CHALLENGES, OPPORTUNITIES AND IMPLICATIONS REGARDING THE INTEGRATION OF ARTIFICIAL INTELLIGENCE IN AUDIT PROCESSES

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Abstract

In the context of rapid technological evolution and continuous changes in the business environment, auditing plays a significant role in ensuring the transparency, integrity and operational efficiency of entities. However, the increased complexity of activities and the growing volume of data with which auditors have to work have generated new challenges and required the continuous adaptation of audit methodologies and tools. In this context, artificial intelligence (AI) has emerged as a promising solution to improve the quality of the audit process. In this context, artificial intelligence (AI) has emerged as a promising solution to improve the quality of the audit process. AI technologies, such as machine learning, advanced data analytics, and natural language processing, provide auditors with powerful tools to perform deeper analysis, identify risks and anomalies, and streamline audit processes. These technologies allow the automation of repetitive tasks, the reduction of human errors and the provision of real-time information, thus contributing to increasing audit quality. The research focuses on exploring the potential of AI to improve the quality of the audit process. By analyzing the impact of AI technologies on traditional audit methods, it aims to identify the benefits, challenges, opportunities and implications associated with integrating AI into audit practice. The goal is to provide a deep understanding of how AI can contribute to optimizing the audit process and to propose practical recommendations for the effective implementation of this technology.

Keywords: audit, artificial intelligence (AI), integration of AI in audit, quality of audit process, challenges, opportunities, implications, internal audit.

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1. Introduction

The impact of AI on the accounting information system is to reduce the risk of fraud, improve the quality of accounting information, and promote reform in the field of traditional accounting and auditing (Chukwuani & Egiyi, 2020 [1]). Keeping pace with the continuous improvements of AI in accounting and auditing, both by accountants and by entities, can help reduce costs and add value to the accounting industry by shifting the focus from existing repetitive tasks to data-driven decisions and analysis (Baldwin et al., 2006 [2]; Mohammad et al., 2020 [3]). At the same time, Bizarro & Dorian (2017) [4] emphasize that, at a metadata level, source documentation, document processing, teleconferences, emails, and press releases can be evaluated and compared with the help of AI, facilitating automation. Although the implementation of AI in auditing is not new, its impact is expected to be more significant now, due to the availability of massive data processing power (Kokina & Davenport, 2017 [5]). For accounting and auditing firms, the intensive nature of the traditional audit process and the increasing requirements for compliance with regulations and policies in force make the use of these emerging technologies imperative to improve productivity (KPMG, 2018 [6]). Several initiatives are being tested around the world and the big four accounting firms EY, Deloitte, KPMG and PwC are investing millions of dollars in AI to build capabilities with the aim of providing clients with more cost-effective and high-quality audits.

Auditing, a relatively static process over the years, is likely to be affected by the disruptive potential of AI on industries characterized by repetitive and predictable tasks (Chui et al., 2016 [7]). Given that auditing typically involves recurring, high-volume, and anticipated transactions, AI has significant potential to influence the audit process (Baldwin et al., 2006 [2]). AI's ability to efficiently analyze large volumes of data could enable auditing of the entire financial statement data set and speed up auditors' work (Issa et al., 2016 [8]; Bizarro & Dorian, 2017 [4]). It is argued that the adoption of AI could improve auditors' reasoning and decision-making (Sun & Vasarhelyi, 2017 [9]), with such AI-based judgments being claimed to be more efficient than those of humans. Traditional manual audit procedures are considered inefficient because humans are considered less competent in tasks that involve collecting and analyzing large volumes of transactional data (Dai & Vasarhelyi, 2017 [10]; Issa et al., 2016 [8]). Therefore, it is argued that AI could be useful in audit processes such as materiality and risk assessment, control assessment, audit planning, opinion selection, and reporting (Bierstaker et al., 2014 [11]). Other benefits identified in the literature include reducing human error (Murphy, 2017 [12]), facilitating continuous auditing (Brennan et al., 2017 [13]), and the ability to audit all transactions, as well as reducing the cost and time required for auditing (Issa et al., 2016 [8]; Westhausen, 2016 [14]).

