study, Mayer et al. (2024) examine optimal approaches for developing and implementing human-AI collaborative systems in auditing contexts. Their multiple case study analysis of four successful implementations, grounded in work system theory, identifies nine critical implementation challenges along with nine corresponding best practices. The research further delineates two distinct implementation roles - technical implementers responsible for system development and organizational implementers focused on operational integration - each confronting unique obstacles and employing specialized strategies. These findings provide actionable insights for audit professionals seeking to effectively incorporate AI into their workflows.

Parallel to these developments, Devane (2023) advances an innovative Hybrid AI framework that synergistically combines symbolic reasoning for logical analysis with deep learning for pattern detection. This dual-approach system demonstrated particularly strong performance in financial auditing applications, achieving a 33% reduction in false positives for fraud detection while maintaining crucial interpretability - a fundamental requirement for audit quality assurance.

The emergence of Explainable AI (XAI) techniques has addressed critical transparency requirements in auditing. Zhang et al. (2022) demonstrate how methods like Local Interpretable Model-agnostic Explanations (LIME) and Shapley Additive exPlanations (SHAP) can meet audit documentation standards, particularly in risk assessment tasks. Song (2023) further elaborates on XAI's role in bridging the gap between AI automation and auditors' need for interpretability, finding that these techniques significantly improve professional confidence in AI-driven decisions.

2.2 Benefits and Enhancements to Audit Quality

Empirical evidence suggests hybrid systems offer substantial improvements to audit processes. Shabir and Khalid (2024) report that AI implementation reduces false positives in fraud detection by 40-60% and improves detection rates by 35%, while machine learning models enhance risk prediction accuracy by 25% through alternative data integration. Kommanaboina and Kumar (2025) propose a hybrid audit automation approach that combines quantitative financial data with qualitative auditor insights, showing potential to significantly improve efficiency and accuracy throughout the audit lifecycle.

At the organizational level, Kokina et al. (2025) identify through interviews with audit professionals that AI adoption enables a shift from traditional periodic audits to continuous monitoring capabilities. This transformation allows auditors to focus on higher-value analytical work while AI handles routine tasks. Kotivirta (2025) supports this finding, noting in interviews with Finnish executives that AI augmentation creates opportunities for auditors to develop more strategic roles within organizations.

2.3 Challenges and Limitations in Adoption

- **Ethical and Transparency Barriers**

The adoption gap between "simple AI" (e.g., OCR, data extraction) and "complex AI" (e.g., predictive analytics, fraud detection) stems from unresolved ethical and operational concerns:

- Bias and Reliability: AI systems may inherit biases from training data or produce inconsistent outputs, undermining audit integrity. Munoko et al. (2020) emphasize that AI’s inherent features (e.g., opacity) necessitate governance frameworks to mitigate risks.

- Explainability: Kokina et al. (2025) note that auditors struggle to justify AI-driven decisions when tools lack transparency, especially in high-stakes scenarios like fraud detection.

- Regulatory Uncertainty: Leocádio et al. (2024) highlight challenges in real-time monitoring compliance, as existing standards (e.g., PCAOB guidelines) lag behind AI advancements.

  - **Technical and Operational Challenges**

- Integration Complexities: Devane (2023) reports that hybrid systems (combining symbolic and subsymbolic AI) face conflicts in 15% of cases, requiring manual resolution and increasing costs.
- Data Quality Issues: Shabir and Khalid (2024) find that poor data quality reduces AI effectiveness by 15–20%, particularly in unstructured data processing (e.g., contracts, emails).
- Evaluation Overhead: Barr-Pulliam et al. (2023) show that while AI improves evidence access, it complicates evidence assessment, demanding updated auditor training.

  - **Human-AI Collaboration Gaps**

- Skill Shortages: Henry and Rafique (2021) identify a mismatch between traditional auditing skills and AI literacy, with smaller firms disproportionately affected due to resource constraints.
- Judgment Preservation: Prakash and Mathewson (2020) argue that all AI systems are inherently hybrid, requiring human oversight to contextualize outputs (e.g., distinguishing errors from fraud). Hooshangi and Sibdari (2022) advocate for "collaborative models" where AI handles repetitive tasks while humans focus on exceptions.
- Behavioral Resistance: Gajewski et al. (2024) demonstrate that auditors may over-trust or distrust AI; interventions like "nudges" can recalibrate professional skepticism.

3. Research Gap and Problem Statement

Although recent literature has advanced the integration of human-machine hybrid systems into auditing, a critical gap remains in understanding how these technologies influence and reshape auditor professional judgment. Most existing studies focus on system architecture and performance outcomes (Gerber, 2025; Devane, 2023; Shabir & Khalid, 2024; Kommanaboina & Kumar, 2025), often treating auditor judgment as a static oversight function rather than a dynamic, context-sensitive process shaped by AI outputs. Explainable AI (XAI) frameworks such as LIME and SHAP (Zhang et al., 2022; Song, 2023) enhance transparency but do not fully address how auditors interpret, challenge, or internalize machine-generated evidence in complex decision scenarios. Behavioral research (Gajewski et al., 2024; Henry & Rafique, 2021) highlights trust and skill gaps, yet lacks longitudinal insight into how auditors adapt their judgment strategies within hybrid environments. Ethical and regulatory concerns (Munoko et al., 2020; Leocádio et al., 2024) further complicate the integration of human discretion with algorithmic accountability. Notably, no prior studies have examined Human-Machine Hybrid Decision Making and its impact on auditor professional judgment within the context of developing countries. This study addresses that gap by exploring Egypt as a representative case, offering empirical insights into how hybrid systems affect professional judgment in resource-constrained audit environments.

Based on the above, the study problem can be formulated through the following main research question:

"What is the impact of Hybrid AI on auditor professional judgments within the context of Egypt?"

There are tree sub-questions that stem from this main question, as outlined below:

- What is the impact of Hybrid AI on auditor ability to assess risks?
- What is the impact of Hybrid AI on auditor Professional Skepticism?
- What is the impact of Hybrid AI on auditor to solve complex problems?

4.Conceptual Framework

4.1 Auditor Professional Judgment:

Auditor professional judgment is the core of the auditing profession. It involves an auditor using their knowledge, skills, and experience to make informed and critical decisions in complex situations. Instead of just following a set of rules, this judgment allows auditors to navigate issues not covered by standards, assess risks, and decide what evidence is needed. Ultimately, it is the crucial human element that guarantees the quality and value of an audit, distinguishing the auditor from a simple automated process.

4.1.1 Auditor Professional Judgment definition

Many researchers describe audit professional judgment in slightly different ways, but they all agree it means making smart and thoughtful decisions during an audit.

- **Starting Point**: According to Setianwan (2017), judgment begins with the auditor taking a careful look at the situation before doing anything. It helps guide their next steps.

- **Using Skills and Standards**: Heyrani et al. (2016) explain that good judgment involves applying the right skills, knowledge, and training while following professional standards—especially when the issue isn't just about numbers.

- **Thinking Ahead**: Jackson et al. (2017) and the Canadian Society of Certified Public Accountants say judgment means actively planning and solving problems when things are unclear or risky. It's not just reacting—it's thinking things through.

- **Ongoing Process**: Ali et al. (2023) point out that judgment isn't a one-time decision. It's a continuous way of thinking that happens throughout every part of the audit.

In short, professional judgment is a behavior where an auditor must make decisions, analyses, or evaluations based on their knowledge, skills, training, and experience, in accordance with the standards, laws, regulations, and principles of the applicable financial reporting framework.

4.1.2. Factors Influencing Professional Judgment

An auditor’s judgment isn’t merely an internal feeling; it’s shaped by the auditor’s background and the specific circumstances of the audit process.

- **The Auditor’s Background and Experience**

Auditor’s professional background serves as a cornerstone for exercising robust judgment. Empirical research indicates that the breadth of an auditor’s general knowledge, cumulative audit hours, and sector-specific expertise significantly enhances their capacity to identify misstatements, formulate corrective strategies, and reach accurate conclusions in a timelier manner (Pimentel et al., 2021; Cardona & Ríos, 2013, 2013). Furthermore, specialization within a particular industry fosters a profound understanding of organizational processes and risk profiles, enabling auditors to execute complex audit procedures with greater precision (Dekeyser et al., 2023).

A specialized background also yields practical benefits in the audit process: (Cardona & Ríos, 2013; Dekeyser et al., 2023).

- Plan audits strategically by identifying key risk areas and optimal timing for substantive procedures.

- Maintain professional independence and resist client pressures, thereby underpinning objective judgment.

