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# The role of artificial intelligence in enhancing internal audit quality: A resource-based view approach

**Rania Rejjaoui**[a] | **Adil El Amri**[a] | **Abdelhak Sahib Eddine**[a] | **Yassine Marzougui**[b]

[a]Department of Business and Management, National School of Business and Management (ENCG), Laboratory of Studies and Research in Economic Sciences and Management (LERSEM), University of Chouaib Doukkali, El Jadida, Morocco.
[b]Faculty of Science and Technology, Laboratory of Engineering, Industrial Management and Innovation, Hassan I University, Settat, Morocco.

**Abstract** Nowadays, artificial intelligence (AI) has experienced a remarkable resurgence of interest in the business world due to its ability to perform tasks traditionally carried out by humans, replicating cognitive capacities and professional judgment through machines and computers. This technological advancement, now in its golden age, enables organizations to respond to rapidly evolving market demands, achieve competitive advantages, and ensure long-term sustainability. Consequently, managers are increasingly adopting AI tools to integrate them into their organizational processes and decision-making activities. Internal auditing, as a key function within organizations, has been profoundly affected by this technological revolution, experiencing significant transformations through the automation of audit processes, expansion of its scope, reduction of processing times, and, ultimately, improvement in audit quality. The present article aims to theoretically explore how AI techniques contribute to enhancing the quality of internal auditing, relying on the Resource-Based View (RBV) framework as a guiding theoretical framework. Specifically, it identifies five explanatory dimensions through which AI supports auditing practices: task automation, document processing and analysis, risk and fraud detection, communication of results, and the reduction of human errors. Each dimension represents a critical pathway through which AI can increase audit efficiency, accuracy, and overall effectiveness. Furthermore, the competence of internal auditors is introduced as a moderating variable, as it conditions the extent to which these technological contributions can be effectively utilized and translated into meaningful improvements in audit performance. By highlighting the interaction between technological resources and human expertise, this study emphasizes the strategic value of integrating AI within internal auditing practices.

**Keywords:** AI technologies, audit process automation, auditor competencies, competitive advantage

## 1. Introduction

Over the past decade, AI has garnered significant attention in the business world owing to its capacity to simulate human intelligence through machines, enabling computers to replicate human behaviors and engage in continuous learning, thereby enhancing their performance (Mach, 2021). It enables the accomplishment of tasks previously performed by humans by reproducing their cognitive abilities and judgment through machines or computers.

This technological advancement, now in its golden age, also allows organizations to align with market demands for technological innovation and gain a competitive advantage over their rivals, thus ensuring long-term sustainability.

In this context, managers are increasingly turning to AI tools to integrate them into their activities. Internal auditing is, moreover, one of the functions most impacted by the rise of AI, serving as an essential pillar of governance, corporate oversight, and risk management (Chen, 2022). This development has redefined the internal audit landscape by providing auditors with significant advantages over traditional approaches, which slow down audit work due to large volumes of documentation to be collected and analyzed, sample-based planning, and the inability to identify risks on time.

By leveraging AI systems, audit processes are automated, allowing internal auditors to focus on judgment-intensive tasks, compile and analyze vast quantities of data, and complete their assignments faster than ever before. In this context, AI has become a key driver, significantly improving audit quality, efficiency, and accuracy.

This study aims to examine the various dimensions of AI's impact on internal audit quality, drawing on the Resource-Based View (RBV) theory. Based on a wide range of scientific literature, empirical studies, and case analyses, this work seeks to synthesize the effects of AI on enhancing internal audit quality. In this perspective, we aim to answer the following research question:

How does the integration of artificial intelligence influence the improvement of internal audit quality?

To address this research question, our work is structured into five sections exploring the different facets of AI's impact on internal audit quality. First, we present a conceptual framework. Second, we discuss the theoretical foundation. Third, we


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analyze AI’s contributions to improving internal audit quality. In a fourth section, we examine auditor competence as a complementary strategic resource. Finally, we present the research hypotheses and the conceptual model.

## 2. Methodology

In order to establish the theoretical framework for our study and examine the mechanisms through which artificial intelligence contributes to improving the quality of internal auditing, a structured literature review was conducted. It covers work published between 2010 and 2025, a period marked by the growing integration of AI into organisations. This review aims to provide an overview of scientific advances, identify the main explanatory dimensions of the impact of AI on internal auditing, and analyze contributions within the theoretical framework of the RBV. It also highlights the limitations of the literature and justifies the development of a theoretical model incorporating the competence of the internal auditor as a moderating variable. To ensure the robustness of the sources, several international databases were consulted, including Scopus, Web of Science, Google Scholar, and ScienceDirect. Articles were selected according to inclusion criteria based on their scientific relevance, their connection to the theme of AI and internal auditing, and their conceptual contribution to the RBV framework. Non-academic, technical, redundant, or inaccessible publications were excluded. The quality of the selected articles was assessed based on theoretical clarity, methodological rigour and consistency of contributions. This approach has enabled us to establish a solid foundation for our study and to highlight the fundamental conceptual dimensions that structure the proposed model.