2. Literature review

There are several perspectives on the definition of AI. The most important definitions belong to authors who have studied the field in the last decade. Colom et al. (2008) [15] defines AI in the context of problem solving, reasoning and learning, while Munoko et al. (2020) [16] defines it as a new technology that resembles and reproduces human cognitive abilities and judgments. Hassani et al. (2020) [17] describe it as intelligent systems designed for data analysis and decision making, supporting the generation of results and insights from the analysis of voluminous and complicated data. AI is defined as a technology that attempts to replicate or imitate human cognitive abilities, including judgment and reasoning. With the advancement of the fourth industrial revolution, the use of AI technologies has become increasingly common in various fields, such as education, security, health, and including accounting and auditing (Mhlanga, 2021) [18]. At the same time, AI is defined as the application of information systems and engineering with intelligent machines and computers capable of exhibiting human traits of reasoning, learning, and autonomous action, and analyzing big data and making quality decisions. Hasan (2021) [19] describes AI as a form of rare intelligence manifested by machines or robots, which perceive the environment and act to maximize their chances of achieving their goals, based on programming and commands received.

Allami (2022) [20] provides a nuanced perspective on the multifaceted environment of AI by summarizing the defining characteristics of this concept. These encompass not only basic aspects such as perception, decision-making and prediction, but also more complex functions such as automated information extraction, interactive communication, logical thinking and the dynamic process of machine learning. AI aims to replicate and enhance human cognitive capabilities, helping companies see and understand their environment using digital computers or computer-controlled machines. Over the years, AI applications have become increasingly relevant in a variety of social and economic areas, including public health, transportation, education, security, communications, and defense. Autonomous algorithms are currently driving progress in this field and are having a substantial impact across numerous industries. In short, AI, developed by humans, has evolved to a point where it is effortlessly integrated into everyday life and business. Characteristics included in this context are the use of data to guide operations, the ability to understand and interact with people, adaptability to change, and enhancement of human capabilities ***(Figure 1.):***

Characteristics of AI

- Improves financial reporting by enabling the rapid replication of human intelligence, knowledge, and awareness in a programmed computer.
- Mimics and displays cognitive skills associated with learning and problem-solving.
- Represents a tool for the logical extraction of data and providing accurate forecasts.
- Contributes to the automation of accounting processes and risk detection in data sets.
- Enhances audit quality by automating accounting tasks and saving time.
- Allows accountants to focus on advisory roles and strategic decision-making.
- Includes components such as neural networks, genetic algorithms, and natural language processing.
- Neural networks simulate the structures of the human brain and facilitate machine learning.
- Genetic algorithms use natural selection and evolution to find solutions to complex problems.
- Contributes to the optimization of processes and innovation in various fields, including accounting..
- Enables communication between AI systems using human natural language.
- Improves audit quality and the credibility of financial reporting.
- New technologies disrupt existing structures and may replace outdated ones.
- Technological innovations allow new businesses to compete with established firms and introduce new ways of conducting operations.

Figure 1: Characteristics of AI[5]

In a strict definition, AI represents the imitation of human intelligence by computers. However, purists emphasize that many current applications are still relatively simple and, therefore, cannot be considered true AI. This observation makes the definition inadequate, as it would suggest that AI does not exist today. A common definition considers AI as a technology that enables machines to imitate various complex human abilities. However, this definition remains vague without specifying these "complex human abilities."

A similar definition was presented by the High-Level Expert Group on Artificial Intelligence (AI HLEG) of the European Commission (EC): "Systems that exhibit intelligent behavior by analyzing their environment and taking actions – with a certain degree of autonomy – to achieve specific goals." (European Commission, 2018). The definition provided by the AI HLEG encompasses all applications that we currently classify as AI, while also leaving room for future changes to that classification. The defining elements of the two fundamental areas of AI are presented in ***Figure no.2***.

[5] Source: Author conception based on the review of the specialized literature.