- Enhance detection of material misstatements and conduct more effective risk assessments.

- **An Auditor’s Education and Personal Qualities**

Formal education and continuous professional development constitute the technical foundation of effective audit practice. A university degree in accounting imparts essential knowledge of financial reporting frameworks, auditing standards, and quantitative analysis techniques, while ongoing professional training—such as CPA certification courses, specialized workshops, and refresher seminars—ensures auditors stay current with evolving regulations and best practices. Through structured curricula and real-world case studies, auditors cultivate the skills needed to assess risk, design appropriate audit procedures, and interpret complex financial information under stringent regulatory scrutiny (Chen et al., 2020).

Personal attributes further reinforce an auditor's capacity for ethical judgment and objective decision-making. Honesty underpins transparent reporting and fosters stakeholder trust in audit opinions (Exemplar Global, 2025). Independence shields auditors from client influences and conflicts of interest, thereby preserving the impartiality of their judgments (Alnawaiseh & Alnawaiseh, 2015). Competence—demonstrated through deep technical expertise and analytical acumen—enables auditors to detect material misstatements and execute sophisticated audit strategies (Prasanti et al., 2019). Confidentiality safeguards sensitive client information and upholds professional ethical obligations. Objectivity demands that auditors evaluate evidence without personal bias, ensuring their conclusions rest solely on audit evidence (ECA, 2024). Together, these academic qualifications and personal qualities form the dual pillars of auditor effectiveness, marrying technical proficiency with unwavering ethical integrity.

- **Professional Skepticism**

Professional skepticism is the auditor's disposition to critically assess audit evidence and maintain a questioning mindset rather than accept client representations at face value. This attitude, as characterized by Hurtt et al., (2013), requires auditors to recognize that conditions may exist that cause material misstatement, whether due to error or fraud, and to remain alert for contradictory evidence before forming conclusions.

By guarding against confirmation and overconfidence biases, professional skepticism prevents auditors from prematurely assuming a client's honesty or dishonesty (Putra & Dwirandra, 2019). Auditors who adopt this stance will deliberately seek corroborating evidence, probe management explanations, and challenge inconsistencies, ensuring that their judgments are grounded in sufficient, appropriate evidence (Hurtt et al., 2013).

Embedding skepticism throughout the audit process enhances audit planning, execution, and judgment quality. Skeptical auditors are more adept at identifying fraud risk factors, tailoring audit procedures to address those risks, and adjusting their approach when new information arises. As a result, the incidence of undetected misstatements and flawed audit opinions is reduced, strengthening the overall reliability of financial reporting. Ultimately, professional skepticism is essential for uncovering material misstatements and upholding audit quality (Gajewski et al., 2024).

4.1.3 Key Audit Procedures and Associated Judgments:

Auditors exercise professional judgment at every stage of the audit engagement, from client acceptance through issuance of the auditor’s report. These judgments shape the audit strategy, the nature and extent of procedures, and ultimately the reliability of the auditor’s opinion.

(Hurtt et al., 2013; IAASB, 2019; Arens et al., 2017; Barr-Pulliam et al., 2023)

- Understanding the Client’s Business and Environment: Auditors must evaluate the entity’s industry, regulatory landscape, and internal structure to identify significant accounts and inherent risk factors. This foundational understanding informs the overall audit strategy and risk assessment.

- Assessing the Internal Control System: Professional judgment is required to determine whether internal controls are appropriately designed and effectively implemented. Auditors must also decide whether reliance on these controls can reduce the extent of substantive testing.

- Evaluating Internal Control Risk: Auditors estimate the probability that internal controls may fail to prevent or detect material misstatements. This assessment directly influences the acceptable level of detection risk and the nature, timing, and extent of audit procedures.

- Designing and Performing Audit Tests: Decisions regarding which substantive procedures to perform, their timing, and the quantity of evidence to gather are guided by risk assessments and auditor experience. These choices are critical to obtaining sufficient and appropriate audit evidence.

- Evaluating Audit Evidence and Results: Exercising professional skepticism and critical thinking is essential to ensure that contradictory or insufficient evidence is properly considered. Auditors must avoid confirmation bias and ensure that conclusions are well-supported.
- Forming and Reporting the Audit Opinion: Based on the nature and pervasiveness of identified misstatements or scope limitations, auditors determine the appropriate type of opinion—unqualified, qualified, adverse, or disclaimer. This judgment reflects the overall reliability of the financial statements.

Engagement acceptance itself requires nuanced judgment concerning firm-level risks, professional capacity, and reputational considerations. Factors influencing this decision include the significance and likelihood of errors, effectiveness of management controls, prior audit lessons learned, and evidence reliability. When drafting the final report, auditors apply judgment to present findings clearly, offer constructive recommendations, and appropriately classify internal control deficiencies ((Johnson-Snyder & Chandrasekran, 2017)).

4.2 Hybrid Artificial Intelligence:

Hybrid Artificial Intelligence (Hybrid AI) represents a new paradigm that moves beyond viewing humans and machines as separate entities. Instead, it is a synergistic approach that integrates the unique strengths of human expertise with the computational power and data-processing capabilities of artificial intelligence (GeeksforGeeks, 2024). At its core, Hybrid AI is founded on the principle that the most effective solutions to complex problems emerge from a collaborative partnership between human and machine intelligence.

Traditional AI systems excel at tasks involving massive datasets, pattern recognition, and rapid computation. However, they often lack the contextual understanding, ethical reasoning, and professional judgment that are fundamental to human cognition. Hybrid AI bridges this gap by creating frameworks where AI's analytical strengths are used to augment, rather than replace, human expertise. For example, AI can sift through vast quantities of data to flag anomalies and provide predictive insights, while the human expert applies critical thinking, professional skepticism, and real-world experience to validate those insights and make the final, informed decision (Saiwa, 2024).

This collaborative model is rapidly transforming professional fields such as finance, medicine, and, most notably, auditing. It promises not only to enhance efficiency and accuracy but also to elevate the quality of professional work by freeing human experts from routine tasks and allowing them to focus on high-value, complex problem-solving. This shift highlights a future where the successful application of AI is defined not by its ability to operate independently, but by its capacity to create a more intelligent, adaptable, and robust system in partnership with human professionals (Surur et al., 2025).

4.2.1. Core Components of Hybrid AI Architectures

Hybrid AI systems derive their strength from the synergistic integration of diverse AI techniques, with each component contributing unique capabilities to the overall system's performance. (Verma, 2024; Saiwa, 2024).

- **Foundational Elements**

  These elements are fundamental to the operation of many AI systems, including hybrid ones:

  - **Data**: This constitutes the essential input, serving as the fuel for machine learning algorithms to learn and evolve. The quality and relevance of this data directly influence the hybrid system's effectiveness.

  - **User Interface**: This crucial element facilitates interaction between humans and the AI system. It allows users to input data, view results, and provide feedback, ensuring a user-friendly and collaborative experience.

- **Core AI Paradigms within Hybrid Systems**

Hybrid AI architectures are typically built upon the following core AI paradigms, often combining their strengths:(GeeksforGeeks, 2024; Saad & Elson, 2025)

- **Symbolic AI (Rule-Based AI):** This paradigm operates on explicit rules and logical reasoning. It employs predefined knowledge representations and symbolic manipulation to solve problems, making its decision-making process transparent and easily understandable. Symbolic AI excels in tasks requiring explainability, such as expert systems for medical diagnosis or legal reasoning. However, it can struggle with handling uncertainty, adapting to new situations not explicitly covered by rules, and managing very large datasets. Its core components typically include a Knowledge Base, which is an organized repository storing facts, rules, and relationships that form the logical foundation, and a Rule Engine, which executes these predefined rules and logic.
- **Machine Learning (ML):** ML algorithms empower systems to learn from data without explicit programming. They identify patterns, make predictions, and improve their performance over time through exposure to data. ML excels in tasks involving complex patterns and large datasets, such as image recognition, natural language processing, and predictive analytics. Common ML algorithms leveraged in hybrid AI include decision trees, neural networks, and reinforcement learning models. These algorithms enable the system to learn from data, identify patterns, and make predictions or decisions. A key challenge is that its decision-making process can be opaque, often referred to as a "black box," and susceptible to biases present in the training data.
- **Deep Learning (DL):** As a specialized subset of machine learning, deep learning utilizes artificial neural networks with multiple layers to extract hierarchical representations from data. This layered architecture allows DL models to learn complex patterns and representations directly from raw data, making them particularly effective with unstructured data like images, audio, and text. The main drawbacks are the requirement for massive amounts of data for training and its

computationally intensive nature, demanding significant processing power and resources.