## 3. Conceptual Framework

### *3.1. Definition of artificial intelligence*

The origins of AI can be traced back to 1948, when William Grey Walter developed two small robots, ‘Elmer’ and ‘Elsie,’ designed to detect and respond to stimuli when confronted with obstacles (Bizarro & Dorian, 2017). At that stage, AI was still regarded as an emerging technology, owing to the profound advancements in the techniques employed for its implementation (Stahl et al., 2017).

While the renewed interest of scientists in this technological advance date back to the 1950s, when Alan Turing laid the first foundations for AI by proposing the principle that any human activity can be translated into an algorithm. However, the official birth of the term "artificial intelligence" occurred in 1956 during the seminar on thinking machines at Dartmouth University, situated in New Hampshire, where the American mathematician John McCarthy laid the foundations for a technology that was still unexplored at the time, yet is now omnipresent in our daily lives (Nilsson, 1982). Similarly, this date also marked the recognition of AI as a new scientific discipline.

Intelligence is a broad discipline within computer science, encompassing areas such as machine learning, computer vision, and natural language processing. The central objective is to replicate, using programmed machines, tasks previously performed by human intelligence. It is an ambiguous term that is difficult to define uniformly because each AI program is customized based on the developer's goals and the tools used (Zouhri, 2019).

According to Accenture (2017), AI encompasses all technologies that enable machines to develop human-like capabilities, such as natural language processing, machine learning, deep learning, chatbots, and facial voice recognition.

AI is commonly defined as the ability of machines to emulate cognitive functions characteristic of human intelligence, encompassing learning, communication, decision-making, and problem-solving. It establishes a modern learning system capable of autonomous learning, adaptation, and action. AI can interpret data, extract the necessary knowledge from it, and leverage this knowledge to accomplish specific tasks and objectives flexibly and efficiently (Haenlein & Kaplan, 2019).

Puthukulam et al. (2021) clarify that AI constitutes a combination of hardware and software systems aimed at simulating the functions of the human brain, enabling the evaluation of information, decision-making, and the execution of complex judgment processes based on available data.

In addition, according to Haenlein and Kaplan (2019), AI is defined as the capability of a system to accurately comprehend external data, learn from it, and apply the acquired knowledge to accomplish specific objectives and tasks through adaptive flexibility (Rizvan, 2022).

These definitions converge on the same objective, which is to provide AI with intelligence similar to that of human beings in various aspects of life.

Furthermore, AI is a multidisciplinary field, encompassing a multitude of areas that drive its development and enable its application across sectors. Other key areas of AI include:

- Machine Learning: This is a crucial element of AI, focused on constructing algorithms capable of analyzing and interpreting data, allowing machines to predict or decide without explicit programming. According to Roder (2019), machine learning refers to “a technique that generalizes reasoning from examples without relying on a predetermined equation as a model.” He gave us the example of a real estate agent who estimates property prices based on his expertise and the properties' characteristics (surface area, floor, neighborhood, etc.). This estimate can be identical to the reality of the market price. In this vein of ideas, if this task is delegated to machine learning algorithms, they can reproduce this estimation capacity by relying on the same criteria as the real estate agent and with a low margin of error. For the algorithms to make reliable predictions, they need to be fed with input data called "features", for example, surface area, location, etc.

• Expert systems: Expert systems are defined as computer systems that solve complex problems by emulating experts, using a knowledge base of specialized information and applying reasoning rules to deduce solutions (Jackson, 1999). According to MR Tolun and Sahin (2016), these systems aim to use specific knowledge to solve problems that, due to their high complexity, require human experts.

• Natural Language Processing (NLP): This is a significant area within AI that facilitates human-computer interaction via natural language (Jones, 1972). It focuses on developing systems capable of understanding, interpreting, and producing linguistic data.

• Machine reasoning: Machine reasoning is the field of AI concerned with building systems capable of drawing valid conclusions and solving problems with logical and algorithmic models.

• Computer Vision: It involves teaching machines to extract, analyze, and understand visual information. According to Erragragui and Aoufir (2023), it represents is "a technology that detects and interprets visual information captured by cameras."