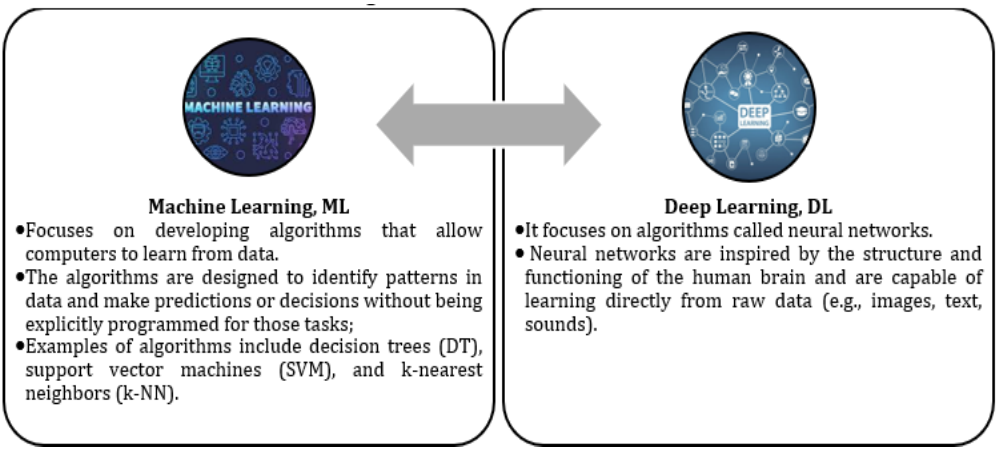


Figure 2: Subdomains of AI[6]

3. Research Methodology

In conducting the study, both qualitative and quantitative analyses were used. The arguments for using both approaches were: i) **Holistic perspective**: The qualitative analysis provided an in-depth understanding of the issues and the context in which AI technologies are applied in auditing. It allowed for exploring the perspectives and perceptions of industry experts, as well as identifying unforeseen aspects and problems that could affect audit quality; ii) **Exploring complexity**: Auditing and the application of AI in this field involve complex aspects such as ethics, regulations, technical precision, etc.; iii) **Identifying emerging trends and patterns:** Quantitative analysis was useful for identifying emerging trends and patterns in audit data and AI usage. This provided solid evidence to support certain conclusions and the development of research hypotheses; iv) **Validating conclusions and generalizing results**: The use of both qualitative and quantitative analysis helped validate the conclusions and ensure that the results obtained are robust and can be generalized within the scientific community and in practice; v) **Multidisciplinary approach**: A comprehensive study of AI application in auditing required a multidisciplinary approach. Using both qualitative and quantitative analysis allowed for the integration of perspectives from multiple fields, such as computer science, accounting, auditing, organizational psychology, etc.; vi) **Assessing impact and effectiveness**: Quantitative analysis was used to evaluate the impact and effectiveness of AI in auditing by measuring performance indicators and comparing the results with traditional audit methods.

4. The Multiple Facets of Artificial Intelligence in Auditing

In recent years, advances in IT, particularly in the field of AI, have had a significant impact on the accounting and auditing industry. These professions have undergone fundamental changes as a result of progress in cognitive machine technologies, with a focus on the

[6] Sursa: Ongsulee, P. (2017). Artificial intelligence, machine learning and deep learning. *2017 15th International Conference on ICT and Knowledge Engineering (ICT&KE)*

development and application of AI. Dunn and Hollander (2017) [21] focus on the influence of AI on auditing, redesigning AI system development based on the identified benefits and limitations. *This research explores how AI can enhance the effectiveness and quality of the auditing process*. The findings indicate that auditing firms, especially large ones, will continue to invest in specialized expert systems and neural networks tailored to the industry and specific audit tasks in order to minimize audit risks (Bogdan et al., 2023 [22]). Additionally, large multinational corporations can develop their audit functions to use such systems and strengthen internal control systems while reducing business risks. AI technology allows them to manage large volumes of data, identify anomalous transactions, and assess risks (Dincă et al., 2023 [23]).
The auditing profession is guided by International Standards on Auditing (ISA). According to ISA 200, the application of AI in auditing represents the replication of human intelligence functions by machines in performing the audit function. The general objective of a financial statement audit performed by an independent auditor is to carry out the audit in accordance with these standards. The auditor's objective, as per ISA 200, is to obtain reasonable assurance to express an opinion regarding the absence of fraud and errors in the financial statements and to issue an audit report communicating the audit findings. According to Baldwin et al. (2006) [2], AI can be applied in auditing to perform a series of specific tasks ***(Figure 3).***