- **Evolutionary Computation (EC):** Drawing inspiration from biological evolution, EC algorithms employ mechanisms like mutation, crossover, and selection to optimize solutions. EC is particularly effective in exploring complex search spaces and finding optimal or near-optimal solutions for problems where traditional optimization methods struggle. However, it can be computationally expensive, especially for large-scale problems, and requires careful parameter tuning to achieve optimal performance.

- **Fuzzy Logic (FL):** Fuzzy logic addresses uncertainty and imprecise information by representing knowledge in terms of degrees of truth rather than absolute true or false values. This enables fuzzy logic systems to handle vagueness and ambiguity, making them suitable for applications where precise measurements are difficult or impossible to obtain, such as controlling complex industrial processes or modeling human decision-making. The challenge lies in designing appropriate fuzzy sets and rules, which often requires expert knowledge.

- **Probabilistic Reasoning (PR**): This component uses probability theory to represent and reason about uncertainty. It allows systems to make decisions based on incomplete or uncertain information by quantifying the likelihood of different outcomes and making informed choices based on probabilities. This is particularly useful in domains like medical diagnosis, risk assessment, and decision-making under uncertainty. However, probabilistic reasoning can be computationally complex for large and intricate problems, necessitating efficient algorithms and data structures.

4.2.2. Advantages and challenges of Hybrid AI in Business

Hybrid Artificial Intelligence (AI) offers substantial advantages for businesses, significantly enhancing decision-making, efficiency, and scalability by integrating diverse AI methodologies. The importance of

Hybrid AI stems from its ability to overcome the inherent limitations of systems relying solely on either rule-based or learning-based approaches

- **Key Business Advantages of Adopting Hybrid AI**

Businesses implementing hybrid AI models can experience several critical benefits:

- **Increased Accuracy:** By integrating deep learning with classical models, hybrid AI achieves superior predictive performance, especially with complex datasets. This approach ensures models are optimized to detect both macro and micro-level patterns in data, leading to more precise insights (Saiwa, 2024).
- **Scalability and Efficiency:** Hybrid AI solutions enable organizations to optimize computational resource allocation. They use classical algorithms for simpler, less resource-intensive tasks while reserving deep learning for more complex inferences. This strategy reduces processing time and facilitates a more scalable AI deployment, making efficient use of computational power (Raju et al., 2024).
- **Improved Interpretability:** One of the main challenges with deep learning is its "black box" nature. Hybrid AI mitigates this by allowing classical models to explain AI-driven decisions. This transparency is crucial for industries that demand clear accountability, such as finance, healthcare, and legal sectors. This directly addresses the explainability concern in AI (Doshi-Velez & Kim, 2017).
- **Adaptability to Structured and Unstructured Data:** Traditional machine learning techniques excel at handling structured data (e.g., tabular data), whereas deep learning is superior for processing unstructured data (e.g., images, text, videos). A hybrid approach ensures businesses can effectively leverage insights from both data types, leading to more comprehensive analysis (Surur et al., 2025).
- **Cost-Effectiveness:** Deep learning models typically demand significant computational power and expensive hardware. By intelligently utilizing classical AI methods where feasible, businesses can significantly reduce

operational costs while still benefiting from advanced AI capabilities. Hybrid AI thus ensures a balance between technological advancement and practical business applications, fostering more cost-effective and intelligent AI systems. This also contributes to overall efficiency in resource utilization (Saiwa, 2024).

- **Risks, Challenges, and Limitations of Hybrid Intelligence**

Despite its benefits, HI introduces several challenges that must be addressed through governance, technical safeguards, and ethical oversight**.**

- **Legal and Regulatory Risks**

These include liability concerns, regulatory ambiguity, and audit trail integrity. Mitigation strategies involve contractual clarity, compliance boards, and robust logging/versioning systems (Mökander, 2023).

- **Technical Challenges**

Issues such as data quality, model drift, and scalability require data governance frameworks, automated monitoring, and distributed computing solutions (Del Caprio, 2025; Lacmanovic & Skare, 2025).

- **Organizational and Cultural Barriers**

Auditor resistance, skill gaps, and cultural inertia can hinder adoption. Solutions include early auditor engagement, targeted training, and structured change management programs (Koshiyama et al., 2024; Odeyemi et al., 2024).

- **Ethical and Social Considerations**

Bias, fairness, and data protection are critical concerns. Countermeasures include bias audits, integration of XAI, and adherence to GDPR and ISO standards (Munoko et al., 2020; Lacmanovic & Skare, 2025).

- **Technological Limitations**

HYPERD AI systems may lack contextual understanding, rely heavily on proprietary platforms, and suffer from standardization gaps. Addressing these requires hybrid rule-based-AI models, open standards, and participation in expert committees (Mökander, 2023).

4.2.3. Understanding the Hybrid AI Ecosystem

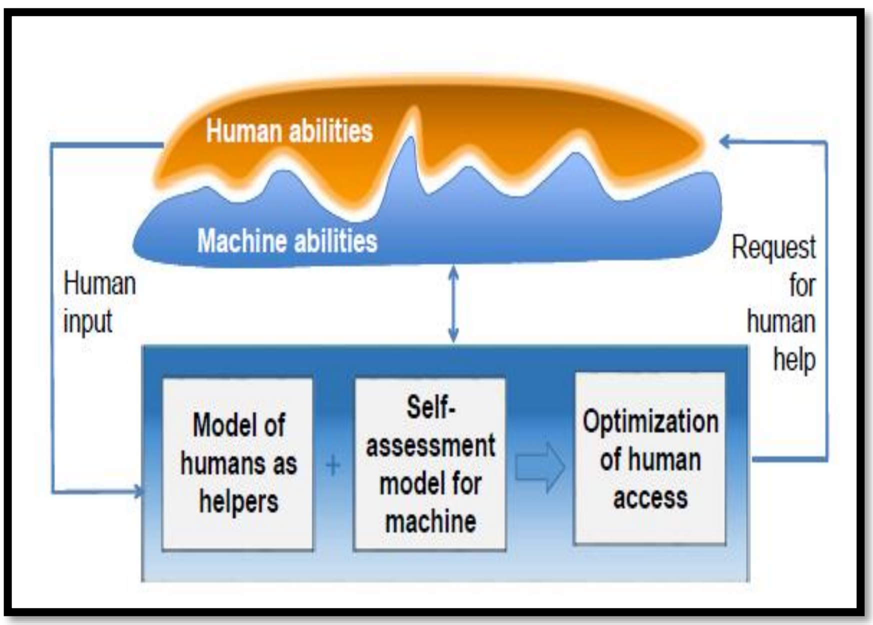
Hybrid AI combines different AI approaches, specifically mixing rule-based systems (which follow explicit instructions) and learning-based systems (which learn from data). Here are the main types (Staff, 2025; Milvus, 2025):

- Expert Systems with Machine Learning: Imagine a traditional expert system built on human-defined rules (like "if A, then B"). This hybrid type enhances those rules by letting machine learning fine-tune and update them based on new data. So, human knowledge provides the foundation, and AI refines it.
- Learning-based Systems with Rules: In this setup, machine learning algorithms do most of the heavy lifting. However, they operate within a defined framework of rules. These rules act as guardrails, ensuring the learning system stays on track and produces sensible results.
- Hybrid Reasoning Systems: These systems are designed to handle both clear-cut, logical problems and more ambiguous, real-world situations. They do this by combining symbolic reasoning (which uses rules and logic, like traditional AI) with subsymbolic reasoning (which involves machine learning's ability to deal with less defined data). This combination allows for a more comprehensive understanding and better decision-making.
- Ensemble Systems: Think of this as a "team" of AI. Ensemble systems bring together multiple machine learning algorithms, each potentially having its own set of guidelines. By combining their strengths, these systems can achieve more accurate and robust predictions than any single algorithm could on its own.

4.2.4. Hybrid AI in Financial Auditing

Hybrid AI in financial auditing combines human expertise with Artificial Intelligence (AI) to enhance audit processes. By integrating AI's analytical capabilities with human judgment, auditors can efficiently analyze large datasets, detect anomalies, identify complex risk patterns, and generate actionable insights—leading to more effective audit planning and execution. (Kamar, 2016; Kokina & Davenport, 2017). Importantly, human auditors remain essential in verifying AI-generated results, interpreting findings within the broader business context, and making nuanced decisions in complex scenarios (Verma, 2024).

