# Intelligent Auditing: Exploring the Transformative Impact of Artificial Intelligence on Internal Audit Quality

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## Abstract:

The main objective of this study is to examine the relationship between the impact of using artificial intelligence techniques and improving the quality of internal auditing activities. Artificial Intelligence is measured through dimensions such as Expert systems, Representation of Knowledge, Automatic Learning.

Quality of internal auditing is evaluated through the dimensions of Efficiency, Objectivity, performance, information technology, Continuous Improvement. The study utilizes a descriptive analytical approach, relying on both secondary and primary data.

The research addressed the hypothesis stating there is a statistically significant impact of Artificial Intelligence on the quality of internal auditing. The study indicates a high level of availability of Artificial Intelligence dimensions and found a high level of availability of internal auditing dimensions. the results support the presence of statistically significant impacts between the Artificial Intelligence dimension and the quality of internal auditing. The study recommends Enhance Integration of Intelligent Systems in Internal

Auditing Processes, Investigate Specific Phrases and Aspects within the AI Dimension, Focus on Continuous Improvement and Efficiency in Intelligent Auditing.

**Keywords:** Artificial Intelligence, Quality of internal auditing, Expert systems.

**المستخلص:**

يهدف هذا البحث إلى فحص العلاقة بين تأثير استخدام تقنيات الذكاء الاصطناعي وتحسين جودة أنشطة التدقيق الداخلي. يتم قياس الذكاء الاصطناعي من خلال أبعاد مثل أنظمة الخبراء، وتمثيل المعرفة، والتعلم التلقائي. ويتم تقييم جودة التدقيق الداخلي من خلال أبعاد الكفاءة، والموضوعية، والأداء، وتكنولوجيا المعلومات، والتحسين المستمر.

تستخدم الدراسة نهجاً وصفياً تحليلياً، مع الاعتماد على البيانات الثانوية والأولية، ويتناول البحث الفرضية التي تفيد بأن هناك تأثيرًا إحصائياً للذكاء الاصطناعي على جودة التدقيق الداخلي. تشير نتائج البحث إلى وجود مستوى عالٍ من توفر أبعاد الذكاء الاصطناعي، ووجود مستوى عالٍ من توفر أبعاد التدقيق الداخلي. تدعم النتائج وجود تأثيرات إحصائي بين بُعد الذكاء الاصطناعي وجودة التدقيق الداخلي، كما يوصي البحث بتعزيز التكامل بين الأنظمة الذكية في عمليات التدقيق الداخلي، واستكشاف عبارات وجوانب محددة ضمن بُعد الذكاء الاصطناعي، والتركيز على التحسين المستمر والكفاءة في التدقيق الذكي.

**الكلمات المفتاحية:** الذكاء الاصطناعي، جودة التدقيق الداخلي، الأنظمة الخبيرة.

## 1. Introduction:

Research on artificial intelligence (AI), dating back to Alan Turing (1950), stands as one of the most pivotal and ground-breaking developments in recent times. It is evident that AI has permeated, or is on the verge of permeating, every facet of our lives, affecting societies at large, international trade dynamics, and fundamentally transforming various institutions and businesses (OECD, 2019).

This overarching perspective can be viewed as a "macro" outlook, encompassing the entire economy and trade. However, delving into the intricacies of this macro view necessitates an examination of the meson and micro perspectives. At these levels, it becomes crucial to assess how the AI advancements discussed impact not only business processes but also social aspects, including the profiles of individual employees (Commander et al. 2011).

This investigation focuses on the impacts of the swift progression of AI applications on the functions of internal audit and risk assessment, both of which play crucial roles within organizational structures. The research aims to elucidate the necessary adjustments required in the framework of internal audit and risk assessment to maintain their relevance amidst global transformations, enabling them to effectively serve as "trusted advisors." The identification of opportunities and challenges is based on the evolving landscape of business processes, workplaces, and the workforce, particularly those engaged in internal audit and digitalization (Bresnahan et al., 2002; Capitani, 2018). The incorporation of AI necessitates substantial organizational changes and transformations, prompting a thorough examination of the areas where internal audit must adapt. Moreover, the study delves into the ethical dilemmas linked with AI and their implications on internal audit and risk assessment (Sambamurthy & Zmud, 2017).

Numerous scholars anticipate a significant transformation in the auditing profession's landscape, propelled by advancements in data analytics technologies and artificial intelligence (Gepp, et al., 2018; Issa, et al., 2016). Projected alterations include increased automation, expanded audit scope, reduced processing times, and heightened audit quality facilitated by these technological strides (Nonnenmacher, et al, 2021). It's noteworthy that major accounting firms, commonly known as the big four, are actively investing in and incorporating AI functionalities into their external auditing practices (Sun, et al, 2018).

AI, crafted to replicate human judgment and cognitive abilities, acquires knowledge from data and adjusts to new information autonomously, without explicit human programming (Shaw, 2019). The Big Four have made significant investments in AI, particularly in consulting and assurance practices, with a pronounced focus on the insurance sector. In this domain, AI plays a pivotal role in auditing and accounting procedures, encompassing tasks such as tax compliance, fraud detection, and decision-making (Munoko, et al., 2020). The potential of AI lies in its capability to comprehensively analyze real-time unstructured data, effectively directing attention to higher-risk areas amidst the surge of big data (Munoko, et al., 2020).

## 2. Literature Review

In the Study conducted by **(Agustí, & Orta-Pérez, 2023),** the central objective was to examine the impact of Big Data and Artificial Intelligence (AI) techniques on the realms of accounting and auditing. Acknowledging the substantial significance of these technologies, the study aimed to comprehend their influence on processes and performance within these pivotal sectors.

The findings of the study revealed that the application of AI techniques and the utilization of Big Data have a positive contribution to enhancing accounting and auditing practices. The study underscored the pressing need for further research and in-depth analysis in this area, highlighting the limitations of previous studies that lacked detailed exploration. This emphasizes the ongoing importance of comprehending the evolving impact of advanced technologies on accounting and auditing practices.

**Study (Steira, & Bangsund, 2023)** This study explores the impact of integrating artificial intelligence (AI) into internal audit procedures on the occurrence of internal control weaknesses in US-listed companies. The study finds a statistically significant, albeit weak, relationship between AI usage and a reduction in internal control weaknesses. In essence, incorporating AI in internal audit processes contributes positively to enhancing the effectiveness of internal control over financial reporting by lowering identified weaknesses.

**Study (Altaayiy, 2023)** This research aims to showcase the role of artificial intelligence, encompassing expert systems, knowledge representation, and inference, as well as automatic learning, in enhancing the quality of the audit process. The focus is on supporting internal audit operations in Iraqi banks, with an emphasis on achieving confidence in financial statements, preventing fraud, reducing risks, and promoting high-quality audit services. The researcher utilized a descriptive analytical approach, employing a questionnaire and analyzing the data through the statistical analysis program (SPSS).

The findings underscore the importance of enhancing auditors' awareness in Iraqi banks regarding the significance of employing artificial intelligence techniques for electronic internal audit services. The recommendation emphasizes the transition from traditional methods to leverage artificial intelligence, aiming to achieve quality in providing audit services.

In the Study conducted by **(Minkkinen et al., 2022),** the primary goal was to tackle the challenges faced by traditional auditing processes concerning artificial intelligence (AI) systems, with a specific emphasis on continuous auditing (CA) and its application to AI systems. The study introduced the innovative concept of Continuous Auditing of AI (CAAI).

CAAI is characterized as an (almost) real-time electronic support system designed for auditors, providing continuous and automated assessments of an AI system's adherence to pertinent norms and standards. The study takes a bottom-up approach, scrutinizing CAAI tools and methodologies within both academic and grey literature.

The results indicate that current frameworks exhibit limitations in their applicability to Continuous Auditing of AI (CAAI), frequently having a restricted scope confined to specific sectors or problem domains. Consequently, there is a need for additional refinement and development of CAAI frameworks, leveraging insights from existing Continuous Auditing (CA) frameworks.

In the research conducted by **(Ali et al., 2022),** the primary objective was to examine the connection between artificial intelligence (AI) techniques and internal auditing activities. Employing a survey methodology with a structured questionnaire distributed to 100 participants, the study delved into the statistically significant relationship between the utilization of AI techniques and internal auditing activities within organizational settings. Out of the distributed surveys, 66 responses were accurately completed and successfully collected.

The outcomes of the statistical analysis revealed a favorable impact of artificial intelligence techniques on the effectiveness of internal auditing activities. Consequently, the study recommended the adoption of AI applications in remote audit processes, highlighting potential benefits such as providing additional information to financial statement users, reducing costs, saving time, and enhancing internal audit efficiency. The research also proposed widespread use of AI across various corporate activities to cut costs and emphasized the need for continuous review and improvement of AI mechanisms, particularly in the context of remote internal auditing during epidemics.