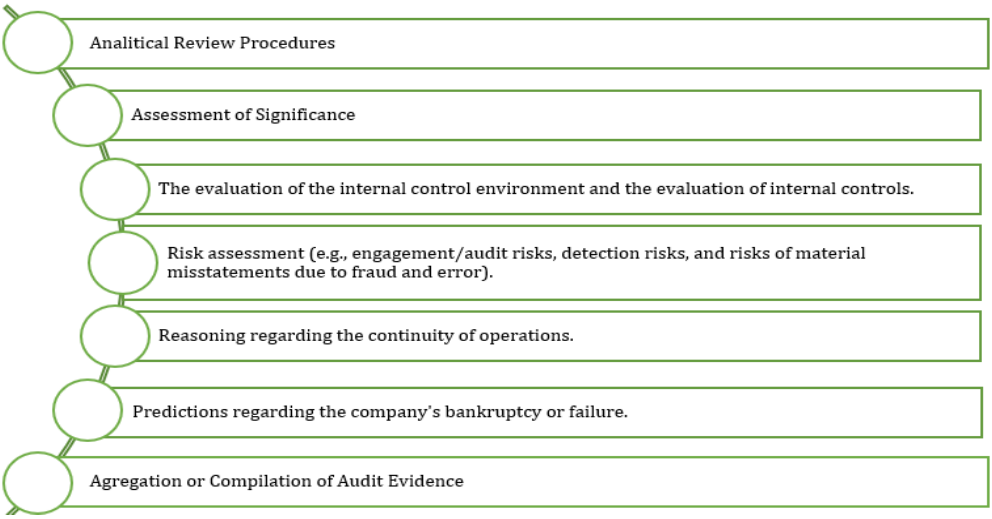


Figure 3: Specific Audit Tasks Suitable for AI Utilization[7]

The integration of data analysis into audits represents a giant leap in efficiency. Traditional audit processes, which often rely on manual examination of financial records, are now supported by sophisticated algorithms capable of processing vast data sets with remarkable speed and accuracy. Auditors can use data analytics tools to identify patterns, anomalies, and trends, allowing a more focused and targeted approach to the audit process. Data

[7] Source: Baldwin, A.., Brown, C.E., & Trinkle, B.S. (2006). Opportunities for Artificial Intelligence Development in the Accounting Domain: The Case for Auditing. *Intelligent Systems in Accounting, Finance and Management*, *14*(3), 77-86. https://doi.org/10.1002/isaf.277

analysis not only accelerates the audit process but also allows auditors to explore the data in-depth, revealing insights that would otherwise remain hidden in a manual review. This enhanced efficiency results in time savings, enabling auditors to allocate resources more strategically and focus more on areas with inherently higher risks.
Auditors are increasingly using continuous audit techniques, powered by data analysis and blockchain technology. Continuous auditing enables real-time monitoring of financial transactions, reducing the gap between the occurrence of an event and its detection. Additionally, auditors are adapting to the dynamic nature of technology by integrating IT audit skills into their toolkit. Assessing and understanding internal controls over information systems becomes essential as technology increasingly blends with business processes. Despite the rapid advancement of AI technologies in other areas, their adoption in the audit and accounting profession has been slower. This is surprising, given the nature of the field for applying AI technology, due to the various audit functions. However, there are clear signs that AI adoption is gradually increasing in the audit and accounting profession (Kokina et al., 2021 [24]).

5. Possible Solutions for Optimizing Audit Processes through the Use of Advanced Technologies

Optimizing audit processes through the implementation of advanced technologies involves utilizing the following elements (***Figure no. 4):***

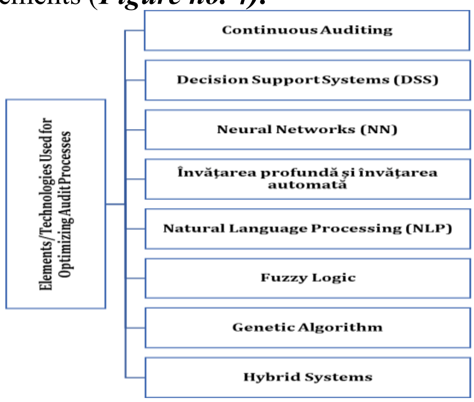


Figure 4: Elements/technologies used for optimizing audit processes[8]

Continuous Auditing is defined as the systematic process of collecting electronic audit evidence, providing a solid basis for issuing an opinion on the fair presentation of financial statements in a real-time electronic accounting system. Continuous auditing is also considered a detailed form of electronic auditing, allowing auditors to provide a certain level of assurance regarding data as they are disclosed or immediately after disclosure. Zhao et al. (2004) [25] emphasized that continuous auditing is associated with electronic accounting systems, facing significant technical obstacles, lack of standards and guidelines, the increased value of real-time financial information, and timely audit reporting. Continuous auditing can generate either an "evergreen report" or an "on-demand report,"

[8] Source: Authors' design

and its use cases can cover all three professional services typically provided by independent auditors – assurance, attestation, and audit services.