Figure 1. Hybrid AI farmwork



source: Kamar (2016)

Hybrid AI is built on collaboration between human and artificial intelligence within a unified system. While AI excels at processing vast amounts of data, recognizing patterns, and making predictions, human auditors contribute domain expertise, ethical judgment, and contextual understanding—elements that AI alone cannot fully replicate (Kokina et al., 2025).

4.2.4.1 Key principles underpinning Hybrid AI in auditing include (Gerber, 2025):

- **Augmented Intelligence:** AI supports rather than replaces human decision-making. In auditing, AI generates insights that auditors review, validate, and contextualize before taking action.
- **Human-in-the-Loop (HITL):** This approach ensures continuous human oversight during AI model development and deployment. Auditors provide feedback, correct errors, and refine AI systems to improve accuracy over time.
- **Explainable AI (XAI):** XAI techniques make AI decision-making transparent, fostering auditor trust and compliance with regulatory standards. Tools like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) help auditors understand how specific factors influence AI predictions, ensuring accountability and traceability.

4.2.4.2. Requirements for Integrating Hybrid Intelligence in Financial Auditing ((Kokina et al., 2025; Zhang et al., 2022).

The integration of Hybrid Intelligence (HI) into financial auditing constitutes a pivotal evolution that necessitates rigorous adherence to multifaceted standards. These include legal, regulatory, professional, and technical dimensions, each serving to uphold the integrity, transparency, and reliability of the audit process.

- **Legal and Regulatory Compliance**

Despite increasing reliance on AI technologies, auditors retain full accountability for professional judgments rendered during the audit. Accordingly, every element of the HI process—including input data, model architecture, algorithm parameters, decision logic, and output results—must be comprehensively documented. Version control and audit logs are essential components. Moreover, AI models must demonstrate explainability, ensuring that the rationale behind decisions is clearly interpretable by a qualified third-party auditor. This is critical to maintaining both procedural transparency and regulatory alignment.

- **Quality Assurance and Technical Standards**

HI implementation demands robust quality management systems that extend beyond conventional audit protocols. Models should be tested and validated in controlled environments prior to deployment, with performance metrics monitored on an ongoing basis. Independent reviews are essential to affirm audit reliability. Furthermore, any changes to data pipelines, algorithm parameters, or software configurations must undergo formal evaluation, receive appropriate approvals, and be meticulously documented. Real-time monitoring tools should also be employed to detect deviations in model performance and trigger recertification procedures when necessary.

- **Data Protection and Security Protocols**

Given the sensitive nature of financial and personal data involved in HI systems, data protection constitutes a non-negotiable requirement. Personal data must be minimized, and where applicable, anonymized or pseudonymized. Data Protection Impact Assessments (DPIAs) are essential to evaluate systemic risks and mitigation strategies. Role-based access controls, segregation of duties, and encrypted data handling help prevent unauthorized access. Foundational safeguards—including regular security updates, firewalls, and intrusion detection systems—should be reinforced by - **Organizational Governance and Capacity Building**

Successful integration of HI requires the establishment of a dedicated governance structure responsible for policy formulation, accountability assignment, and escalation procedures. Auditors must receive targeted training in AI fundamentals, machine learning concepts, and tools for explainable AI (XAI). A multidisciplinary support system involving data scientists and cybersecurity professionals is imperative. Transparency, stakeholder engagement, and iterative feedback loops further facilitate the acceptance and effective integration of HI technologies across auditing environments.

4.2.4.3. Architecture of Hybrid Intelligence Systems in Financial Auditing

The integration of hybrid intelligence (HI) into financial auditing necessitates a modular architecture composed of three interdependent layers: data infrastructure, AI analytical components, and human-machine interfaces. Each layer plays a critical role in ensuring system scalability, security, interpretability, and compliance with auditing standards.

- **Data Infrastructure and Management**

A foundational data infrastructure is required to enable scalable and secure access to audit-relevant datasets. This infrastructure typically consolidates booking and master data from enterprise resource planning (ERP) systems into a centralized data lake capable of storing both structured and unstructured formats. ETL (Extract, Transform, Load) or ELT (Extract, Load, Transform) pipelines are employed to cleanse, harmonize, and prepare the data for analytical processing. Subsequently, the information is moved into a data warehouse optimized for audit analytics. Data quality and regulatory compliance are enforced through robust governance frameworks that utilize profiling tools to evaluate completeness, consistency, and plausibility. Encryption protocols and role-based access control mechanisms are also applied to safeguard sensitive information from unauthorized access (Leocádio et al., 2024).

- **AI Components and Algorithms**

The second layer comprises a suite of AI algorithms tailored to audit-specific tasks. Unsupervised learning models such as Isolation Forest and Autoencoders are leveraged to detect anomalies and irregular transaction patterns across high-volume datasets. Supervised algorithms—namely Random Forest and Gradient Boosting—are trained on historical financial records to predict the likelihood of misstatements, risk factors, or procedural deviations. Transformer-based natural language processing (NLP) models, including BERT and GPT, are deployed to extract contextual entities and audit-relevant insights from textual documents such as contracts, emails, and audit memos. Continuous performance monitoring is facilitated via precision, recall, and area under the curve (AUC-ROC) metrics displayed through interactive dashboards. When significant deviation in model accuracy is detected, retraining cycles are automatically initiated (Odeyemi et al., 2024; Yadav et al., 2024).

- **Human-Machine Interfaces**

The effectiveness of hybrid intelligence in audit workflows depends heavily on user-centric design. Human-machine interfaces must facilitate interpretability and trust in AI-generated outputs. Interactive dashboards allow auditors to drill down from aggregated metrics to individual transaction details, enhancing contextual understanding. Visual aids such as heatmaps, risk matrices, and relationship graphs assist in anomaly analysis and risk assessment. Explainability frameworks like LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (SHapley Additive exPlanations) are embedded within the interfaces to illuminate the rationale behind model predictions. Crucially, user feedback systems allow auditors to validate, annotate, or override AI-generated results. These inputs are logged and integrated into iterative training cycles to ensure the continuous evolution of the HI system (Henry & Rafique, 2021; Kotivirta, 2025).

4.2.4.4 Hybrid Intelligence Approaches in Financial Auditing

Hybrid intelligence integrates human expertise with artificial intelligence to improve audit precision, efficiency, and adaptability. The following methodologies illustrate its application in modern financial audits:

- **Transactional Analysis & Anomaly Detection**

This technique automates the examination of comprehensive booking data to uncover irregularities. Enterprise Resource Planning (ERP) data is standardized, and master data is systematically coded. Unsupervised learning algorithms, trained on historical datasets, model typical transaction patterns and flag deviations. Each transaction is assigned an anomaly score, enabling auditors to prioritize high-risk entries. Human feedback refines these models, improving accuracy over time through iterative learning (Odeyemi et al., 2024).

- **Risk-Based Auditing with Predictive Analytics**

  Predictive models assess the likelihood of errors, guiding resource allocation. Supervised learning algorithms utilize past audit outcomes to identify risk indicators such as transaction frequency, data volatility, and financial metrics. These models generate risk scores for audit areas, allowing auditors to set thresholds and assign complex cases to experienced professionals, while automating routine checks (Leocádio et al., 2024).

- **Document Intelligence via Natural Language Processing**

  Natural Language Processing (NLP) automates the review of unstructured documents like contracts and emails. Texts are preprocessed and tokenized, while entity recognition models extract key details (e.g., dates, amounts, parties). Documents are categorized by audit relevance, and sentiment analysis of communications helps detect early signs of non-compliance. Summarized insights assist auditors in determining the need for manual review (Arham ,2025).

- **Visualization & Decision Support Tools**

  Advanced visualization enhances auditor judgment and fosters trust in AI systems. Heat maps highlight anomaly concentrations, network graphs reveal inter-entity relationships, and interactive dashboards allow drill-down from summaries to individual records. Explainable AI interfaces provide transparent rationales for model decisions, supporting informed human oversight (Kommanaboina & Kumar, 2025)

- **Professional Skepticism in Hybrid Audits**

  Maintaining professional skepticism is essential when integrating AI into audits. Auditors critically assess flagged transactions, contextualize AI outputs, and validate findings across multiple models. They document decisions alongside AI-generated evidence to ensure transparency. Training programs help auditors recognize biases and limitations in AI systems, reinforcing the role of human judgment (Balakrishnan & Popat, 2025).

4.2.4.5 Opportunities and Benefits of Hybrid Intelligence in Auditing

Hybrid intelligence (HI) offers transformative potential across four key dimensions: efficiency, audit quality, risk coverage, and strategic advantage.