• Task planning (automated planning): This signifies the potential of a machine to plan actions, establish schedules, and work plans.

The main areas of AI are illustrated in Figure 1:

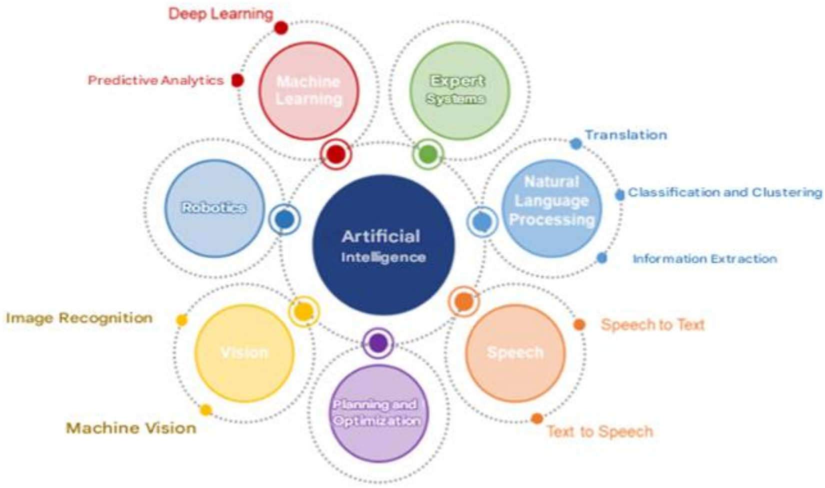


**Figure 1** Overview of the main areas of AI. *Source:* Barraud (2019).

As shown in Figure 1, AI encompasses multiple areas, including analytics, recognition, extraction, speech, and optimization.

### *3.2. Internal audit*

Internal auditing is a relatively recent function that emerged with the economic downturn of 1929 in the United States, particularly within industrial companies**.** At that time, they suffered the economic recession and were therefore obliged to minimize their expenses to survive**.** To this end, companies considered reducing expenses related to external-audit fees while preserving the quality of certification by internalizing part of the preparatory work (inventories of diverse types, financial account analyses, and a range of surveys, etc.) to internal personnel of companies. External audit firms agreed to delegate this work, but under their supervision, marking the emergence though not yet the full institutionalization of what we now call internal audit.

After the crisis, this delegation of tasks became established, and companies continued to use the work carried out by their internal staff**,** as they acquired expertise, making it lasting legacy. However, the internal audit function in the private sector was formally institutionalized with the establishment of the Institute of Internal Auditors (IIA) in 1941.

In its latest definition of internal audit, dated June 1999, the Institute introduced a new approach to the function: Internal auditing is an autonomous and impartial function that evaluates the effectiveness of operational controls and provides guidance to optimize processes and create value. Through systematic assessments of risk management, internal controls, and governance, it contributes to the achievement of organizational objectives by offering recommendations aimed at enhancing performance (Renard, 2017).

Fundamentally, internal audit is the function tasked with providing independent assurance that an organization's risk management, governance, and internal control processes are operating effectively (Chartered Institute of Internal Auditors, 2019), in accordance with the standards established by the CRIPP**.**

The internal audit process follows four structured steps aimed at evaluating and improving the internal control system, risk management, and governance, as outlined below:

• The preparation phase: The objective of this first phase is to define the goals and extent of the audit mission, which is the subject of a guidance report. This report is prepared based on familiarization with the applicable framework (regulations, work procedures, organizational chart, objectives and control environment of the processes or activities to be audited) and the identification of high-risk areas. However, this phase will only take place after the establishment and approval of a mission order that formalizes the mandate assigned to internal auditors by management or the audit committee.

• The execution phase: The implementation phase begins with an opening meeting during which internal auditors and auditees primarily review the orientation report. The auditors then establish the audit program under the supervision of the mission leader and allocate tasks. They subsequently establish or update the QCI. Finally, they intervene in the field, obtaining answers to the key questions in the questionnaire and carrying out tests using the tools at their disposal. At the same time, the auditors complete a FRAP (Problem Revelation and Analysis Sheet) if any malfunctions are detected.

• The conclusion phase: During this phase, the audit team prepares the provisional audit report, which brings together the findings from the FRAP and the recommendations matrix. This report is then discussed and approved at the closing meeting.

• The post-audit phase: During this phase, internal auditors are responsible for overseeing the implementation of recommendations by establishing a specific follow-up procedure, which is then approved by management.