Decision Support Systems (DSS) are interactive, adaptable, and versatile software platforms that assist in decision-making processes. These systems are designed to handle structured management problems to enhance the decision-making process.

Neural Networks (NN) are a machine learning system that mimics the organization of the human brain, composed of neurons and connections, and has the ability to adjust its structure to perform tasks learned more efficiently. When neural networks become more complex and include multiple layers, the term "deep learning" can be applied. Baldwin et al. (2006) [2] and Deloitte (2018) examined the application of neural networks in the Analytical Review Procedure used by auditors to obtain audit evidence.

Natural Language Processing (NLP) is a research field focusing on developing and using artificial models to understand and process human language in a manner similar to humans (Deloitte, 2018). Applications of NLP include processing unstructured textual information, searching and analyzing documents automatically and systematically, as well as identifying high-risk cases that deviate from preset targets. Fuzzy Logic is a reasoning technique that mimics human thinking by allowing the evaluation of truth degrees of variables, with values ranging from 0 to 1 (Baldwin et al., 2006) [2]. This approach allows handling the concept of "partial truth" or "degrees of truth," better reflecting the complexity of the real world. Fuzzy logic is used in areas such as assessing the risk of managerial fraud and making significant decisions involving qualitative issues. Genetic Algorithm is a search method inspired by the theory of evolution, where the best-adapted individuals are selected to reproduce and pass on their traits to offspring. In the field of computing, genetic algorithms use biologically inspired operators such as mutation, crossover, and natural selection to develop efficient solutions to optimization and search problems. These algorithms are effective in solving problems like transaction and account classification (Baldwin et al., 2006 [2]). Genetic algorithms are also suggested for modeling auditor behavior in making fraud-related decisions. Other applications of this algorithm include predicting bankruptcy and making decisions regarding business continuity. Hybrid Systems are more suitable in audit tasks that involve both quantitative analysis and qualitative judgment. These hybrid IA technology systems combine various IA technologies, such as neural networks, fuzzy logic, and genetic algorithms, to offer complex and adaptable solutions to the specific requirements of audit tasks. Digital Audit represents a significant evolution of the auditing process, characterized by the use of technology and digital data to perform and improve audit procedures. This modern form of auditing relies on several defining characteristics that give it uniqueness and efficiency in today's digital business environment: i) Use of technology, ii) Process automation, iii) Extensive data analysis, iv) Real-time data monitoring, v) Data security and confidentiality.

6. Challenges of Integrating Artificial Intelligence in Audit Processes: Overcoming Technical and Ethical Obstacles, Managing Risks

The review of specialized studies reveals that there are several significant challenges associated with the integration of AI in auditing ***(Figure no. 5):***

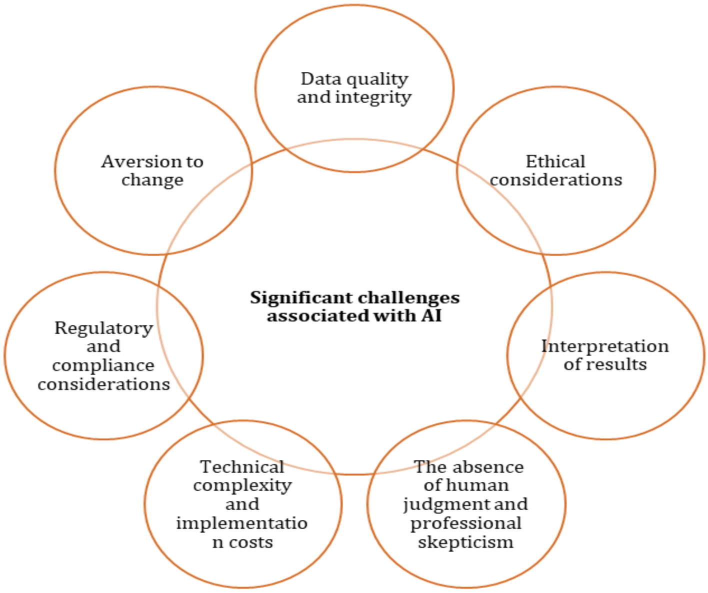


Figure 5: Significant challenges associated with the integration of AI in auditing[9]