In the investigation conducted by **(Rehman, & Hashim, 2022),** the focus was on examining the impact of the internal audit function on artificial intelligence (AI) within Omani public listed companies. The research sought to evaluate whether the internal audit function contributes to enhancing AI's role in delivering improved services and aiding in making informed strategic decisions for organizational management.

The results indicate a significant and direct impact of the internal audit function on AI, emphasizing the crucial role of control activities overseen by internal audit in influencing AI evaluations. This unique study suggests that AI has the potential to function as both a support tool and a governance management system within organizations. The findings imply implications for regulatory frameworks and organizational policies to enhance shareholder satisfaction and support organizational development.

In the study conducted by **(Zhang, et al., 2022),** the primary objective is to enhance clarity and comprehensibility in the implementation of artificial intelligence (AI) for auditing purposes, with a specific focus on meeting the requirements for audit documentation and evidence standards. The research highlights commonly used Explainable AI (XAI) methods, such as Local Interpretable Model-agnostic Explanations (LIME) and Shapley Additive explanations (SHAP), within the context of assessing the risk of material misstatement.

The study concludes by addressing the interpretability challenge in AI application for auditing through the introduction of Explainable AI (XAI) to researchers and practitioners. The paper maps various XAI techniques to existing audit documentation standards, showcasing their application, especially LIME and SHAP, in an ML-based auditing task. It provides auditing professionals with knowledge and tools to develop transparent AI applications. However, a limitation is noted in the measurement of material misstatement using a binary variable.

**Study (Singh, K.S.D., 2021)** This study examines the factors that influence internal audit effectiveness and their impact on internal audit quality, with a specific focus on independence, objectivity, and competence. The research underscores the increasing significance of internal control in corporate governance. The findings highlight a significant relationship between these factors and the quality of internal audit, contributing to agency theory by emphasizing their role in safeguarding client interests and ensuring compliance with corporate governance standards. The study also underscores the importance of interagency coordination and the supportive role of auditees in recognizing and accepting internal audit effectiveness, addressing a gap in the current literature.

**study (Fedyk et al, 2021)** This study investigates the impact of artificial intelligence (AI) on the efficiency and quality of audit firms, utilizing data from the 36 largest firms. Through the analysis of over 310,000 individual resumes, the study provides insights into the demographics and distribution of AI workers in the auditing sector. Results indicate that concentrated AI usage in specific teams and locations enhances audit quality, reduces fees, and gradually displaces human auditors. A one standard-deviation increase in AI investments correlates with a 5.0% decrease in audit restatements, a 0.009 drop in log per client fees, and a decline in accounting employees by 3.6% after three years, reaching 7.1% after four years.

**Study (Betti, & Sarens, 2021)** This study seeks to comprehend the evolution of the internal audit function in a digitalized business environment through 29 interviews with management committee members and internal auditors in Belgium. The analysis uncovers three primary impacts: an expanded scope with an increased emphasis on agility and digital knowledge, a heightened demand for consulting activities, and a transformation in the day-to-day practices of internal auditors with the integration of data analytics tools. The study underscores the significance of incorporating IT and data analytics skills within the internal audit function and stresses the importance of developing consulting activities to effectively address the challenges of digitalization in the business environment.

In the research by **(Lois, et al., 2020),** the primary objective was to investigate continuous auditing in the digital era, with a specific focus on the perspectives of employees in auditing firms and the contemporary factors influencing its implementation. The study involved engaging with internal audit departments in private companies, and a questionnaire was designed based on existing literature. The sample encompassed 105 individuals from major audit institutions in Greece, and the gathered data underwent analysis using multiple regression.

The study underscores the significance of establishing an effective digital auditing system in response to technological advancements. It reveals that factors such as data protection measures, employee skills, and training significantly influence the implementation of continuous auditing. The research highlights the importance for companies to devote attention to the preparation and formation of virtual audit teams. However, limitations are acknowledged due to the early stage of the digital age, making precise predictions and conclusive results challenging.

**Having examined the existing body of research, the investigators reached the following conclusions:**

- The current research addresses the impact of artificial intelligence (AI) on the enhancement of internal auditing activities, a topic related to existing studies focusing on AI techniques within this context. Notably, this study contributes as one of the pioneering efforts to analyze how AI influences the quality of internal auditing activities.
- There is a noticeable research gap in developing countries concerning the examination of AI's impact on improving the quality of internal auditing activities. Interviews with prominent accounting firms, including the Big 4 (Deloitte, Ernst & Young, PricewaterhouseCoopers, and KPMG), reveal an anticipation that 30% of corporate audits will be AI-driven by 2025. This insight underscores the transformative role technology is playing in reshaping the responsibilities of auditors. Continuous auditing and AI are projected to gain significance within the auditing profession.
- AI, denoting cognitive abilities that simulate human thinking, is increasingly prevalent in daily life. The researcher's synthesis of previous studies highlights deficiencies in internal auditing quality attributed to the underutilization of AI techniques. This deficiency, combined with the delayed issuance of financial reports, has resulted in the dissemination of inaccurate information

to investors and other consumers of financial data, influencing their decision-making process.

- Notably, audit firms' AI investments share a common objective of enhancing staff productivity and reducing manual efforts. This aligns with the broader industry trend of adopting AI to streamline workforce operations, as evidenced by associates citing the automation of manual accounting processes and the adoption of solutions to diminish manual tasks, improve quality, and expedite delivery time.

## 3. Research problem

Given the recent trend of companies automating their operations, and despite internal auditors adopting technology in recent years to enhance the efficiency of the auditing process, it has remained limited to routine tasks and low-skilled activities. The absence of technical knowledge in detecting risks and manipulation in financial accounting systems persists. Technology alone has been unable to address these issues, leading internal auditors to strive for providing their services at the highest level of quality. Therefore, there is a need to explore new techniques such as artificial intelligence. This involves simulating artificial intelligence processes that occur within the human mind, enabling computers to solve problems and make sound decisions in a logical and organized manner.

The efficiency of internal audit functions in large organizations has been hindered by the sheer volume of documents. Signs of this inefficiency include sluggish audit response times, reliance on sampling-based audit planning, and the dependence on keyword searches. These challenges underscore the necessity for automation to expedite internal audit processes and overcome inherent human limitations. By incorporating artificial intelligence dimensions such as expert systems, knowledge representation, inference, and automated learning during the execution of audit procedures, the goal is to enhance the overall quality of internal audit within the organization. **In light of the aforementioned considerations, the primary issue can be framed as follows:**

The effectiveness of internal audit activities faces challenges arising from deficiencies in the internal audit function, limited utilization of artificial intelligence techniques, and delays in the issuance of financial reports. This scenario has resulted in the dissemination of inaccurate information, influencing the decision-making process for investors and other consumers of financial data. The central research issue can be encapsulated in the following question:

**What is the impact of using artificial intelligence with its dimensions on improving the quality of internal auditing activities?**

## 4. Hypotheses

***"There is a Statistically Significant impact of Artificial Intelligence on the quality of internal auditing". Several hypotheses emerge from this hypothesis:***

- **H1:** There is a statistically significant impact of Expert Systems as one dimension of Artificial Intelligence on the quality of internal auditing.
- **H2:** There is a statistically significant effect of the Representation of Knowledge as one dimension of the role of Artificial Intelligence on the quality of internal auditing.
- **H3:** There is a statistically significant effect of the Automatic Learning as one dimension of the role of Artificial Intelligence on the quality of internal auditing.

## 5. Research model

The following figure (1) shows the general framework for the study variables, as follows:

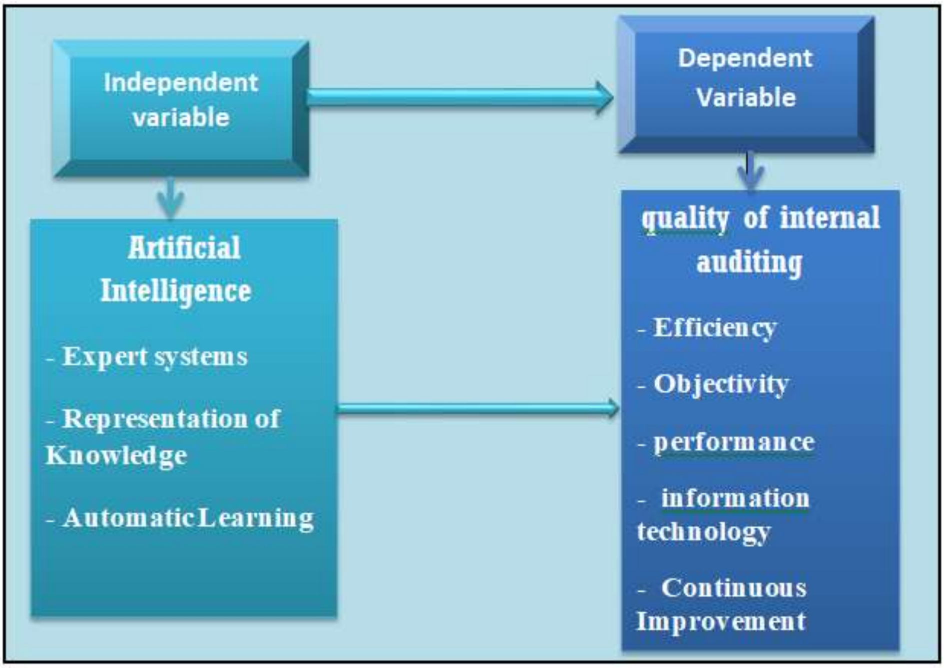


**Figure No. (1): Study Framework.**

**Source: Prepared by the researcher.**

## 6. Research Objectives.

This research aims to investigate the impact of using artificial intelligence techniques and improving the quality of internal auditing activities.