- **Improve Efficiency and Cost Reduction**

By automating repetitive tasks, HI can reduce audit examination hours by 20–30% and cut audit budgets by 15–25%, streamlining workflows and minimizing manual labor (Del Caprio, 2025; Odeyemi et al., 2024).

- **Improved Audit Quality**

HYPERD AI systems leverage adaptive learning and explainable AI (XAI) to enhance audit transparency and coverage, contributing to a 40% reduction in undetected risks (Munoko et al., 2020).

- **Expanded Risk Coverage**

Through real-time monitoring, granular risk profiling, and dynamic adaptability, HYPERD AI enables early detection of anomalies, achieving up to 90% identification of critical transactions (Lacmanovic & Skare, 2025).

- **Strategic Competitive Advantage**

HYPERD AI fosters innovation leadership and scalability, while generating actionable insights from audit data that support long-term positioning and decision-making (Koshiyama et al., 2024).

4.2.4.6 Future Developments in Hybrid Intelligence for Auditing

The accelerating evolution of hybrid intelligence (HI) technologies is poised to reshape the auditing landscape through advanced automation, decentralized systems, and collaborative ecosystems.

- **Adaptive Learning and Scalable Models**

Next-generation HI platforms will incorporate adaptive learning mechanisms that dynamically refine analytical models using real-time auditor input. This continuous feedback loop enhances model accuracy and responsiveness, enabling scalable audit solutions tailored to evolving operational contexts (Leocádio et al., 2024; Odeyemi et al., 2024).

- **Semantic Automation via Large Language Models**

The integration of large language models (LLMs) will revolutionize audit workflows by enabling semantic interpretation of complex documents, automated report generation, and conversational analysis assistants. These capabilities streamline decision-making and reduce manual effort in data interpretation (KPMG, 2025; Accounting Insights, 2025).

- **Blockchain-Enabled Audit Trails**

Blockchain technology will redefine audit trail integrity through immutable transaction records, decentralized verification protocols, and distributed ledger systems. These innovations enhance transparency, reduce fraud risk, and support regulatory compliance across multi-party environments (Accounting Insights, 2025).

- **Real-Time Insights from IoT and Edge Computing**

The deployment of IoT sensors and edge computing will facilitate real-time data acquisition for asset tracking, operational monitoring, and supply chain auditing. This shift enables auditors to perform continuous assessments and respond proactively to anomalies (Leocádio et al., 2024).

- **Collaborative Audit Ecosystems**

Future HI environments will emphasize interconnected audit platforms, fostering collaboration through shared data repositories, modular system integration, and cross-organizational workflows. These ecosystems promote transparency, scalability, and collective intelligence in audit practices (Odeyemi et al., 2024).

5. Field Study

The researcher relied on the survey form as one of the data collection tools, and he prepared the questions that he formed after completing the theoretical study. The researcher tried to consider the accuracy as much as possible when formulating the questions, through the following:

• Clarification of some terms.

• Obtaining general information from the respondents related to current job and educational qualification.

• The design of the survey list was based on a five-point Likert scale to measure the responses of the sample, as shown in the following table:

Table (1)

Five-point Likert scale

Strongly Disagree	Disagree	Neutral	Agree	Strongly agree	Category
	2	3	4	5	Degree

Thus, the item that takes an arithmetic average of more than three degrees is considered an Agree and influential item and therefore it is accepted, while the item that does not achieve this average is considered an ineffective item and therefore it is rejected.

5.1 Testing the Stability and Validity.

The reliability and validity of the research scales were assessed to ensure the quality of the data. Reliability, an essential characteristic of any measurement tool, refers to its consistency and stability. This is demonstrated by a tool's ability to produce similar or equal measurements when applied repeatedly to the same sample under consistent conditions.

To test the internal consistency and stability of the questionnaire, Cronbach's alpha coefficient was calculated. This coefficient, with values ranging from 0 to 1, indicates the degree of scale reliability; values closer to 1 signify higher reliability. A coefficient of 0.60 or higher is generally considered acceptable for social science research. Additionally, any variable with a total correlation coefficient of less than 0.30 with the rest of the variables in its scale was excluded from the analysis.

The table below summarizes the results of the reliability test for each hypothesis's scale.

Table (2)

Results of the validity and reliability test

Items	No of items	Reliability
Hypotheses 1	6	.757
Hypotheses 2	5	.772
Hypotheses 3	7	.825
Total	18	.874

From these results, it is clear that the Cronbach's alpha values for all scales range between 0.757 and 0.825. These values all exceed the acceptable threshold of 0.60, confirming the internal consistency and reliability of the research variables for subsequent statistical analysis.

Field Study Population and Sample

To achieve the study's objectives, a simple random sampling method was utilized to select the study sample. The sample included university faculty members, postgraduate students, and professional auditors.

The questionnaire was distributed electronically to the sample via Google Forms. A total of 137 responses were received, and all were deemed suitable for statistical analysis.

5.2 Sample Characteristics

To identify the demographic characteristics of the study sample, frequencies and percentages were calculated and are presented below.

First: Job Title:

The following table presents the distribution of the study sample based on their job titles.

Table (3)

Frequencies and percentages by Job Title

<table>
<tr><th rowspan="2">Categories</th><th colspan="2">Member of teaching staff</th><th colspan="2">Auditor</th><th colspan="2">Postgraduate Student</th><th rowspan="2">Total</th></tr>
<tr><th>N0.</th><th>%</th><th>N0.</th><th>%</th><th>N0.</th><th>%</th></tr>
</table>

Total	35	25.6	54	39.4	48	35	137

Second: Educational Level:

The following table details the distribution of the study sample according to their educational level.

Table (4)

Frequencies and percentages by Educational Level

Categories	Bachelor		Diploma		Master		Ph.D.		Total
	N0.	%	N0.	%	N0.	%	N0.	%	
Total	61	44.5	33	24.1	17	12.4	26	19	137

Third: Experience:

The frequencies and percentages were extracted for the distribution of the study sample according to number of years of job experience, as shown in the following table:

Table (5)

Frequencies and percentages by Experience

Categories	Less than 5 years		5 To less than 10 Years		10 To less than 15 Years		More than 15 Years		Total
	N0.	%	N 0.	%	N0.	%	N0.	%	
Total	57	41.6	45	32.9	17	12.4	18	13.1	137

5.3 Statistical Symbols

For the purpose of statistical analysis, the variables in the survey were coded as follows:

- Hypothesis 1 (H0.1) Items: Coded from X1.1 to X1.6
- Hypothesis 2 (H0.2) Items: Coded from X2.1 to X2.5
- Hypothesis 3 (H0.3) Items: Coded from X3.1 to X3.7

5.4 The statistical methods and Data Distribution

To test the study's hypotheses, the researcher used the statistical software package SPSS 26. The initial step was to determine the statistical distribution of the data to select the appropriate analytical methods.

The Kolmogorov-Smirnov Test was performed to assess whether the data followed a normal distribution. The results are presented in the table below:

Table (6)

Results of Kolmogorov-Smirnov Test

Items	Kolmogorov-Smirnov Z	Asymp. Sig. (2-tailed)	Items	Kolmogorov -Smirnov Z	Asymp. Sig. (2-tailed)
X1.1	0.297	.000c	X2.4	0.320	.000c
X1.2	0.293	.000c	X2.5	0.282	.000c
X1.3	0.337	.000c	X3.1	0.267	.000c
X1.4	0.306	.000c	X3.2	0.290	.000c
X1.5	0.301	.000c	X3.3	0.259	.000c
X1.6	0.332	.000c	X3.4	0.264	.000c
X2.1	0.292	.000c	X3.5	0.250	.000c
X2.2	0.264	.000c	X3.6	0.267	.000c
X2.3	0.310	.000c	X3.7	0.263	.000c

As shown in the table, the significance value (Asymp. Sig.) for all items is 0.000, which is less than the conventional α level of 0.05. This indicates that the data does not follow a normal distribution. Consequently, the study will rely on non-parametric statistical tests for hypothesis testing.

5.5 Examination of Study Hypotheses:

The results of the statistical analysis and testing the validity of the study hypotheses are dealt with as follows**:**

Test of Hypothesis 1

Hypothesis: There is a significant impact of Hybrid AI on an auditor's ability to assess risks.

Descriptive Statistics

The descriptive statistics for the items related to Hypothesis 1 are presented in the table below. This analysis provides an initial overview of the study sample's opinions.