i) Data Quality and Integrity: The accuracy and reliability of AI algorithms critically depend on the quality and integrity of the data fed into the system. Incomplete, inaccurate, or biased information can distort results and lead to erroneous conclusions. Ensuring data quality, implementing appropriate data governance frameworks, and establishing data validation processes are essential to mitigate this challenge (Srinivasan & de Boer, 2020 [26]); ***ii) Ethical Considerations:*** The use of AI in auditing raises ethical concerns, especially when dealing with sensitive financial and personal data. Protecting privacy, data security, and compliance with relevant laws and regulations is imperative. Auditors must consider ethical guidelines and establish protocols to protect data confidentiality and maintain stakeholder trust; ***iii) Interpretation of Results:*** AI algorithms generate results based on complex models and mathematical algorithms. Understanding and interpreting these results can be challenging for auditors, particularly in the absence of adequate expertise in AI and data analysis. Proper training and skill development for auditors are necessary to correctly interpret and utilize information generated by AI (La Torre et al., 2021 [27]); ***iv) Absence of Human Judgment and Professional Skepticism:*** AI systems rely on predefined rules and algorithms, which may limit their ability to apply skepticism and professional reasoning. Auditors bring valuable experience, intuition, and critical thinking to the audit process, aspects that AI cannot fully replicate. Maintaining a balance between AI-driven automation and human reasoning is essential for the integrity of the auditing profession; ***v) Technical Complexity and Implementation Costs:*** Implementing AI technologies in auditing requires specialized knowledge, infrastructure, and resources. The initial costs of acquiring and implementing AI systems, as well as ongoing maintenance and updates, can be significant. Small and medium-sized audit firms may face difficulties in adopting AI due to the costs and technical complexities involved; ***vi) Regulatory and***

[9] Source: Own design

Compliance Considerations: The use of AI in auditing must comply with relevant regulations and standards. However, the rapid pace of AI technology development often outpaces regulatory frameworks, creating uncertainties and challenges. Auditors must stay updated on regulatory developments and ensure that AI systems comply with applicable legal requirements; ***vii) Aversion to Change:*** The adoption of AI in auditing may face resistance from auditors and other stakeholders who are attached to traditional audit practices. Concerns about job losses and the reliability of AI systems can slow down the process of adopting and accepting AI in the auditing profession. Effective management of these concerns, through change management, training programs, and clear communication, is crucial.

According to Rebstadt et al. (2022) [28], while the importance of AI in auditing is evident both academically and practically, the challenges associated with applying AI technologies in the auditing profession remain largely unexplored. These challenges impact audit outcomes, the decision-making process, and audit quality, raising ethical implications as well. Despite the advantages of using machine learning algorithms in auditing, auditors may fail to notice certain weaknesses associated with them, such as the "overfitting" phenomenon. This refers to a situation where auditors cannot identify data features that do not reflect real-world patterns. Additionally, machines may struggle to recognize that statistically significant correlations between variables do not always indicate causal relationships. These weaknesses highlight the potential challenges in results, emphasizing the continued need for human evaluation and critical judgment in the audit decision-making process, based on machine learning algorithm outputs. The predictive reliability of the results from machine learning algorithm processing is closely tied to the quality of input data, system design, methods used, and interpretation of output information. Thus, the quality of the evidence generated through the use of these algorithms may be affected.

According to Gao & Han (2021) [29], implementing AI in auditing generates significant changes in the audit process, influencing how evidence is generated and its quality. Audit evidence should be generated from comprehensive and independent processes, such as expert opinions, because investors rely on financial statements to make informed economic or investment decisions. To make informed decisions, it is essential that financial statements are audited, and managers provide accurate and reliable information to shareholders and investors, who depend on the auditor's opinion to ensure the reliability of the information provided. This assurance refers to the certainty and credibility of financial statements, based on sufficient and appropriate audit evidence, according to ISA 500. Traditionally, auditors have manually gathered this evidence, but the deficiencies of manual systems have often affected the quality of evidence and audits in general.