### *3.3. Internal audit quality*

The quality of internal auditing is a multifaceted concept (International Auditing and Assurance Standards Board, 2014) that has been defined in numerous ways in the literature and continues to evolve over time.It constitutes a relevant research topic (Krichene & Baklouti, 2021) and has sparked significant debate, particularly due to the absence of a single model that fully captures its scope (Cohen & Sayag, 2010).

According to DeAngelo (1981), audit quality is assessed based on the probability that an auditor will identify and report material misstatements in an organization's financial statements.This approach emphasizes professional competence assessed through the auditor's expertise and experience (El Gharbaoui et al., 2021) as well as independence, reflected in the ability to perform responsibilities without interference, proactively manage conflicts of interest, maintain an appropriate hierarchical position, enjoy unrestricted access to information and audited entities, avoid management involvement in the appointment or dismissal of the chief audit executive, and refrain from engaging in activities beyond audit assignments (Ait Mouzoun & El Mezouari, 2019). These elements are essential to ensuring credible and reliable results, thereby reflecting the value and quality of the internal audit function.

Francis (2004) highlights that audit quality is influenced not only by auditors' competence and independence, but also by the size and reputation of the audit firm, as well as the prevailing regulatory and normative framework. The author further notes that the relationship between the auditor and the audited entity can affect perceptions of quality, with organizational pressures or a lack of support potentially limiting the effectiveness of internal controls and audit recommendations.

Knechel et al. (2013) propose an integrated view of internal audit quality, identifying four main dimensions: inputs (resources, skills, and auditors' experience), process (methodologies and practices applied during audits), outputs (quality of reports and recommendations), and context (organizational environment and regulatory framework). This holistic approach allows quality to be considered not only as an outcome but also as the product of an interconnected set of human, structural, and organizational factors.

Samagaio and Felício (2023) demonstrate that improving internal audit quality depends on strengthening organizational commitment and auditor independence, while effectively managing time pressure. Their findings highlight the importance of creating a work environment conducive to rigorous and reliable audit practices, even though certain individual factors may have a limited impact.

Moreover, the adoption of AI technologies in internal auditing significantly enhances audit quality by improving efficiency, accuracy, and data coverage, while enabling faster fraud detection. Nevertheless, challenges remain, particularly with regard to auditor training and the quality of data used (Ajayi & Akinrinola, 2023; Shawaqfeh et al., 2024; Institute of Internal Auditors, 2024; INTOSAI Journal, 2025).

In summary, the quality of internal auditing is inextricably linked to its ability to support governance, risk management, and the reliability of organizational information. It relies on a combination of auditors' expertise, impartiality, management commitment, effective internal processes, cooperation with external auditors, quality assurance and continuous improvement programs, and the integration of AI technologies.

## 4. Theoretical Foundation: The Resource-Based View (RBV)

The Resource-Based View (RBV), introduced by Barney (1991), asserts that organizations attain sustainable competitive advantage by leveraging resources and capabilities that are valuable, rare, inimitable, and non-substitutable. Within this perspective, AI can be regarded as a strategic resource, insofar as it reshapes the foundations of competitiveness by acting simultaneously as a substitutive resource, a complementary resource, and an integrated organizational capability.

Traditionally, human cognitive skills were considered scarce resources that generated competitive advantage (Helfat & Peteraf, 2015). However, AI, with its virtually unlimited capabilities in processing, prediction, automation, and solving complex problems, can now perform tasks that were historically reserved for human experts. Empirical studies indicate that AI can equal or even exceed human performance across various domains, including medical diagnosis (Esteva et al., 2017; Jiang et al., 2017), recruitment (Chamorro-Premuzic et al., 2019), and finance (Blohm et al., 2022). AI enables the generation of novel alternatives, process optimization, and complex decision-making with greater speed and accuracy than humans (Verganti et al., 2020; Radford et al., 2019). This dynamic consequently reduces the value of traditional human skills (Ahuja et al., 2005) and may even render them obsolete (Agrawal et al., 2018), thereby positioning AI as a strategic substitutive resource capable of reconfiguring the very basis of competitive advantage (Raisch & Krakowski, 2021).

Nonetheless, AI does not merely act as a substitute. It also represents a complementary resource, fostering the emergence of new resource combinations. According to RBV, sustainable competitive advantage arises precisely from such complementarities (Argyres & Zenger, 2012). In this context, Davenport and Kirby (2016) introduced the notion of human augmentation, whereby machines enhance rather than replace human capabilities. While AI can analyze and synthesize information at scale, complex decision-making and contextual interpretation remain distinctly human prerogatives. This human–machine interaction thus becomes an innovative and sustainable source of competitive advantage (Davenport & Kirby, 2016).