## 7. Methodology

**Analytical Study:** Through an examination of relevant literature encompassing analytical measures, this research aims to facilitate an in-depth understanding of digital transformation, internal audit quality, and financial reporting quality. The focus is on extracting information and evidence necessary to conduct a comprehensive analytical study.

**Empirical Study:** Employing a survey methodology, we gathered primary data through a meticulously designed questionnaire. One hundred surveys were disseminated, resulting in 66 appropriately filled and thorough responses. The data analysis encompassed the use of percentages, tables, and Spearman rank-order correlation methods. Furthermore, a regression analysis was performed to evaluate the impact of digital transformation on the quality of internal audit and its subsequent influence on financial reporting quality. This analysis was conducted at a 95% confidence level using SPSS.

## 8. Research Structure:

**Introduction Section:** This segment provides a comprehensive overview, offering insights into the context, objectives, and significance of the research. It lays the foundation for the study.

**The First Section:** This section delves into the theoretical background, exploring the foundational concepts and principles relevant to the study.

**The Second Section:** This part focuses on the empirical study, examining real-world data and practical applications to validate or challenge the theoretical foundations established in the first section.

**The Third Section:** Concluding the study, this section presents findings, draws conclusions, offers recommendations, and identifies potential **areas for future research.**

**a. Artificial Intelligence**

The origin of artificial intelligence (AI) can be traced back to the 1940s. A significant moment occurred in 1942 when Isaac Asimov, an American Science Fiction writer, released his short story titled "Runaround." In this tale, engineers Gregory Powell and Mike Donovan create a robot that embodies Asimov's Three Laws of Robotics. These laws underscore that a robot should refrain from causing harm to a human being, must follow human orders unless conflicting with the first law, and should safeguard its own existence without conflicting with the first or second laws. Asimov's groundbreaking contribution served as a catalyst for researchers in robotics, AI, and computer science, leaving a lasting impact on American cognitive scientist Marvin Minsky, who subsequently co-founded the MIT AI laboratory.

Meanwhile, in a different geographical setting, the English mathematician Alan Turing addressed practical challenges by creating a code-breaking machine named The Bombe during the Second World War on behalf of the British government. Recognized as the initial functional electro-mechanical computer, The Bombe had dimensions of approximately 7 by 6 by 2 feet and weighed around a ton. Turing's remarkable achievement in decoding the Enigma code, a task deemed impossible for even the most adept human mathematicians, piqued his interest, and played a significant role in shaping the course of AI development.

In the domain of taxation, this dynamic technology possesses the potential to enhance the efficiency of automated tax auditing and decision-making processes, thereby strengthening government oversight and monitoring. Artificial intelligence, characterized as the fusion of hardware and software mimicking human brain functions, is endowed with the ability to analyze, make decisions, and execute intricate judgment processes based on available data (Puthukulam, G., et al., 2021).

AI-powered software systems play a crucial role in boosting operational efficiency and managing daily transactions effectively. Despite having its roots in the 1940s, artificial intelligence is seen as an ever-evolving technology, showcasing different levels of intelligence according to Munoko et al. (2020). The ongoing advancements in AI, noted by Copeland (2004) and Stahl et al. (2017), highlight a continuous refinement in implementation techniques. Businesses are making substantial investments in AI development, anticipating considerable social impact, signaling a widespread acknowledgment of AI's transformative potential across various sectors.

As per PwC's projections, sustained investments in artificial intelligence (AI) hold the potential to generate a global increase in productivity reaching $6.6 trillion by 2030. The report categorizes three types of AI artifacts contributing to financial gains. The first type, assisted AI systems, aids human decision-making by managing routine tasks, enabling users to retain decision-making responsibilities. For instance, Microsoft's AI application excels in speech transcription, facilitating customer call analysis and agent performance evaluation (Munoko, I., et al., 2020). The second type, augmented AI systems, integrates human decision-making and learns from interactions, demonstrating analytical intelligence. In this scenario, humans and AI become co-decision makers. Lastly, the third type, Autonomous AI systems, operates independently without human assistance, showcasing intuitive and empathetic intelligence (Munoko, I., et al., 2020). Examples of autonomous AI applications in the service industry include customer support chatbots. As AI artifacts progress from assisted to autonomous, their benefits and cost savings become increasingly apparent (Huang, M. H. & Rust, R. T., 2018).

**b. Artificial Intelligence Applications.**

The 1980s marked a period of significant growth in the creation of expert systems, aimed at emulating the decision-making abilities of human specialists in various fields. These systems were designed with a wide range of business applications in mind, with a focus on practical commercial applications in areas such as robotics, computer vision, natural language processing, and expert systems. Despite considerable progress, the quest to develop truly intelligent expert systems, especially those that replicate sensory functions, has not been entirely successful. While expert systems have been expanded into new areas where conventional computer applications have struggled, obstacles remain, particularly when dealing with decisions that involve ambiguous data and incomplete information (Stahl et al., 2017).

### c. Neural Network

Neural networks epitomize a groundbreaking AI technology that mirrors the intricate functionality of the human brain within a computer system. Diverging significantly from conventional algorithmic computing, these systems leverage parallel and distributed processing, enabling them to excel in addressing problems with numerous variables.

What distinguishes neural networks from expert systems is their capacity for direct learning from examples. In contrast to expert systems requiring an information engineer, users can train the network by presenting examples of inputs paired with their desired outputs. The system acquires an understanding of the associations between input and output examples, going beyond mere repetition to form connections for inputs and outputs not explicitly employed during the training phase. This learning process closely emulates the human learning experience, involving neurons and sensory inputs.

**Dimensions of Artificial Intelligence:**

***This study relies on several dimensions of artificial intelligence, outlined as follows:***

- **Expert systems (ESs)**

Expert systems (ESs) serve as a method for sharing and disseminating information acquired directly or indirectly from domain experts across various scientific fields. (Sabine, A., et al., 2021). Their role extends beyond assisting users with specific knowledge gaps; they also provide support.

The design of expert systems revolves around an iterative decision-making process, often involving human experts in solving particular problems. As per (Ali, et al., 2022). Two categories of specialized knowledge exist: facts and heuristics. Facts form the core of an information system, and expert systems are typically designed to be user-friendly and interactive, providing explanations for decision outcomes based on facts and rules.

An expert system is an information system based on computer technology that aims to offer solutions for issues associated with a particular system. It is termed a system, not a program, as it encompasses elements dedicated to problem-solving and others supporting its functioning. These components constitute the support that aids user interaction with the system. The system may also integrate auxiliary tools and a high level of forecasting future events grounded in precise scientific principles. Moreover, the system streamlines user interaction upon activation.

Expert systems are defined as technologies that work to identify and find suitable solutions for problems requiring specialized knowledge and skills. The system operates in a way that simulates the thinking and skills of an expert to mimic them. Expert systems are one of the methods of artificial intelligence. (Dweik et al., 2013).

Motivations for Using Expert Systems: The motivations for using expert systems include:"

- It aims to simulate human thinking and style.
- It works to stimulate new ideas that lead to innovation in work.
- Reducing dependence on human experts in the job.
- Providing multiple copies of the programs used in the system, compensating for the reliance on human experts in the job.
- Shortening the time, eliminating the feeling of fatigue and boredom at work.

- **Representation of knowledge:**

The intelligent artificial system should be capable of adapting to its environment, acquiring knowledge, and drawing inferences describing that environment. It stores acquired knowledge in a way that allows a quick and sufficient response to any stimulus generated by the environment. In short, representing knowledge and the method of obtaining it mean shaping how knowledge is represented and accessed. The representation and acquisition of knowledge hold significant importance in intelligent data processing, particularly when managing vast and intricate datasets. As real-world data becomes more voluminous and complex, addressing related challenges hinges on effectively representing the existing knowledge in the field.

This requires intelligent data processing based on the Representation of knowledge used by these systems in tasks such as interpretation, analysis, and processing (Rajangam and Annamalai, 2016).

Representation of knowledge in relation to artificial intelligence is highlighted by how knowledge is represented and processed algorithmically through expert systems. Effectively representing knowledge and making inferences play a critical role in establishing the connection between human knowledge and its portrayal through programming languages (Lucas et al., 2012).