Table (7)

Descriptive statistics for H0.1 Items

Items	Mean	Std. Deviation	Mode	General trend
Hybrid AI system Improve auditor ability to assess control risks	4.3534	.71980	5	Strongly agree
Hybrid AI Improve auditor ability to assess inherent risks	4.3609	.72130	5	Strongly agree
Hybrid AI Improve auditor ability to assess detection risk	4.4511	.73305	5	Strongly agree
Hybrid AI increase the ability to detect material misstatements.	4.4060	.76908	5	Strongly agree
Hybrid AI help the auditor reducing the audit risk.	4.3534	.73025	5	Strongly agree
Hybrid AI increasing the level of trust in financial statements.	4.4511	.70136	5	Strongly agree

Source: SPSS statistical analysis results

The previous table shows that the opinions of the study sample showed a trend of completely agreeing (Strongly agree) on the impact of Hybrid AI on auditor ability to assess risks

Second: Chi-Square Test

The Chi-Square test was used to determine whether the distribution of responses for each item was significantly different from a uniform distribution.

Table (8)

Chi-Square Test for H0.1 Items

Items	Chi-Square	Df	Asymp. Sig
Hybrid AI system Improve auditor ability to assess control risks	83.090	3	.000
Hybrid AI Improve auditor ability to assess inherent risks	87.782	3	.000

Hybrid AI Improve auditor ability to assess detection risk	104.564	3	.000
Hybrid AI increase the ability to detect material misstatements.	155.459	4	.000
Hybrid AI help the auditor reducing the audit risk.	81.406	3	.000
Hybrid AI increasing the level of trust in financial statements.	104.203	3	.000

Source: SPSS statistical analysis results

The results indicate that the significance level (Sig) for all items is 0.000, which is less than the conventional α level of 0.05. This confirms that the observed opinions of the study sample are statistically significant and not due to chance, further supporting the strong agreement seen in the descriptive statistics

Third: Friedman Test

Since the data does not follow a normal distribution, the Friedman Test was conducted to determine if there were significant differences in the mean rankings of the different items within this hypothesis.

Table (9) Friedman Test for H0.1 Items

Items	Mean Rank	Ranking	Chi-Square	Sig
Hybrid AI system Improve auditor ability to assess control risks	3.41	4	4.911	.427
Hybrid AI Improve auditor ability to assess inherent risks	3.38	5		
Hybrid AI Improve auditor ability to assess detection risk	3.70	1		
Hybrid AI increase the ability to detect material misstatements.	3.53	3		
Hybrid AI help the auditor reducing the audit risk.	3.38	6		
Hybrid AI increasing the level of trust in financial statements.	3.6	2		

Source: SPSS statistical analysis results

the significance level (Sig) of the Friedman test is 0.427, which is greater than 0.05. This means there is no statistically significant difference in the relative importance that respondents assigned to the various items within Hypothesis 1. In other words, all six aspects of Hybrid AI's impact on risk assessment (X1.1 to X1.6) are considered similarly important by the respondents.

Based on the statistical analysis, the descriptive statistics and Chi-Square test demonstrate a significant and positive consensus that Hybrid AI impacts an auditor's ability to assess risks. Furthermore, the Friedman test shows that the individual items within the hypothesis are considered to have a similar level of importance. Therefore, the first sub-hypothesis is accepted.

Test of Hypothesis 2

Hypothesis: There is a significant impact of Hybrid AI on an auditor's professional skepticism.

Descriptive Statistics

The descriptive statistics for the items related to Hypothesis 2 are presented in the table below. This analysis provides an initial overview of the study sample's opinions.

Table (10)

Descriptive statistics for H0.2 Items

Items	Mean	Std. Deviation	Mode	General trend
Using Hybrid AI system decrease in an auditor's traditional skills, such as manual data verification.	4.3534	.86336	5	Strongly agree
Using Hybrid AI system facilitate the acquisition of new experiences for auditors.	4.3008	.78803	5	Strongly agree
Using Hybrid AI system leads to an improvement in the quality of the audit report.	4.3835	.73569	5	Strongly agree
Using Hybrid AI system improve the professional skepticism of auditors in small firms.	4.4135	.81768	5	Strongly agree
Using Hybrid AI system assist auditors in making better professional judgments.	4.3534	.71980	5	Strongly agree

Source: SPSS statistical analysis results

As the table shows, the mean scores for all items are consistently high (above 4.30), and the mode for all items is 5, corresponding to "Strongly Agree." This indicates that the study sample overwhelmingly agrees that Hybrid AI has a positive impact on an auditor's professional skepticism.

Second: Chi-Square Test

Table (11)

Chi-Square Test for H0.2 Items

Items	Chi-Square	Df	Asymp. Sig
Using Hybrid AI system decrease in an auditor's traditional skills, such as manual data verification.	146.286	4	.000
Using Hybrid AI system facilitate the acquisition of new experiences for auditors.	136.887	4	.000
Using Hybrid AI system leads to an improvement in the quality of the audit report.	88.203	3	.000
Using Hybrid AI system improve the professional skepticism of auditors in small firms.	98.609	3	.000
Using Hybrid AI system assist auditors in making better professional judgments.	92.609	3	.000

Source: SPSS statistical analysis results

The results indicate that the significance level (Asymp. Sig.) for all items is 0.000, which is less than the conventional α level of 0.05. This confirms that the observed opinions of the study sample are statistically significant and not due to chance, providing strong evidence in favor of the hypothesis.

Third: Friedman Test

Table (12) Friedman Test for H0.2 Items

Items	Mean Rank	Ranking	Chi-Square	Sig
Using Hybrid AI system decrease in an auditor's traditional skills, such as manual data verification.	3.01	3	4.198	.380
Using Hybrid AI system facilitate the acquisition of new experiences for auditors.	2.85	5		
Using Hybrid AI system leads to an improvement in the quality of the audit report.	3.03	2		
Using Hybrid AI system improve the professional skepticism of auditors in small firms.	3.16	1		
Using Hybrid AI system assist auditors in making better professional judgments.	2.95	4		

Source: SPSS statistical analysis results

The significance level (Sig.) of the Friedman test is 0.380, which is greater than 0.05. This means there is no statistically significant difference in the relative importance that respondents assigned to the various items within Hypothesis 2. In other words, all five aspects of Hybrid AI's impact on professional skepticism (X2.1 to X2.5) are considered similarly important by the respondents.

Based on the statistical analysis, the descriptive statistics and Chi-Square test demonstrate a significant and positive consensus that Hybrid AI impacts an auditor's professional skepticism. The Friedman test further confirms that the individual items within the hypothesis are considered to have a similar level of importance. Therefore, the second sub-hypothesis is accepted.

Test hypothesis No. 3

Hypothesis: There is a significant impact of Hybrid AI on an auditor's ability to solve complex problems.

Descriptive Statistics

The descriptive statistics for the items related to Hypothesis 3 are presented in the table below.

Table (13)

Descriptive statistics for H0.3 Items

Items	Mean	Std. Deviation	Mode	General trend
Hybrid AI systems improve an auditor's ability to identify and define complex problems within an audit.	4.2406	.87170	5	Strongly agree
Hybrid AI helps auditors generate more creative and effective solutions for audit-related problems.	4.3383	.75766	5	Strongly agree
The use of Hybrid AI makes the problem-solving process in an audit more structured and systematic.	4.2481	.81097	5	Strongly agree
Hybrid AI systems empower auditors to make more timely and confident decisions when solving problems.	4.2331	.78709	5	Strongly agree

Auditors retain ultimate responsibility for the final problem-solving decision, even when using Hybrid AI.	4.2556	.71408	4	Agree
Hybrid AI provides new insights that auditors might not have uncovered on their own.	4.2331	.96834	5	Strongly agree
Hybrid AI facilitates more effective collaborative problem-solving among audit team members.	4.2331	.84286	4	Agree

Source: SPSS statistical analysis results

As the table shows, the mean scores are all above 4.23. The modes are either 4 ("Agree") or 5 ("Strongly Agree"), indicating that the study sample generally agrees that Hybrid AI has a positive impact on an auditor's ability to solve complex problems.

The Chi-Square test

Table (14)

Chi-Square Test for H0.3 Items

Items	Chi-Square	Df	Asymp. Sig
Hybrid AI systems improve an auditor's ability to identify and define complex problems within an audit.	66.308	3	.000
Hybrid AI helps auditors generate more creative and effective solutions for audit-related problems.	134.030	4	.000
The use of Hybrid AI makes the problem-solving process in an audit more structured and systematic.	117.188	4	.000
Hybrid AI systems empower auditors to make more timely and confident decisions when solving problems.	61.496	3	.000
Auditors retain ultimate responsibility for the final problem-solving decision, even when using Hybrid AI.	77.737	3	.000
Hybrid AI provides new insights that auditors might not have uncovered on their own.	117.338	4	.000
Hybrid AI facilitates more effective collaborative problem-solving among audit team members.	73.767	3	.000

Source: SPSS statistical analysis results

The results indicate that the significance level (Asymp. Sig.) for all items is 0.000, which is less than the conventional α level of 0.05. This confirms that the observed opinions are statistically significant, providing strong evidence in favor of the hypothesis.