Beyond substitution and complementarity, AI also functions as an integrated organizational capability, combining technical and human resources with operational routines (Mikalef et al., 2021; Mikalef et al., 2023). Once embedded into core activities, AI enables the redefinition of organizational processes, improvement of internal efficiency, support for innovation, and the stimulation of creativity (Ameen et al., 2023; Ameen et al., 2024).

Several studies have demonstrated that AI facilitates the reconfiguration of existing resources and the creation of novel strategic combinations, thereby opening new market opportunities (Haddoud et al., 2018; Ameen et al., 2024). It enables resource recomposition, business process reorganization, and enhanced knowledge management to foster innovation and creativity (Ameen et al., 2024). Thus, AI fully meets the VRIN/O criteria, reinforcing organizational capabilities and supporting the creation of sustainable competitive advantage.

In the specific context of internal auditing, AI particularly embodies this strategic value. It is therefore relevant to rely on the RBV framework to examine how AI contributes to improving the performance and quality of internal auditors and, more broadly, to the sustainable competitive advantage of organizations. However, the impact of AI largely depends on the competence level of auditors, which acts as a moderating variable that conditions their ability to effectively leverage AI's contributions and transform its potential into a genuine driver of performance.

## 5. Contribution of AI to Improving the Quality of Internal Audit

AI is penetrating different sectors of activity, changing the way organizations operate. Traditional management and business processes must then be redesigned in order to adjust to the accelerated pace of the business world and meet the requirements of managers and audit committees. These requirements are highlighted by a study conducted by the audit firm KPMG in 2016, which is summarized in two aspects redefining the function of the internal auditor, namely: the complete coverage of emerging risks and the creation of benefit for the organization. It is in this context that internal auditors will need to reconsider their traditional paradigms in order to incorporate new technologies into their evaluation processes (Pizzi et al., 2021). Moreover, prior research has examined the applications of AI in accounting, finance, and management, particularly in the areas of neural networks and multi-agent systems, which has paved the way for broader adoption.

The growing integration of AI technologies in these management domains can be attributed to their capacity to automate repetitive tasks traditionally performed by humans and to analyze the cognitive complexity inherent in human decision-making processes. This understanding facilitates the translation of mental operations into corresponding accounting processes, thereby enhancing the computer's capacity to solve complex problems (Mohammed & Anbar, 2016).

The advancement of emerging technologies, including AI and ML, equips auditors with enhanced insights into organizational operations, thereby facilitating a more comprehensive understanding and evaluation of risk exposure within each audit domain (Puthukulam et al., 2021).

Additionally, integrating AI into auditing practices helps to effectively direct auditors to high-risk areas, thereby optimizing resource allocation and enhancing the accuracy, reliability, and efficiency of audits. This facilitates the detection of anomalies and fraudulent actions through rapid analysis of large data sets, rather than just sample verification. This new approach to auditing is therefore transforming the auditing profession by making it more efficient and high quality. Furthermore, it enhances stakeholder trust and satisfaction by focusing on high-value activities and complex tasks requiring human expertise.

AI therefore offers considerable potential for the audit profession through the improvement of several dimensions. According to studies conducted by Zhang (2024) and Ghanoum and Alaba (2020), audit processes enable the transformation of input data into audit opinions through modern technologies such as expert systems. In this context, Munoko et al. (2020) identified three categories of AI used in internal auditing: assistive systems, enhanced systems, and autonomous systems. The former help auditors perform their repetitive tasks, while leaving the decisions in their hands. Enhanced systems allow cooperation between auditors and machines to make decisions. Finally, autonomous systems, which are completely independent, make decisions without human intervention.

Also, in the same vein, the integration of AI techniques offers significant advantages for audits, including cost reduction and the capacity to efficiently process and manage large volumes of data, thereby enhancing overall audit effectiveness (Puthukulam et al., 2021). On the contrary, the traditional approach of qualified auditing is less effective because auditors previously performed random tests of data manually to identify factors to be examined and detected.

Furthermore, Ammanath (2020) confirms that automated processes render the traditional audit approach more cumbersome, time-consuming, and heavily reliant on long hours to manually validate specific transaction samples.

In the same vein, Issa et al. (2016) conducted a benchmark comparing traditional auditing practices with AI-assisted auditing, highlighting the benefits of AI integration, with the differences between the two approaches summarized in Table 1.