- **Automatic Learning:**

Automatic learning, also known as machine learning, is a set of programming techniques that enable machines to adapt their behaviour in their environment without human intervention or with partial human intervention. It involves designing algorithms capable of making appropriate decisions independently without prior programming. Automatic learning is divided into three categories:

- **Reinforcement Automatic Learning**: This algorithm learns behaviour through observation and adapts to it. It continually receives feedback from its environment to improve its future steps (Mullainathan and Spiess, 2017).

- **Unsupervised Automatic Learning**: In this case, the designer provides only examples without pre-classifications. The algorithm discovers hidden data structures to extract classifications on its own.
- **Supervised Automatic Learning**: When classifications are predefined, and examples are known in advance, the system learns the classification according to a model provided by the user. It is also known as supervised learning or discriminative learning and is used in solving classification, regression, and self-organization problems (Berk, 2016).

In this context, the researcher sees that the field of artificial intelligence, with its components such as expert systems, knowledge and inference, and automatic learning, aims to understand the complex processes performed by the human mind during its thought processes in the work environment. Subsequently, these processes are translated into auditing and accounting programs that assist computers in solving complex problems and predicting them in advance.

**d. internal audit activities**

The definition of internal audit, as outlined by the International Professional Practices Framework, revolves around an impartial and unbiased assessment aimed at enhancing the operational efficiency of an organization, playing a pivotal role in assisting the organization in achieving its objectives. Typically, the responsibility for conducting the internal audit function lies with internal auditors, who are employed within the organization's internal audit department (IPPF, 2017).

Internal audit activities ensure legal compliance, timely financial reporting, and provide tools for operational efficiency (Jiang et al., 2020). They occur at varying frequencies depending on the department. The audit process involves planning, expert consultation, stakeholder meetings, and program review (Anderson and Al., 2017). These activities add value, improve operations, manage risk, and guard against fraud. They provide management with improvement suggestions, enhance operational efficiency, motivate policy adherence, and allow exploration of specific operational areas (Mahyoro, A.K., et al., 2021).

**e. Internal Audit Quality and the Efficacy of Internal Audit Services.**

The quality of an internal audit is closely connected to the methods internal auditors use in their work, as they evaluate processes following set procedures and standards (Mahyoro, A. K., et al., 2021). Various factors, such as staff competency, the scope of services, and the effectiveness of planning, execution, and reporting during audits, influence this quality (Mansor, 2018). Manifestations of this quality include risk reduction, enhanced controls, reduced external monitoring costs, and the prevention of fraud and opportunistic behaviors within an organization.

Defining audit quality lacks unanimity in both internal and external audit literature. It is characterized by the ability to identify and report anomalies and violations, with the latter serving as a definitive indicator of audit quality (Singh, K. S. D., et al., 2021; Butcher et al., 2013). The capability to detect and report anomalies and violations hinges on the competence, independence, and objectivity of internal auditors, with expectations for a robust function encompassing operational efficiency, regulatory compliance, financial reporting reliability, and asset safeguarding (Hayes et al., 2015). Internal audit quality aligns with compliance with IIA standards, effective planning, execution of findings, and communication..

Regulatory organizations such as the Association of Chartered Accountants (ACCA) and the Institute of Internal Auditors (IIA) emphasize the crucial role of independence and impartiality in auditing. The IIA, in particular, describes internal auditing as an autonomous and unbiased practice of assurance and advice, intended to add value and improve the operations of an organization (IIA, 2020). Both the ACCA and the IIA highlight the necessity for internal auditors to possess the required skills for effective performance. The competence of internal auditors instills confidence in both principals and agents regarding the professional execution of their duties (Singh, K. S. D., et al., 2021).

In a synthesis of pertinent internal audit literature, Turetken et al. (2019) contend that adherence to the International Standards for the Professional Practice of Internal Auditing (ISPPIA) by the Institute of Internal Auditors (IIA) serves as a benchmark for evaluating internal audit effectiveness, where objectivity and the empowerment of internal auditors are acknowledged as crucial dimensions (IIA, 2020).

**f. The Effect of Artificial Intelligence on Internal Auditing.**

The impact of artificial intelligence on internal auditing is significantly manifested in fundamental transformations that touch upon various aspects of this vital field. Artificial intelligence represents an effective transformation that influences all facets of our lives and our institutions. This influence is a multidimensional social, economic, and organizational phenomenon.

One of the primary impacts is in the realm of technology and tools used in internal auditing. Artificial intelligence provides tremendous capabilities in automatically and swiftly analysing data, contributing to the improvement of the efficiency and accuracy of auditing processes. Intelligent systems relying on artificial intelligence can analyse massive datasets quickly, aiding in the effective detection of errors and manipulation.

Furthermore, artificial intelligence affects decision-making processes in internal auditing. Smart systems can provide precise analyses and recommendations based on big data, contributing to informed decision-making and enhancing risk management.

In the context of digital transformation, interaction with employees and auditors within the organization is another point of impact. Effective integration with artificial intelligence requires a good understanding of new technologies and the qualification of human resources to interact effectively with intelligent systems.

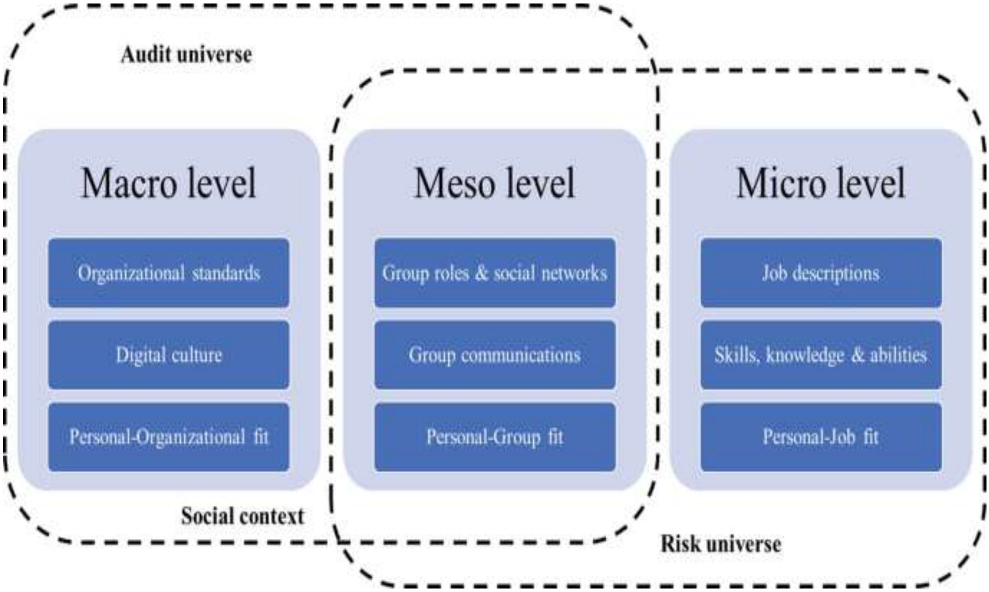


**Figure No. (2): impact of artificial intelligence on internal auditing.**

**Source: Buettner (2014)**

In this context, a crucial aspect involves the reconfiguration of internal audit and risk assessment activities, along with the utilization of audit tools and techniques aligned with the evolving working culture. Consequently, the initial step entails providing information by elucidating the modifications, their nature, and the underlying reasons. It is noteworthy that the "risk universe" at the meso and micro levels plays a pivotal role, forming an integral component for ensuring a value-added audit approach.

**g. Contemporary and Future Applications of Artificial Intelligence in Internal Audit Quality.**

The incorporation of artificial intelligence (AI) into the accounting and auditing sector commenced in the early 1980s, initially incorporating simpler versions like expert systems. These systems leveraged a knowledge base of rules and facts from field experts to support decision-making, enabling professionals to seek recommendations in specific scenarios (Ali, et al., 2022). The emergence of advanced technologies, such as Artificial Intelligence and Machine Learning (ML), has equipped auditors with a more profound understanding of a company's operations, facilitating a comprehensive assessment of potential risks in each audit area (Puthukulam, G., et al., 2021). The application of AI has significantly improved audit efficiency, necessitating auditors to stay abreast of technological advancements.

AI brings substantial benefits to audits, including cost reduction and efficient processing of vast data amounts, thereby enhancing audit efficiency (Puthukulam, G., et al., 2021). In contrast to the pre-AI era where auditors manually tested data randomly, AI now indicates whether specific transactions require further examination and aids in rapidly identifying trends and patterns in datasets (Andrew Struthers & Kyle Nesgood, 2020).

The future of AI technology in auditing holds promise for automating routine low-level audit tasks, with advancements enabling more autonomous functions. Despite facing challenges, the influence of artificial intelligence on auditing is clearly discernible in areas such as data acquisition, verification of transaction processing, and reporting (Kokina, J., and Davenport, T. H, 2017). Researchers suggest that the use of AI systems enhances audit quality by addressing human limitations, improving professional judgment, recognizing the significance of risk, and requiring internal auditors to rely on modern systems (Puthukulam, G., et al., 2021).