The use of AI to collect, evaluate, and process large amounts of information from internal and external environments can provide ample and diverse evidence. According to Gao & Han (2021) [29], AI usage could improve the quality of audit evidence and reduce the gap between audit expectations and reality, thereby altering the objective of the audit. They suggest that the auditing profession could consider revising the ISAs to align them with the use of AI in auditing.

Using artificial intelligence to collect information from independent sources can improve the effectiveness and objectivity of confirmation evidence, separating audit procedures from accounting processes. Even with the use of AI, there is recognition that an incorrect opinion may be issued. Gao & Han (2021) [29] emphasize that when auditors make deductions, they may introduce their own subjective perspectives, individual differences, and thought inconsistencies, which can lead to discrepancies between the audit conclusion and reality or even result in incorrect opinions being issued. AI-assisted comprehensive inferences, based on a rational model, can reduce the subjectivity of practitioners and make their judgment less subjective and harder to contest.

The application of audit standards in the context of AI presents several challenges, especially regarding fairness and transparency. There are issues related to what is measured with the help of AI and the inputs used, without violating the rights and dignity of those using AI technologies, even though these can contribute to correcting deficiencies in sample representation. The use of analytical procedures involves certain assumptions according to ISA guidelines, but machine learning has a distinct power in identifying specific relationships or unexpected trends. Therefore, a revision of ISA standards and their continued applicability in their current form for the auditing profession may be necessary, considering the adoption of AI technologies. ISACA (2018) states that the lack of clear audit standards assimilating emerging technologies affects the effectiveness and acceptance of AI technologies.

Along with the opportunities AI offers, its application also brings a significant volume of threats in the field of auditing and accounting. One of the main issues causing difficulties is the regulatory environment. A study conducted by Deloitte in 2018 highlights the regulation of cloud-based services, which varies globally, with certain European jurisdictions imposing stricter restrictions. This discrepancy may give companies in less restrictive jurisdictions an advantage in developing artificial intelligence technologies.

Apart from issues related to financial regulation, there are also other major risks. The same study by Deloitte consulting highlights the dangers related to the complexity of financial connections at both domestic and cross-border levels, the polarization of communities around the development of artificial intelligence, and the risk of regional conflict or financial exclusion among different population segments. In addition to these, there are general threats associated with AI, such as job reduction and income inequalities caused by the concentration of market power in the AI industry.

Auditors carefully examine the records and financial statements of an organization to determine if they present a true and fair view of its financial position, performance, and cash flows, in accordance with applicable accounting standards and regulations. They follow a set of predefined procedures and standards to collect evidence and assess financial information, which usually involves analyzing financial statements, verifying supporting documentation, interviewing key personnel, and conducting tests and analyses to detect errors, fraud, or non-compliance (Knechel & Salterio, 2016 [30]). The scope of the audit extends beyond the financial statements, so auditors may also assess an entity's internal control systems to evaluate the effectiveness of its internal processes and procedures for financial reporting and risk management (Korol et al., 2022 [31]). They may also provide recommendations for improving internal controls and mitigating risks (Knechel & Salterio, 2016 [30]). The introduction of AI in auditing generates significant implications for auditors and the auditing profession as a whole ***(Figure no. 6)***.