**Table 1** Traditional audit approach VS AI-supported audit approach.

| Phase | AI-Enabled Automated Audit Approach | Traditional Audit Approach |
| --- | --- | --- |
| Pre-Planning | AI gathers and analyzes large volumes of external (exogenous) data while concurrently integrating information about the client's organizational structure, operational procedures, and accounting and financial systems. | The auditor performs a comprehensive analysis of the client's industry, organizational structure, operational processes, and accounting and financial systems. |
| Contracting | AI leverages the estimated risk from Phase 1 to determine audit fees and required hours, and then analyzes a contract database to draft the engagement letter, which is finalized upon signatures from both auditor and client. | The auditor prepares the engagement letter based on the estimated client risk, which is subsequently signed by both auditor and client. |
| Understanding Internal Controls and Identifying Risk Factors | AI system integrates various inputs, including flowcharts, questionnaire responses, and narrative documents, utilizing image recognition and text mining to conduct a thorough analysis. Additionally, drones are employed to perform operational walkthroughs, with video footage processed by AI. Advanced visualization and pattern recognition techniques are applied to identify risk factors, while the system aggregates and examines data to detect indicators of fraud and illicit activities. | The auditor reviews flowcharts, questionnaires, and narrative descriptions to understand internal controls. Walkthroughs are performed manually, and analytical techniques are applied to identify risk factors and potential fraud indicators. |
| Control Risk Assessment | Continuous control monitoring systems perform ongoing examinations of internal controls, while AI conducts process mining to verify their implementation. Automatic log generation is utilized to ensure data integrity and maintain traceability. | The auditor examines the client's internal control policies and procedures and performs a risk assessment for each attribute. Tests of controls are then conducted and reassessed to ensure their effectiveness. Procedures, findings, and results are documented to provide a comprehensive record. |
| Substantive Tests | Continuous data quality assurance ensures the reliability of data and audit evidence. AI verifies the provenance of the data and continuously tests all transactions and balances. Advanced analytical techniques pattern recognition, outlier detection, benchmarking, and data visualization detect anomalies and support ongoing evaluation. | Periodic sampling-based tests are performed, with their nature, extent, and timing based on control assessments. The auditor examines sample transactions and balances, applying analytical procedures to evaluate accuracy, consistency, and potential anomalies. |
| Evaluation of Evidence | Integrated into the substantive testing phase. | The auditor assesses the sufficiency, clarity, and appropriateness of the evidence and may collect additional evidence or withdraw it if necessary. |
| Audit Report | AI employs predictive models to estimate a range of identified risks, generating a continuous-scale report (e.g., score from 1 to 100) for a more nuanced risk evaluation. | The auditor consolidates all information to issue a categorical report (clean, qualified, or adverse) reflecting the audit findings. |

*Source:* Issa et al. (2016).

Furthermore, the study conducted by Mohammed and Anbar (2016) focuses on the development of a computerized system designed to perform all auditing tasks, including sample size selection, compilation and documentation of audit working papers, preparation of the audit report, and the evaluation of internal control effectiveness. It concludes that incorporating AI technologies into the audit process substantially supports the successful execution of audit engagements and improves the overall quality of the audit.

Similarly, the work of Fedyk et al. (2022) examines the effect of AI on improving the efficiency of large audit firms by analyzing a dataset associated with AI-specialized staff from 36 largest audit firms. It shows that investment in AI contributes to improving audit quality, reducing costs, and gradually reducing the number of accounting staff.

Furthermore, the adoption of AI techniques in internal audit activities offers immense potential for achieving quality and efficient internal auditing. This is because they contribute to a transparent and collaborative internal audit process through cooperation between different audit teams located in different geographical areas by enabling them to share an extensive array of documentation and information in real time (Bizarro & Dorian, 2017).

It thus contributes to improving audit efficiency by automating routine tasks such as reviewing tables and comparing data. By delegating these tasks, the auditor has more time and can deploy his mind and skills for more strategic tasks that require key professional judgments. At the same time, he avoids delays in responding and communicates identified risks to stakeholders in a timely and transparent manner, which consequently promotes the quality of internal auditing. In this context, researchers Chukwuani and Egiyi (2020) have demonstrated that AI is making significant progress in automating routine tasks, particularly those related to data entry and invoice processing, thereby improving efficiency and reducing human errors.

Furthermore, AI offers superior analytical capabilities to detect fraudulent actions and deviations quickly and comprehensively by examining all transactions carried out. In other words, it offers proactive solutions, anticipating fraudulent behavior and facilitating the identification of anomalies from the in-depth analysis of complex databases. Moreover, the work of Mohammad et al. (2020) and Ghanoum and Alaba (2020), highlighted that AI contributes to the rapid identification of abnormal activities in transactional data, reducing the risks of fraud by continuously monitoring financial operations and alerting auditors in case of suspicious transactions.