## 9. Descriptive statistics

### 9.1. Artificial Intelligence variable:

The strength of the dimensions of the independent variable (Artificial Intelligence) was measured to assess their availability, and these dimensions were ranked in order of importance from the perspective of the study participants, as follows:

**Table (1): Descriptive Statistics for the Artificial Intelligence Variable.**

| N | Phrases | Mean | Standard Deviation | Importance Ranking |
|---|---|---|---|---|
| 1 | Expert systems help auditors find solutions to various anticipated problems in organizations. | 4.02 | 0.75 | 1 |
| 2 | Expert systems assist auditors in making appropriate decisions based on information stored in databases. | 3.92 | 0.87 | 2 |
| 3 | This system allows users to anticipate future events based on precise scientific principles. | 3.54 | 0.74 | 5 |

| N | Phrases | Mean | Standard Deviation | Importance Ranking |
|---|---|---|---|---|
| 4 | The use of expert systems leads to an improvement in auditors' ability to select evidence accurately and with high efficiency. | 3.78 | 0.76 | 3 |
| 5 | Expert systems replicate the thought process and methodology of auditors to ensure the quality of audit services. | 3.63 | 0.84 | 4 |
| | **Expert systems** | **3.77** | **0.79** | **first** |
| 1 | Knowledge and inference enable auditors to securely store and protect large datasets from manipulation. | 3.63 | 0.77 | 3 |
| 2 | Knowledge and inference assist intelligent systems in adapting to the auditing environment of organizations. | 3.40 | 0.67 | 5 |
| 3 | Knowledge aids in the auditing process by retrieving and inferring data when an issue arises and processing it quickly | 3.98 | 0.91 | 1 |
| 4 | Leveraging knowledge and inference aids in the precise interpretation, processing, and analysis of accounting operations. | 3.44 | 0.88 | 4 |
| 5 | Utilizing knowledge and inference helps bridge auditors' human expertise with its representation in computer programming for auditing procedures. | 3.69 | 0.84 | 2 |
| | **Representation of knowledge** | **3.62** | **0.81** | **second** |
| 1 | Audit and control systems possess the capability to autonomously identify any form of manipulation. | 3.38 | 0.79 | 3 |
| 2 | Automatic learning links accounting systems with audit systems through computer programs automatically | 3.45 | 0.75 | 1 |
| 3 | Auditors automatically backup financial data for error prevention. | 3.18 | 0.93 | 5 |
| 4 | Automatic smart programs perform audit operations efficiently and quickly. | 3.43 | 0.85 | 2 |
| 5 | Automated auditing systems enhance the efficiency of accounting and financial processes through their automatic execution | 3.31 | 0.77 | 4 |
| | **Automatic Learning** | **3.35** | **0.81** | **third** |
| | **Overall Indicators** | **3.58** | **0.80** | |

Analyzing the preceding table reveals the prevalence of various dimensions of A.I. The findings indicate that the dimensions are ranked as follows: Expert Systems, with a mean of 3.77 and a rate of 75.4%; Representation of Knowledge, with a mean of 3.62 and a rate of 72.32%; and Automatic Learning, with a mean of 3.35 and a rate of 67%.

The collective average of the dimensions is 3.58, signifying a consensus rate of 71.6%.

### 9.2. Quality of internal auditing variable:

The dimensions of the dependent variable (quality of internal auditing) were measured to assess their availability, and these dimensions were ranked in order of importance from the perspective of the study participants, as follows:

**Table (2): Descriptive Statistics for the quality of internal auditing Variable.**

| N | Phrases | Mean | Standard Deviation | Importance Ranking |
|---|---|---|---|---|
| 1 | The ability and skill to use computer-based artificial intelligence technologies and auditing software. | 3.62 | 0.74 | 1 |
| 2 | The auditor completes assigned auditing tasks in a timely manner. | 3.46 | 0.71 | 3 |
| 3 | The auditor possesses the competence and auditing skills necessary to accomplish tasks with high accuracy. | 3.32 | 0.86 | 4 |
| 4 | The management is committed to offering training programs aimed at improving the effectiveness of internal auditors. | 3.51 | 0.81 | 2 |
| | **Efficiency** | **3.47** | **0.78** | **third** |
| 1 | The auditor enjoys independence during the auditing process | 3.71 | 0.85 | 1 |
| 2 | Presenting audit reports to top management is characterized by accuracy, objectivity, and clarity. | 3.70 | 0.79 | 2 |
| 3 | The necessity of considering independence for the internal audit management. | 3.62 | 0.91 | 3 |
| 4 | Enhancing the quality of internal auditing involves ensuring objectivity within the internal audit team and coordinating reporting and administrative subordination to the internal audit committee. | 3.41 | 0.69 | 4 |
| | **Objectivity** | **3.61** | **0.81** | **first** |

| N | Phrases | Mean | Standard Deviation | Importance Ranking |
|---|---|---|---|---|
| 1 | Artificial intelligence enhances internal audit performance by improving schedules and completion rates, thereby elevating overall effectiveness | 3.88 | 0.82 | 1 |
| 2 | Artificial intelligence improves performance schedules and completion rates in internal audit operations. AI enhances the effectiveness of internal audit operations and elevates performance levels. | 3.72 | 0.70 | 2 |
| 3 | AI provides opportunities to enhance the quality of audit reports submitted to senior management. | 3.37 | 0.93 | 4 |
| 4 | AI assists in designing automatic systems to monitor operations and detect any deviations in performance. | 3.43 | 0.77 | 3 |
| **Performance** | | **3.60** | **0.80** | **second** |
| 1 | Precision, reliability, and data trust are available in information technology techniques, ensuring the accuracy of the information contained in the information system. | 3.12 | 0.90 | 1 |
| 2 | Information technology techniques aid in preparing internal audit reports and issuing them promptly. | 2.93 | 0.74 | 3 |
| 3 | Information technology techniques help achieve objective results by documenting the internal audit process accurately. | 2.69 | 0.96 | 4 |
| 4 | Information technology techniques assist in the internal audit process by preparing and presenting observations, recommendations, and reports to be submitted to management. | 2.94 | 0.81 | 2 |
| **Information technology** | | **2.93** | **0.85** | **Fifth** |
| 1 | The company encourages the adoption of continuous improvement principles in all aspects of internal audit operations. | 3.59 | 0.73 | 1 |
| 2 | The internal audit team undergoes regular assessments to identify areas for improvement. | 3.43 | 0.87 | 3 |
| 3 | Providing opportunities for training and skill development is considered part of the continuous improvement strategy for the internal audit team. | 3.26 | 0.69 | 4 |
| 4 | Regular reviews are conducted of the results of internal audits, allowing for immediate corrective and improvement actions. | 3.51 | 0.78 | 2 |
| **Continuous Improvement** | | **3.44** | **0.77** | **fourth** |
| **Overall Indicators** | | **3.41** | **0.80** | |

Examining the data from the preceding table reveals the prominence of different dimensions within I.A. The order of prevalence is as follows: Objectivity, with a mean of 3.61 and a rate of 72.2%; Performance, with a mean of 3.60 and a rate of 72.6%; Efficiency, with a mean of 3.47 and a rate of 69.4%; Continuous Improvement, with a mean of 3.44 and a rate of

68.8%; and Information Technology, with a mean of 2.93 and a rate of 58.6%.

Consequently, there exists a substantial abundance of I.A dimensions, and the perspectives expressed converge. The aggregate average across the dimensions is 3.41, indicating a consensus rate of 68.2%.

## 10.Test the Hypotheses of the Research:

This section deals with testing the hypotheses through some statistical methods used to study the validity or incorrectness of the hypotheses. Structural equation modeling was employed to examine the impact of an independent variable on the dependent variable, with the evaluation of the model conducted through various criteria to assess its quality and reliability. These criteria were elucidated before conducting the actual testing of hypotheses. In light of the above description of the study sample and its variables, the validity of the hypotheses was tested statistically, with the results of the statistical analysis presented and interpreted as follows:

**Structural Equation Modeling (SEM):** is a widely adopted technique in various research disciplines, particularly in the social sciences. It has become indispensable for researchers due to its ability to analyze complex relationships among variables. However, achieving a model that effectively represents the data and aligns with the underlying theory, known as model fit, remains a subject of ongoing debate.

**Normed Chi-Square:** is a metric calculated by dividing the chi-square index by the degrees of freedom. The purpose of this index is to be less sensitive to sample size variations, although there is a lack of consensus on an acceptable ratio. Recommendations on an acceptable normed chi-square ratio can vary, with suggested values ranging from as high as 5.0 to as low as 2.0.

**Goodness-of-Fit Statistic (GFI):** evaluates the extent to which the estimated population covariance accounts for the variance in the data. It assesses how closely the model replicates the observed covariance matrix. With a range from 0 to 1, larger sample sizes tend to increase its value, indicating a better fit.