Third: Friedman Test

Table (15)

Friedman Test for H0.3 Items

Items	Mean Rank	Ranking	Chi-Square	
Hybrid AI systems improve an auditor's ability to identify and define complex problems within an audit.	4.01	3	1.646	.949
Hybrid AI helps auditors generate more creative and effective solutions for audit-related problems.	4.16	1		
The use of Hybrid AI makes the problem-solving process in an audit more structured and systematic.	3.98	4		
Hybrid AI systems empower auditors to make more timely and confident decisions when solving problems.	3.92	7		
Auditors retain ultimate responsibility for the final problem-solving decision, even when using Hybrid AI.	3.93	6		
Hybrid AI provides new insights that auditors might not have uncovered on their own.	4.03	2		
Hybrid AI facilitates more effective collaborative problem-solving among audit team members.	3.96	5		

Source: SPSS statistical analysis results

The significance level (Sig.) of the Friedman test is 0.949, which is greater than 0.05. This means there is no statistically significant difference in the relative importance that respondents assigned to the various items within Hypothesis 3. In other words, all seven aspects of Hybrid AI's impact on problem-solving are considered similarly important by the respondents.

Based on the statistical analysis, the descriptive statistics and Chi-Square test demonstrate a significant and positive consensus that Hybrid AI impacts an auditor's ability to solve complex problems. The Friedman test further confirms that the individual items within the hypothesis are considered to have a similar level of importance. Therefore, the third sub-hypothesis is accepted.

Overall Conclusion

Based on the acceptance of all three sub-hypotheses, the researcher can confidently accept the main hypothesis of the study: "There is a significant impact of Hybrid AI on auditor professional judgments within the context of Egypt."

6. Results and Recommendations

6.1 Results

- **Impact on Risk Assessment**
  - Hybrid AI significantly enhances auditors' ability to assess control risks, inherent risks, and detection risks.
  - Respondents strongly agreed (mean scores >4.3) that Hybrid AI improves detection of material misstatements and reduces audit risk.
- **Impact on Professional Skepticism**
  - Hybrid AI fosters professional skepticism by improving audit report quality and assisting auditors in making better judgments.
  - Auditors in small firms particularly benefited from Hybrid AI's ability to facilitate new experiences and maintain skepticism.
- **Impact on Complex Problem-Solving**
  - Hybrid AI improves auditors' ability to identify, define, and solve complex audit problems systematically.
  - It provides new insights and supports collaborative problem-solving, though auditors retain ultimate decision-making responsibility.
- **Overall results**
  - All hypotheses were accepted, confirming Hybrid AI's positive influence on auditor judgment in Egypt.
  - No significant differences were found in the perceived importance of Hybrid AI's benefits across risk assessment, skepticism, or problem-solving.

6.2 **Recommendations**

- **For Auditing Firms & Professionals**
  - **Adopt Hybrid AI Tools**: Implement Hybrid AI systems to automate risk assessment, anomaly detection, and data analysis while preserving human oversight.
  - **Training Programs**: Upskill auditors in AI literacy, interpretability tools (e.g., XAI), and ethical AI use to mitigate over-reliance or distrust.
  - **Enhance Skepticism Protocols**: Use Hybrid AI to flag anomalies but require auditors to critically validate AI outputs.
- **For Regulatory Bodies**
  - **Develop AI Auditing Standards**: Establish guidelines for Hybrid AI integration, ensuring transparency, bias mitigation, and compliance with audit standards.
  - **Promote Explainability**: Mandate the use of XAI techniques (e.g., SHAP, LIME) to align AI decisions with audit documentation requirements.
- **For Academia & Research**
  - **Expand Local Studies**: Investigate Hybrid AI's long-term effects on auditor judgment in emerging markets beyond Egypt.
  - **Interdisciplinary Collaboration**: Foster partnerships between AI researchers and auditing professionals to refine Hybrid AI architectures.

References

Accounting Insights. (2025, January 19). *Emerging technologies transforming the future of auditing*. https://accountinginsights.org/emerging-technologies-transforming-the-future-of-auditing/

Ali, A. Shehata, S. & Elsayed, M. (2023). The influence of Auditors Firm Professional Solvency on Quality of Key Audit Matters Judgment: Evidence from Egypt: An Experimental Study. *Alexandria Journal of Accounting Research*, 7(1), 1-94.

Alnawaiseh, M. L., & Alnawaiseh, M. (2015). The effects of the threats on the auditor's independence of mind and appearance. *International Business Research, 8*(8), 141–151. http://dx.doi.org/10.5539/ibr.v8n8p141

Arens, A. A., Elder, R. J., & Beasley, M. S. (2017). *Auditing and assurance services: An integrated approach* (16th ed.). Pearson.

Arham, M. (2025). Natural Language Processing for Financial Document Analysis: A Hybrid Intelligence Application. American Journal of Industrial and Business Management, 15(3), 122–136. https://www.scirp.org/journal/paperinformation?paperid=139907

Balakrishnan, R., & Popat, S. (2025). Skepticism Meets AI: Human Oversight in Hybrid Audits. Financial Technologies and Audit Forum, 9(2), 211–228. https://journals.shu.ac.uk/index.php/FinTAF/article/view/43

Barr-Pulliam, D., Calvin, C. G., Eulerich, M., & Maghakyan, A. (2023). Audit evidence, technology, and judgement: A review of the literature in response to ED-500. *Journal of International Financial Management and Accounting, 35*(1). https://doi.org/10.1111/jifm.12192

Cardona, R., & Ríos-Figueroa, C. (2013). Does experience affect auditors' professional judgment? Evidence from Puerto Rico. *Accounting & Taxation, 5*(1).

Chen, Y.-S., Yang, C.-C., & Yang, Y.-F. (2020). Higher Academic Qualifications, Professional Training and Operating Performance of Audit Firms. *Sustainability*, *12*(3), 1254. https://doi.org/10.3390/su12031254

Dekeyser, S., He, X., Xiao, T., & Zuo, L. (2023). Auditor industry range and audit quality. *Journal of Accounting and Economics*, *77*(2-3), 101669–101669. https://doi.org/10.1016/j.jacceco.2023.101669

Del Caprio, L. (2025). *Artificial intelligence in auditing: Transforming risk assessment and fraud detection.* Master's thesis, Haaga-Helia University of

Applied Sciences. Theseus. https://www.theseus.fi/bitstream/handle/10024/888303/Del%20Caprio_Laura.pdf?sequence=2

Devane, L. (2023). *Hybrid AI for complex decision-making: Integrating symbolic reasoning and deep learning within autonomous systems*. DOI: 10.13140/RG.2.2.13249.57447

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. *arXiv:1702.08608*. https://arxiv.org/abs/1702.08608

European Court of Auditors. (2024). *Ethics Committee annual report for the year 2023 on the application of the Code of Conduct*. https://www.eca.europa.eu/ContentPagesDocuments/Transparency_portal/2023_Ethics_annual_report.pdf

Exemplar Global. (2025). Ethical auditing and professional conduct: Upholding integrity, objectivity, and standards. Retrieved August 7, 2025, from https://exemplarglobal.org/ethical-auditing-and-professional-conduct-upholding-integrity-objectivity-and-standards/

Gajewski, J.-F., Heimann, M., Pierre-Majorique Léger, & Teye, P. (2024). Enhancing auditors' professional skepticism through nudges: an eye-tracking experiment. *Accounting and Business Research*, 1–19. https://doi.org/10.1080/00014788.2024.2364215

GeeksforGeeks. (2024, May 16). Understanding hybrid AI and its structural design. GeeksforGeeks.

Gerber, F. (2025, May 19). Hybrid intelligence in the financial audit [Post]. LinkedIn.