AI-assisted auditing helps maintain mission traceability and facilitates the audit process, which reduces the risk of fraud associated with audits.

By fully exploiting the potential of AI in data analysis, auditors improve the quality of their decisions, relying on advanced analysis of a large variety of data and the identification of trends and consequently more proactive and quality audit missions.

Based on the findings from an extensive review of academic articles and case studies, it can be concluded that the integration of AI techniques into internal audit practices significantly enhances audit quality. The impact of AI on both the effectiveness and efficiency of internal auditors can be evaluated across several dimensions, including the automation of audit procedures, the expansion of audit scope, the rapid and comprehensive detection of anomalies and fraudulent activities, the automation of routine tasks, the reduction of data processing time, the increased accuracy and reliability of audits, and the improvement of the decision-making process.

Internal Audit Quality in the Age of AI is illustrated by eight essential elements:

- Reduction of data processing times;
- Automation of audit processes;
- Reducing the risk of error;
- Rapid and comprehensive detection of anomalies and fraud;
- Accuracy and reliability of audits;
- Expansion of the audit scope;
- Audit accuracy;
- Improved decision making.

Figure 2 consolidates all of these contributions.

## 6. Auditor Competencies as a Strategic Complement

In the age of artificial intelligence, the auditing profession is undergoing a major structural transformation. AI based technologies provide enhanced capabilities for large-scale data processing, automation of routine tasks, and rapid detection of anomalies, thereby contributing to a profound redefinition of auditors' practices and intervention models. However, these technological advances alone are not sufficient to ensure the quality and reliability of audit engagements. Human competencies remain indispensable, particularly in terms of professional judgment, critical reasoning, and contextualization of results. Indeed, while AI increases the accuracy of analyses and facilitates the production of predictive models, the interpretation of data and its transformation into meaningful information still rely on the expertise of auditors. Professional judgment, shaped by experience and the ability to integrate ethical and relational dimensions, remains central to making complex and unprecedented decisions (Dong & McIntyre, 2014; Helfat & Peteraf, 2015). Thus, AI acts as a lever of efficiency, but it is the human auditor who ensures meaning and value.


**Figure 2** The influence of AI on the quality of internal audit.

Several studies also emphasize that AI cannot replace essential attributes such as professional skepticism, credibility, and trust, which only auditors can embody (ISACA, 2019; Liburd & Vasarhelyi, 2015; KPMG, 2023). Auditors must not only interpret results but also ensure their relevance in specific contexts. Conversely, excessive reliance on automated systems may diminish critical thinking and compromise the very value of auditing (Baharom, 2025). The literature, therefore, converges in recognizing that AI represents a major innovation but must necessarily be complemented by human expertise to guarantee the quality of audit engagements. In reality, audit performance depends more on the synergy between technological resources and professional skills than on substitution logic.

AI capabilities enable more precise risk assessments, optimal allocation of audit resources, and proactive identification of potential issues, while auditors guide, validate, and interpret the results (Kokina & Davenport, 2017). They also ensure that AI-driven analyses align with organizational objectives and ethical standards, thereby compensating for the limitations of automated systems in contextual understanding and complex decision-making (Pizzi et al., 2021). The joint exploitation of AI and human expertise thus improves the accuracy, efficiency, and reliability of audit processes, while fostering continuous learning and adaptation of audit teams (Munoko et al., 2020). This complementarity provides a sustainable competitive advantage, allowing organizations to combine technological innovation with quality requirements in an increasingly complex and dynamic economic environment.

## 7. Research Hypotheses

Based on the theoretical and conceptual framework, the following hypotheses are formulated exclusively from the literature review and are not subject to empirical validation in this study.

H1: The automation of repetitive tasks through artificial intelligence has a significant positive effect on the quality of internal audit.

H2: The ability of artificial intelligence to process and analyze a wide variety of documents positively influences the accuracy and reliability of internal audits.

H3: The integration of artificial intelligence enhances the detection of risks, anomalies, and fraud, thereby strengthening the quality of internal audit.

H4: The timely and relevant communication of results generated by artificial intelligence contributes positively to the effectiveness of internal audits.

H5: The reduction of human errors enabled by artificial intelligence has a positive effect on the overall quality of internal audit.

H6: The competence of auditors positively moderates the effect of automating repetitive tasks through artificial intelligence on the quality of internal audit.

H7: The competence of auditors positively moderates the effect of artificial intelligence's ability to process and analyze a wide variety of documents on the accuracy and reliability of internal audits.