**Adjusted Goodness of Fit Index (AGFI):** is influenced by sample size, typically increasing with larger samples. Like GFI, AGFI values fall between 0 and 1, and a generally accepted criterion for a well-fitting model is a value of 0.90 or greater. It accounts for the potential detrimental effect of sample size on fit indices.

**Normed Fit Index (NFI):** evaluates a model by comparing its $\chi 2$ value to that of the null model, which assumes no correlation among measured variables. Values for NFI range from 0 to 1, with values surpassing 0.90 indicating a good fit. Recent suggestions propose a higher cut-off criterion, stating that NFI should be greater than or equal to 0.95 for a well-fitting model.

**Comparative Fit Index (CFI):** is an enhanced version of the Normed Fit Index (NFI) that takes sample size into consideration, showcasing robust performance even when dealing with small sample sizes. Like the Normed Fit Index (NFI), the Comparative Fit Index (CFI) assumes uncorrelated latent variables in a null or independence model. It evaluates the fit of a model by comparing the sample covariance matrix with this specified null or independence model. Values for the Comparative Fit Index (CFI) range from 0.0 to 1.0, where values closer to 1.0 suggest a better fit of the model. Currently, a CFI equal to or greater than 0.95 is commonly recognized as indicative of a good fit in Structural Equation Modeling (SEM) analyses. CFI is widely reported in SEM analyses due to its resilience against sample size effects.

**Incremental Fit Indices (IFI):** also known as comparative or relative fit indices, do not rely on raw chi-square values but instead compare them to a baseline model. The baseline model assumes that all variables are uncorrelated. IFI values typically range between 0.1, and the closer the value is to 1.0, the better the fit of the estimated model to the study's data. Higher IFI values indicate a better fit of the specified model compared to the baseline model where all variables are assumed to be uncorrelated.

**Root Mean Square Residual (RMR) and Standardized Root Mean Square Residual (SRMR):** They are statistical metrics employed to assess the fit of a covariance model to observed data in the context of structural equation modeling (SEM). The calculation involves determining the square root of the discrepancy between the residuals of the sample covariance matrix and the hypothesized model. RMR is computed by considering the diverse scales of questionnaire items, ensuring a precise evaluation, particularly when the items exhibit different measurement scales.

**RMSEA:** within the 0.05 to 0.10 range, has historically been deemed indicative of a reasonable fit, while values exceeding 0.10 suggest inadequate fit. Recent perspectives propose that an RMSEA falling between 0.08 and 0.10 now signifies mediocre fit, whereas values below 0.08 are considered indicative of a good fit. RMSEA evaluates the extent to which the model replicates the observed covariance matrix, providing insights into the overall fit of the model.

- **The first sub-hypothesis test:**

**"There is a statistically significant impact of Expert Systems as one dimension of Artificial Intelligence on the quality of internal auditing"**. To test the validity of this hypothesis, structural equation modeling was used to study the impact of Expert Systems as one dimension of the independent variable on the quality of internal auditing as the dependent variable. The results were as follows:

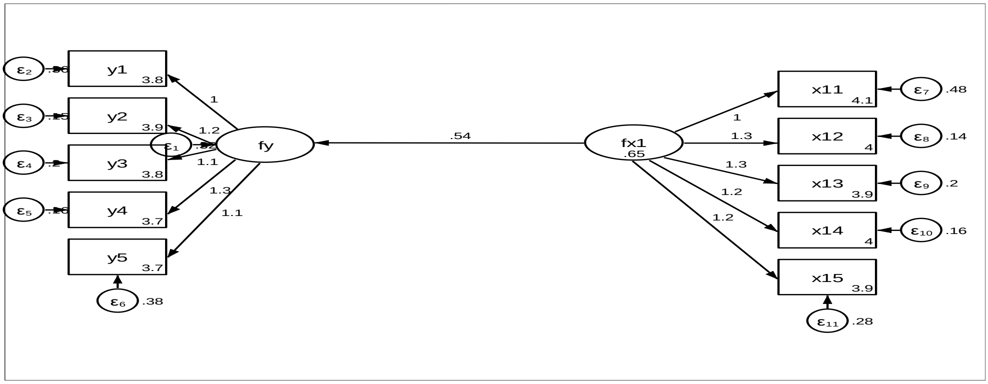


**Figure No. (3): Structural Equation Modeling for the Expert Systems Model.**

**Table (3): The direct impact of the Expert Systems dimension.**

| Hidden Variables | Path | Observed Variables | Standard Estimate | Non-Standard Estimate | Z-Test | Significance |
|---|---|---|---|---|---|---|
| Expert systems | → | quality of internal auditing | 0.535 | 0.054 | 9.84 | *** |
| Expert systems | → | x1.1 | 1.00 | **Constrained** | | |
| | → | x1.2 | 1.274 | 0.068 | 18.76 | *** |
| | → | x1.3 | 1.328 | 0.073 | 18.31 | *** |
| | → | x1.4 | 1.197 | 0.063 | 19.13 | *** |
| | → | x1.5 | 1.59 | 0.066 | 17.55 | *** |
| quality of internal auditing | → | y1 | 1.00 | **Constrained** | - | - |
| | → | y2 | 1.170 | 0.065 | 18.03 | *** |
| | → | y3 | 1.121 | 0.065 | 17.22 | *** |
| | → | y4 | 1.300 | 0.069 | 18.87 | *** |
| | → | y5 | 1.124 | 0.072 | 15.60 | *** |

**Source: STATA Results22** **Significance at the 0.001 Level ******

The preceding table, illustrates the impact of Expert systems on the level of quality of internal auditing, taking into consideration the expressions representing each dimension. The findings are as follows:

- There is a statistically significant effect of the Expert systems dimension on the level of quality of internal auditing at a 99% confidence level, with a standardized coefficient of 0.535.
- There is a statistically significant effect of expressions representing the Expert systems dimension at a 99% confidence level, with standardized coefficients ranging from 1.00 to 1.59.
- There is a statistically significant effect of expressions representing the quality of internal auditing dimension at a 99% confidence level, with standardized coefficients ranging from 1.00 to 1.30.

To verify the model's quality and assess the validity of the assumptions, a set of criteria for judging the model's quality were tested, as outlined in the following table:

## Model Quality Criteria:

**Table (4): Quality Criteria for Expert systems Model.**

| Indicator | Code | Value | Acceptance Level |
|---|---|---|---|
| Standardized Chi-Square Value | CMIN/DF | 3.112 | Less than 5 as a maximum value |
| Goodness of Fit Index | GFI | 0.971 | 0.90 ≥ |
| Normed Fit Index | NFI | 0.955 | 0.90 ≥ |
| Incremental Fit Index | IFI | 0.960 | 0.90 ≥ |
| Tucker Lewis Index | TLI | 0.943 | 0.90 ≥ |
| Comparative Fit Index | CFI | 0.911 | 0.90 ≥ |
| Root Mean Square Error of Approximation | RMSEA | 0.067 | ≤ 0.08 |

The table above, indicates the following:

All indicators are within the required limits. For instance, the acceptable threshold for the standardized Chi-square (CMIN/DF) indicator is not to exceed 5. The value of this indicator here is 3.112, indicating model quality within the acceptable range. The rest of the indicators have an acceptable threshold of not less than 0.90, and they are within the acceptable range. The Goodness of Fit Index (GFI) is 0.971, the Normed Fit Index (NFI) is 0.955, the Incremental Fit Index (IFI) is 0.960, the Comparative Fit Index (CFI) is 0.911, and the Root Mean Square Error of Approximation (RMSEA) is 0.067, which is below 0.08. These values collectively indicate favorable fit indices, suggesting that there is a potential alignment between the actual model and the estimated model.