Henry, L., & Rafique, S. (2021). Impact of artificial intelligence on auditors: A thematic analysis. *IOSR Journal of Business and Management, 23*(9), 1–10. https://www.iosrjournals.org/iosr-jbm/papers/Vol23-issue9/Ser-5/A2309050110.pdf

Heyrani, F., Banimahd, B., & Roudposhti, F. R. (2016). Investigation of the effect of auditors' professionalism levels on their judgment to resolve the conflict between auditor and management. *Procedia Economics and Finance, 36*, 177–188. https://doi.org/10.1016/S2212-5671(16)30029-6

Hooshangi, S., & Sibdari, S. (2022). Human-machine hybrid decision making with applications in auditing. *Proceedings of the 55th Annual Hawaii International Conference on System Sciences* (pp. 1–10). https://doi.org/10.24251/hicss.2022.026

Hurtt, R. K., Brown-Liburd, H., Earley, C. E., & Krishnamoorthy, G. (2013). Research on Auditor Professional Skepticism: Literature Synthesis and Opportunities for Future Research. *AUDITING: A Journal of Practice & Theory*, *32*(Supplement 1), 45–97. https://doi.org/10.2308/ajpt-50361

IAASB. (2019, December 19). *ISA 315 (Revised 2019): Identifying and Assessing the Risks of Material Misstatement*. IFAC. https://www.iaasb.org/publications/isa-315-revised-2019-identifying-and-assessing-risks-material-misstatement

Jackson, S. A., Kleitman, S., Stankov, L., & Howie, P. (2017). Individual differences in decision making depend on cognitive abilities, monitoring and control. *Journal of Behavioral Decision Making, 30*(2), 209–223. https://doi.org/10.1002/bdm.1939

Johnson-Snyder, A. J., & Chandrasekran, R. (2017). Acceptance Or Rejection of An Audit Client: Understanding Risk in The Auditing Environment. *Journal of Business Case Studies (JBCS)*, *13*(2), 49. https://doi.org/10.19030/jbcs.v13i2.9928

Kamar, E. (2016). *Directions in hybrid intelligence: Complementing AI systems with human intelligence*. In *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence (IJCAI-16)* (pp. 4030–4034). AAAI Press. https://www.ijcai.org/Proceedings/16/Papers/603.pdf

Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. *Journal of Emerging Technologies in Accounting, 14*(1), 115–122. https://doi.org/10.2308/jeta-51730

Kokina, J., Blanchette, S., Davenport, T. H., & Pachamanova, D. (2025). Challenges and opportunities for artificial intelligence in auditing: Evidence from the field. *International Journal of Accounting Information Systems, 56*, 100734. https://doi.org/10.1016/j.accinf.2025.100734

Kommanaboina, V., & Kumar, A. (2025). Automating Financial Audits Using Data Pipelines and AI: A Conceptual Hybrid Approach. *International*

Journal of Engineering Research & Technology, 13(7), 803–812. https://www.ijert.org/research/automating-financial-audits-using-data-pipelines-and-ai-a-conceptual-hybrid-approach-IJERTV13IS070098.pdf

Koshiyama, A., Kazim, E., Denny, E., Gopalan, N., Pavey, G., Treleaven, P., Lomas, E., & Leong, T. (2024). Towards algorithm auditing: Managing legal, ethical and technological risks of AI. *Royal Society Open Science, 11*, 230859. https://doi.org/10.1098/rsos.230859

Kotivirta, K. (2025). *The impact of artificial intelligence on the role of auditors in international audit firms* [Master's thesis, University of Vaasa]. Osuva. https://osuva.uwasa.fi/bitstream/handle/10024/19626/Uwasa_2025_Kotivirta_Kia.pdf?sequence=2

KPMG. (2025). All eyes on: The future of audit. Retrieved from KPMG Insights

Lacmanovic, S., & Skare, M. (2025). Artificial intelligence bias auditing – current approaches, challenges and lessons from practice. *Review of Accounting and Finance*, 24(3), 375–400. https://doi.org/10.1108/RAF-01-2025-0006

Leocádio, D., Malheiro, L., & Reis, J. (2024). Artificial intelligence in auditing: A conceptual framework for auditing practices. *Administrative Sciences, 14*(10), Article 238. https://doi.org/10.3390/admsci14100238

Mayer, V., Schüll, M., Aktürk, O., & Guggenberger, T. (2024, December). *Designing human-AI hybrids: Challenges and good practices from a multiple case study*. In *Proceedings of the International Conference on Information Systems (ICIS 2024)*. AIS Electronic Library. https://aisel.aisnet.org/icis2024/aiinbus/aiinbus/3

Milvus.io. (2025). *What are hybrid reasoning models?* https://milvus.io/ai-quick-reference/what-are-hybrid-reasoning-models

Mökander, J. (2023). Auditing of AI: Legal, Ethical and Technical Approaches. *Digital Society*, 2(49). https://doi.org/10.1007/s44206-023-00074-y

Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. *Journal of Business Ethics*, 167, 209–234. https://doi.org/10.1007/s10551-019-04407-1

Odeyemi, K., Musa, S., & Wang, L. (2024). The role of AI in transforming auditing practices: A global perspective review. *World Journal of Advanced*

Research and Reviews, 22(2), 453–462. https://wjarr.com/sites/default/files/WJARR-2024-0460.pdf

Pimentel, M., Sanchez, R., & Lee, J. (2021). Auditor experience and judgment quality: An empirical investigation. *International Journal of Auditing*, 25(1), 30–47.

Prakash, N., & Mathewson, K. W. (2020). Conceptualization and Framework of Hybrid Intelligence Systems. *ArXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2012.06161

Prasanti, D. H., Novita, W. R., & Puspasari, N. (2019). Effect of independence, work experience and competence on audit quality with professional ethics as moderating variable. *International Journal of Scientific & Technology Research, 8*(4), 348–353. https://ijstr.org/final-print/dec2015/Effect-of-Independence-Work-Experience-and-Competence-on-Audit-Quality.pdf

Putra, G., & Dwirandra, A. (2019). The effect of auditor experience, type of personality, and fraud auditing training on auditors' ability in fraud detecting with professional skepticism as a mediation variable. *International Research Journal of Management, IT and Social Sciences, 6*(2), 31–43. https://doi.org/10.21744/irjmis.v6n2.604

Raju, P., Vara, N. V. D. S. S., & Devi, P. N. (2024). A comparative analysis of machine learning algorithms for big data applications in predictive analytics . *International Journal of Scientific Research and Management (IJSRM), 12***(10), 1608-1630.** https://doi.org/10.18535/ijsrm/v12i10.ec09

Saad, F., & Elson, A. (2025). *Next-generation AI architectures: Comparative analysis of neural, symbolic, and hybrid learning approaches*. ResearchGate. DOI: 10.13140/RG.2.2.32002.59843

Saiwa. (2024). *What is hybrid AI? Everything you need to know*. https://saiwa.ai/blog/hybrid-ai/

Setiawan, W. Y. (2017). Need for cognition: does it influence professional judgment? Review of Integrative Business and Economics Research, 6(1), 240-248.

Setiawan, W. Y. (2017). Need for cognition: Does it influence professional judgment? *Review of Integrative Business and Economics Research*, *6*(1), 240–248. http://www.buscompress.com/uploads/3/4/9/8/34980536/riber_h16-176_240-248.pdf

Shabir, G., & Khalid, N. (2024, September 5). *AI-powered fraud detection and risk assessment: The future of financial services*. https://doi.org/10.13140/RG.2.2.32932.08324

Song, M. (2023, April 29). *Using Explainable AI to Enhance Decision-Making in Financial Audits*. https://www.researchgate.net/publication/387133902_Using_Explainable_AI_to_Enhance_Decision-Making_in_Financial_Audits

Staff, S. E. (2025, March 14). *Learning-based approach - Studyopedia*. Studyopedia. https://studyopedia.com/artificial-intelligence/learning-based-approach/

Surur, F. M., Mamo, A. A., Gebresilassie, B. G., Mekonen, K. A., Golda, A., Behera, R. K., & Kumar, K. (2025). Unlocking the power of machine learning in big data: A scoping survey. *Data Science and Management*. https://doi.org/10.1016/j.dsm.2025.02.004

Verma, M. (2024). Hybrid Intelligent Systems: Prompt Science Analysis. *International Journal of Trend in Scientific Research and Development (IJTSRD)*.8(1). 450-455.

Yadav, R., Kumar, M., & Sharma, P. (2024). Automating financial audits using data pipelines and AI: A conceptual hybrid approach. *International Journal of Engineering Research & Technology, 13*(1), 122–128. https://www.ijert.org/automating-financial-audits-using-data-pipelines-and-ai-a-conceptual-hybrid-approach

Zhang, C. A., Cho, S., & Vasarhelyi, M. (2022). Explainable artificial intelligence (XAI) in auditing. *International Journal of Accounting Information Systems, 46*, 100572. https://doi.org/10.1016/j.accinf.2022.100572