H8: The competence of auditors positively moderates the effect of integrating artificial intelligence on the detection of risks, anomalies, and fraud, thereby strengthening the quality of internal audit.

H9: The competence of auditors positively moderates the effect of timely and relevant communication of results generated by artificial intelligence on the effectiveness of internal audits.

H10: The competence of auditors positively moderates the effect of reducing human errors enabled by artificial intelligence on the overall quality of internal audit.

The conceptual model in Figure 3 incorporates these hypotheses.

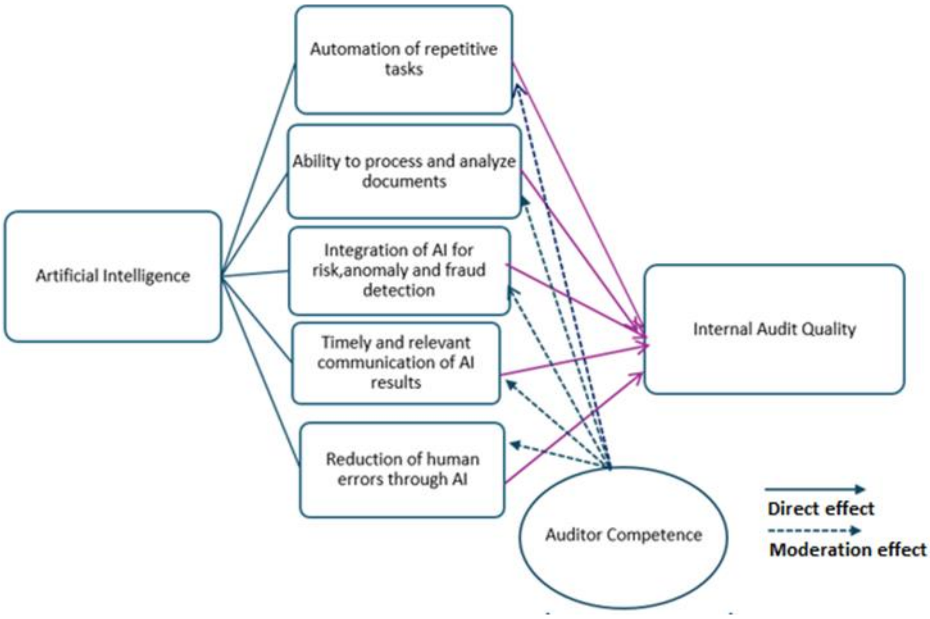


**Figure 3** Conceptual research framework.

As structured in Figure 3, and considering the theoretical and conceptual framework, the subsequent hypotheses are developed solely from the literature review and will not be empirically tested in this study.

## 8. Conclusion

AI has emerged as a major strategic lever for organizations, particularly in the field of internal auditing. Through our theoretical analysis, we have shown that AI is not limited to automating repetitive tasks and managing large volumes of data; it also contributes to improving the accuracy, efficiency, and overall quality of audits. Based on the RBV, this study demonstrates that the value of AI in internal auditing is closely linked to auditor competence, which serves as a moderating variable. In other words, the effectiveness and impact of AI depend on auditors' ability to optimally leverage these technologies and transform their potential into a true performance driver.

Our findings identify five key dimensions through which AI affects internal audit quality: task automation, document processing and analysis, risk and fraud detection, results communication, and the reduction of human errors. Integrating these dimensions allows auditors to focus on higher-value activities, thereby enhancing the relevance, reliability, and quality of audits. AI and auditor competence thus appear as complementary resources whose combination maximizes benefits for the organization.

Based on these findings, we recommend that organizations emphasize the continuous development of internal auditors' skills to ensure the effective adoption of AI technologies. It is also essential to promote a harmonious interaction between human expertise and technological tools, with AI complementing rather than replacing professional judgment. Furthermore, technological monitoring is necessary to track AI developments and adopt best practices, ensuring the sustainability and effectiveness of internal audits.

In summary, this study highlights the importance of an integrated approach combining AI and human competence to sustainably enhance the quality and performance of internal auditing.

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## 9. Declarations

### *9.1. Ethical considerations*

Not applicable.

### *9.2. Use of artificial intelligence (AI)*

The authors declare the use of ChatGPT (OpenAI) and Grammarly exclusively for language editing and grammatical improvement purposes. The use of these artificial intelligence tools did not influence the scientific content, study design, data analysis, data interpretation, results, or conclusions of the manuscript. Full responsibility for the content remains with the authors.

### *9.3. Conflict of interest*

The authors declare no conflict of interest.

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