**Therefore, the validity of the assumption asserting the statistically significant impact of Expert systems on the quality of internal auditing has been confirmed.**

- **The second sub-hypothesis test:**

This subtest posits the following: **There is a statistically significant effect of the Representation of Knowledge as one dimension of the role of Artificial Intelligence on the quality of internal auditing**. To test the validity of this hypothesis, structural equation modeling was employed to examine the impact of Representation of Knowledge as an independent variable on the quality of internal auditing as a dependent variable. The results were as follows:

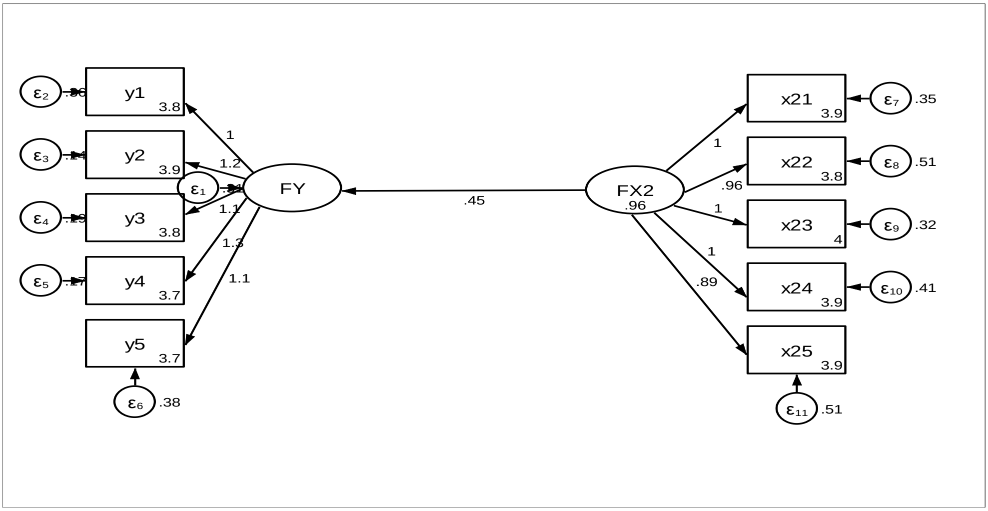


**Figure No. (4): Structural Equation Modeling for the Representation of Knowledge Model.**

## Table (5): The direct impact of the Representation of Knowledge dimension.

| Hidden Variables | Path | Observed Variables | Standard Estimate | Non-Standard Estimate | Z-Test | Significance |
|---|---|---|---|---|---|---|
| Representation of Knowledge | → | quality of internal auditing | 0.453 | 0.0433 | 8.275 | *** |
| Representation of Knowledge | → | x2.1 | 1.00 | Constrained | | |
| | → | x2.2 | 0.959 | 0.053 | 18.07 | *** |
| | → | x2.3 | 1.129 | 0.065 | 17.38 | *** |
| | → | x2.4 | 1.04 | 0.0522 | 19.23 | *** |
| | → | x2.5 | 0.889 | 0.053 | 16.73 | *** |
| quality of internal auditing | → | y1 | 1.00 | Constrained | | |
| | → | y2 | 1.177 | 0.065 | 18.17 | *** |
| | → | y3 | 1.129 | 0.065 | 17.38 | *** |
| | → | y4 | 1.287 | 0.688 | 18.71 | *** |
| | → | y5 | 1.115 | 0.072 | 15.49 | *** |

**Source: STATA Results22** **Significance at the 0.001 Level *****

The previous illustrates the impact of the Representation of Knowledge on the quality of internal auditing, taking into consideration the phrases representing each dimension. The following findings have been revealed:

- There is a statistically significant impact of the Representation of Knowledge dimension on the quality of internal auditing at a 99% confidence level, with a standard parameter of 0.453.
- There is a statistically significant impact of phrases representing the Representation of Knowledge dimension

at a 99% confidence level, with standard parameter values ranging from 0.889 to 1.129.

- There is a statistically significant impact of phrases representing the quality of internal auditing dimension at a 99% confidence level, with standard parameter values ranging from 1.00 to 1.287.

To verify the model's quality and assess the validity of assumptions, a set of criteria for judging model quality was tested, as indicated in the following table:

**Model Quality Criteria**

**Table (6): Quality Criteria for Expert systems Model.**

| Indicator | Code | Value | Acceptance Level |
|---|---|---|---|
| Standardized Chi-Square Value | CMIN/DF | 1.578 | Less than 5 as a maximum value |
| Goodness of Fit Index | GFI | 0.940 | 0.90 ≥ |
| Normed Fit Index | NFI | 0.935 | 0.90 ≥ |
| Incremental Fit Index | IFI | 0.984 | 0.90 ≥ |
| Tucker Lewis Index | TLI | 0.921 | 0.90 ≥ |
| Comparative Fit Index | CFI | 0.968 | 0.90 ≥ |
| Root Mean Square Error of Approximation | RMSEA | 0.049 | ≤ 0.08 |

The table above, indicates the following:

All indicators are within the required limits; for example, the acceptable threshold for the standardized indicator K2 is not to exceed 5. The value of this indicator is 1.578, indicating model quality within the acceptable range. As for the other indicators, the acceptable threshold for them is not less than 0.90, and they are within the acceptable range. The Goodness of Fit Index (GFI) is 0.940, the Normed Fit Index (NFI) is 0.935, the Incremental Fit Index (IFI) is 0.984, and the Comparative Fit Index (CFI) is 0.968. Additionally, the square root of the mean square error is 0.049, which is less than 0.08, indicating that all indicators are within good limits. Therefore, there is a possibility of matching the actual model to the estimated model.

**Therefore, the validity of the assumption asserting the statistically significant impact of Representation of Knowledge on the quality of internal auditing has been confirmed.**

- **The third sub-hypothesis test:**

This subtest posits the following: **There is a statistically significant effect of the Automatic Learning as one dimension of the role of Artificial Intelligence on the quality of internal auditing**. To test the validity of this hypothesis, structural equation modeling was employed to examine the impact of Representation of Knowledge as an independent variable on the quality of internal auditing as a dependent variable. The results were as follows:

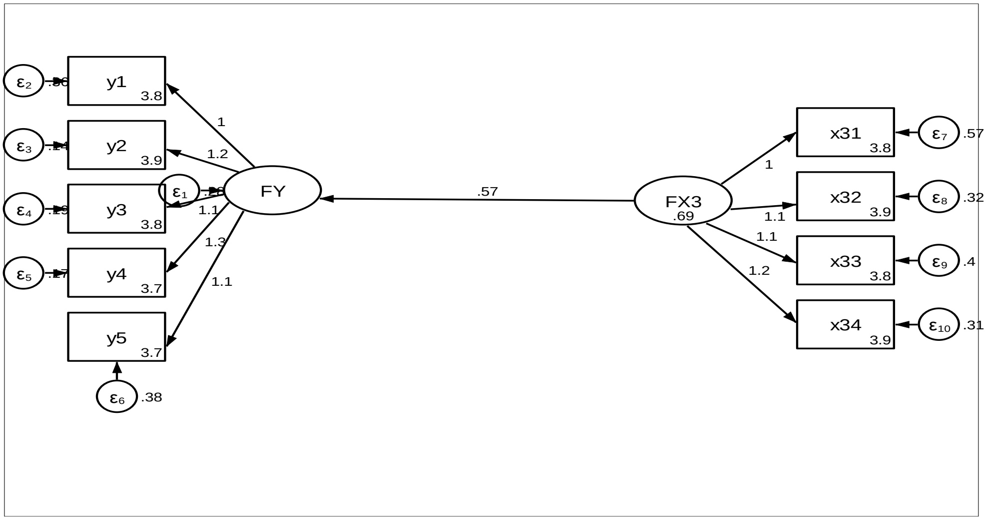


**Figure No. (5): Structural Equation Modeling for the Automatic Learning Model.**

## Table (7): The direct impact of the Automatic Learning dimension.

| Hidden Variables | Path | Observed Variables | Standard Estimate | Non-Standard Estimate | Z-Test | Significance |
|---|---|---|---|---|---|---|
| Automatic Learning | → | quality of internal auditing | 0.571 | 0.055 | 10.36 | *** |
| Automatic Learning | → | x3.1 | 1.091 | 0.066 | 17.03 | *** |
| | → | x3.2 | 1.119 | 0.072 | 15.51 | *** |
| | → | x3.3 | 1.122 | 0.075 | 14.91 | *** |
| | → | x3.4 | 1.169 | 0.075 | 15.69 | *** |
| quality of internal auditing | → | y1 | 1.000 | Constrained | | |
| | → | y2 | 1.183 | 0.066 | 18.03 | *** |
| | → | y3 | 1.134 | 0.066 | 17.23 | *** |
| | → | y4 | 1.298 | 0.069 | 18.58 | *** |
| | → | y5 | 1.127 | 0.073 | 15.48 | *** |

**Source: STATA Results22** **Significance at the 0.001 Level *****

The preceding table, elucidates the impact of Automatic Learning on the level of quality of internal auditing, considering the phrases representing each dimension. The following observations have been revealed:

- There is a statistically significant impact of the Automatic Learning dimension on the level of quality of internal auditing at a 99% confidence level, with a standard parameter of 0.571.
- There is a statistically significant impact of phrases representing the Automatic Learning dimension at a 99% confidence level, with standard parameter values ranging from 1.09 to 1.169.
- There is a statistically significant impact of phrases representing the quality of internal auditing dimension at a 99% confidence level, with standard parameter values ranging from 1.00 to 1.298.

To verify the model's quality and assess the validity of assumptions, a set of criteria for judging model quality was tested, as indicated in the following table:

**Model Quality Criteria**

**Table (8): Quality Criteria for Automatic Learning Model.**

| Indicator | Code | Value | Acceptance Level |
|---|---|---|---|
| Standardized Chi-Square Value | CMIN/DF | 1.981 | Less than 5 as a maximum value |
| Goodness of Fit Index | GFI | 0.909 | 0.90 ≥ |
| Normed Fit Index | NFI | 0.920 | 0.90 ≥ |
| Incremental Fit Index | IFI | 0.944 | 0.90 ≥ |
| Tucker Lewis Index | TLI | 0.931 | 0.90 ≥ |
| Comparative Fit Index | CFI | 0.938 | 0.90 ≥ |
| Root Mean Square Error of Approximation | RMSEA | 0.054 | ≤ 0.08 |

The table above, indicates the following:

All indicators are within the required limits; for example, the acceptable threshold for the standardized indicator K2 is not to exceed 5. The value of this indicator is 1.981, indicating that the model quality is within the acceptable range. As for the other indicators, the acceptable threshold for them is not less than 0.90, and they are within the acceptable range. The Goodness of Fit Index (GFI) is 0.909, the Normed Fit Index (NFI) is 0.920, the Incremental Fit Index (IFI) is 0.944, and the Comparative Fit Index (CFI) is 0.938. Additionally, the square root of the mean square error is 0.054, which is less than 0.08, indicating that all indicators are within good limits. Therefore, there is a possibility of matching the actual model to the estimated model.

**Therefore, the validity of the assumption asserting the statistically significant impact of Automatic Learning on the quality of internal auditing has been confirmed.**

- **The main hypothesis:**

  Studying the main hypothesis reveals the following:

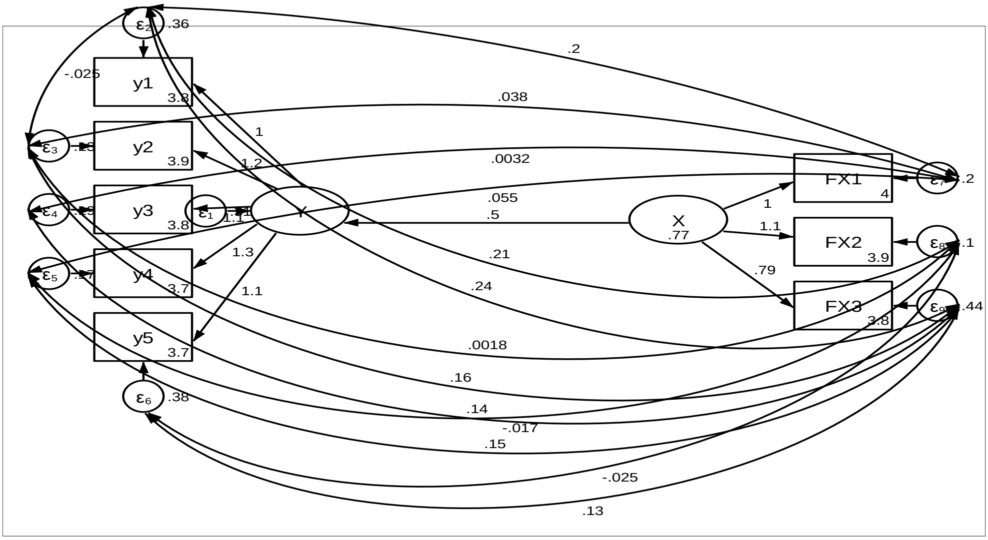


**Figure No. (6): Structural Equation Modeling for the Artificial Intelligence Model.**

## Table (9): The direct impact of the Artificial Intelligence dimension.

| Hidden Variables | Path | Observed Variables | Standard Estimate | Non-Standard Estimate | Z-Test | Significance |
|---|---|---|---|---|---|---|
| Artificial Intelligence | → | quality of internal auditing | 0.571 | 0.055 | 10.36 | *** |
| Artificial Intelligence | → | x3.1 | 1.091 | 0.066 | 17.03 | *** |
| | → | x3.2 | 1.119 | 0.072 | 15.51 | *** |
| | → | x3.3 | 1.122 | 0.075 | 14.91 | *** |
| | → | x3.4 | 1.169 | 0.075 | 15.69 | *** |
| quality of internal auditing | → | y1 | 1.000 | Constrained | | |
| | → | y2 | 1.183 | 0.066 | 18.03 | *** |
| | → | y3 | 1.134 | 0.066 | 17.23 | *** |
| | → | y4 | 1.298 | 0.069 | 18.58 | *** |
| | → | y5 | 1.127 | 0.073 | 15.48 | *** |

**Source: STATA Results22** **Significance at the 0.001 Level *****

The preceding table, illustrates the impact of Artificial Intelligence on the level of quality of internal auditing, considering the phrases representing each dimension. The following observations have been revealed:

- There is a statistically significant impact of the Artificial Intelligence dimension on the level of quality of internal auditing at a 99% confidence level, with a standard parameter of 0.498.
- There is a statistically significant impact of phrases representing the Artificial Intelligence dimension at a 99% confidence level, with standard parameter values ranging from 0.791 to 1.97.

- There is a statistically significant impact of phrases representing the quality of internal auditing dimension at a 99% confidence level, with standard parameter values ranging from 1.00 to 1.299.

To verify the model's quality and assess the validity of assumptions, a set of criteria for judging model quality was tested, as indicated in the following table:

**Model Quality Criteria**

**Table (10): Quality Criteria for Artificial Intelligence Model.**

| Indicator | Code | Value | Acceptance Level |
|---|---|---|---|
| Standardized Chi-Square Value | CMIN/DF | 3.150 | Less than 5 as a maximum value |
| Goodness of Fit Index | GFI | 0.927 | 0.90 ≥ |
| Normed Fit Index | NFI | 0.966 | 0.90 ≥ |
| Incremental Fit Index | IFI | 0.992 | 0.90 ≥ |
| Tucker Lewis Index | TLI | 0.908 | 0.90 ≥ |
| Comparative Fit Index | CFI | 0.957 | 0.90 ≥ |
| Root Mean Square Error of Approximation | RMSEA | 0.021 | ≤ 0.08 |

The table above, indicates the following:

All indicators are within the required limits; for example, the acceptable threshold for the standardized indicator K2 is not to exceed 5. The value of this indicator is 3.150, indicating that the model quality is within the acceptable range. As for the other indicators, the acceptable threshold for them is not less than 0.90, and they are within the acceptable range. The Goodness of Fit Index (GFI) is 0.927, the Normed Fit Index (NFI) is 0.966, the Incremental Fit Index (IFI) is 0.992, and the Comparative Fit Index (CFI) is 0.957. Additionally, the square root of the mean square error is 0.021, which is less than 0.08, indicating that all indicators are within good limits. Therefore, there is a possibility of matching the actual model to the estimated model.

**Therefore, the validity of the assumption asserting the statistically significant impact of Artificial Intelligence on the quality of internal auditing has been confirmed.**

## 11.Results and recommendations

The researcher reached several results that could contribute to solving the research problem, answering its questions, and testing its hypotheses, which are summarized as follows:

The overall assessment of A.I dimensions indicates a high level of availability, with a collective mean score of 3.58 and an agreement rate of 71.6%. This suggests a consensus among participants regarding the prevalence of various A.I dimensions, supporting the notion that opinions are generally aligned in acknowledging the significance and existence of these dimensions in the field of Artificial Intelligence.

The overall assessment of I.A dimensions reveals a high level of availability, with a collective mean score of 3.41 and an agreement rate of 68.2%. This indicates a general consensus among participants regarding the prevalence and significance of various dimensions in the field of quality of internal auditing.

the results support the presence of statistically significant impacts between the Artificial Intelligence dimension and the quality of internal auditing. The provided confidence levels and standard parameter values offer a comprehensive understanding of the strength and direction of these impacts, contributing valuable insights to the relationship between AI and internal auditing quality.

**From the findings point of views in the study. The researcher proposed the following Recommendations:**

- **Enhance Integration of Intelligent Systems in Internal Auditing Processes:** Based on the study findings, it is recommended to enhance the integration and utilization of intelligent systems in internal auditing processes. This could be achieved by adopting advanced AI technologies and ensuring that internal audit teams are well-equipped with the necessary skills to leverage these systems effectively.
- **Investigate Specific Phrases and Aspects within the AI Dimension:** Given the varying impacts of phrases representing the Artificial Intelligence dimension, further research could delve into specific phrases and aspects to understand their individual contributions. This granular

analysis can provide insights into which elements of AI have the most transformative impact on internal audit quality.

- **Focus on Continuous Improvement and Efficiency in Intelligent Auditing:** Considering the statistically significant impact of phrases related to continuous improvement and efficiency, there is a recommendation to emphasize these aspects in the integration of AI within auditing practices. This may involve continuous training, updates in AI systems, and the adoption of efficient auditing processes.
- **Explore the Relationship Between Information Technology and Intelligent Auditing:** The lower impact of the Information Technology dimension suggests a potential area for further exploration. Research could be conducted to understand the specific aspects of information technology that influence intelligent auditing and how advancements in this field can be leveraged for improved internal audit quality.
- **Encourage Collaboration Between AI Experts and Internal Auditors**: To maximize the benefits of AI in internal auditing, it is recommended to encourage collaboration between AI experts and internal auditors. This interdisciplinary approach ensures that technological advancements align seamlessly with the specific needs and objectives of internal audit functions.

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