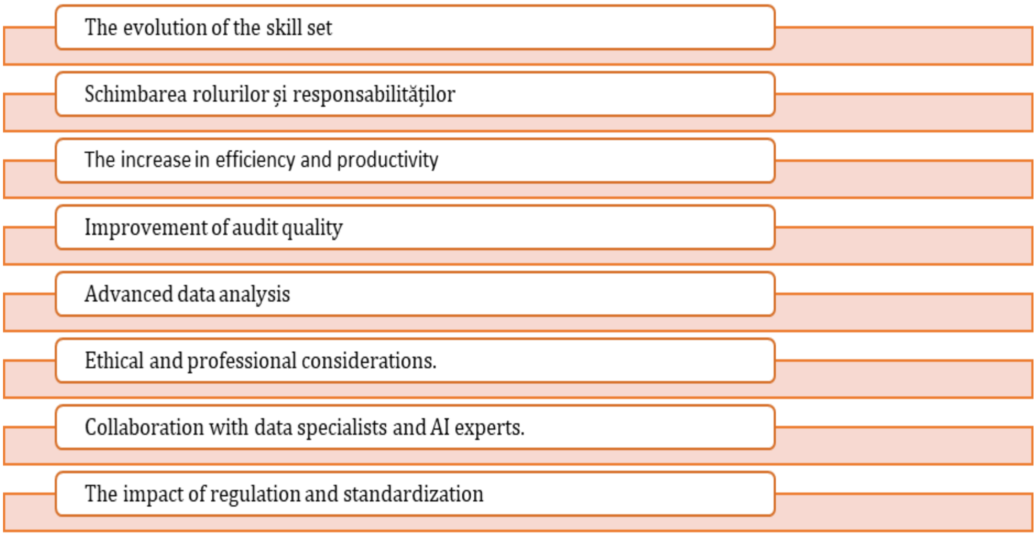


Figure 6: Implications of AI for Auditors[10]

An analysis of each challenge is as follows***: i) Evolution of the skill set***: The integration of AI into auditing requires auditors to develop new skills and expertise. They must gain a solid understanding of AI technologies, data analysis, and programming in order to effectively use AI tools and interpret the results. Investment in continuous professional development and skill enhancement programs is necessary to ensure auditors remain competent and adapted to the AI-based audit environment; ***ii) Changing roles and responsibilities***: With the automation of repetitive tasks through AI, the roles and responsibilities of auditors will undergo changes. As certain manual tasks become redundant, auditors will focus more on value-added activities such as data analysis, risk assessment, and providing strategic insights to clients. Adapting to and embracing their evolving roles as trusted advisors and strategic partners for clients will be essential for their success in this changing environment; ***iii) Increased efficiency and productivity***: AI can automate repetitive and time-consuming tasks, allowing auditors to be more efficient and productive. This increase in efficiency can lead to faster audit cycles, more efficient resource allocation, and an enhanced ability to manage larger volumes of data. This enables auditors to focus their efforts on higher-value tasks that require professional judgment and critical thinking; ***iv) Improved audit quality***: The use of AI technologies can lead to an improvement in audit quality by enhancing accuracy, identifying anomalies, and detecting patterns in large datasets (Noordin et al., 2022 [32]). AI algorithms can process large amounts of data quickly and consistently, reducing the risk of errors and oversight. This leads to more reliable audit findings, improved risk assessments, and an overall improvement in audit quality; ***v) Ethical and professional considerations***: The use of AI in auditing raises ethical concerns, such as confidentiality, data protection, and potential bias. Auditors must ensure that AI systems are transparent, explainable, and comply with ethical standards (Munoko et al., 2020 [16]). At the same time, skepticism and professional judgment remain essential for addressing any limitations or biases that may arise in AI

[10] Source: Original design based on the study of specialized literature.

algorithms; ***vi) Collaboration with data specialists and AI experts:*** Auditors may need to collaborate with data specialists and AI experts to effectively implement and utilize AI technologies in auditing. This collaboration can facilitate the integration of AI into audit processes, knowledge sharing, and ensure a multidisciplinary approach to audit engagements (Noordin et al., 2022 [32]); ***vii) Impact of regulation and standardization***: The introduction of AI into auditing may involve the development of new regulations, standards, and guidelines specific to AI-based audits. Regulatory authorities and standard-setting organizations must adapt to technological advances to ensure the appropriate and responsible use of AI in auditing (Noordin et al., 2022 [32]).

7. The influence of artificial intelligence on audit quality.

Audit service quality refers to complete, reliable, and comparable data that ensures the quality of financial statements and their ability to add economic value to decisions made by stakeholders. The quality of audit services results from auditors with ethical values, integrity, attitude, and professional skills, audit independence, experience, and sufficient time to perform a detailed audit. Some characteristics of high-quality audit services include the use of appropriate and specific disruptive technologies, such as artificial intelligence (AI), in processing and reporting financial-accounting data within public entities. The application of AI has become a growing innovation in financial reporting and auditing globally. The increase in the volume of corporate and business transactions has necessitated the use of information technologies, and disruptive technologies now occupy a central place in this field.

Recently, the value and quality of audit services have declined due to the increase in financial reporting scandals globally (Noordin et al., 2022 [32]). Some have attributed the complexity of audit quality to the use of manual computers, high levels of inaccuracy, and delays in audit reporting. Moreover, recent research has highlighted favorable results and economic benefits from the adoption and implementation of artificial intelligence. For example, improvements have been reported in specific elements of AI, as shown in ***(Figure no 7).***

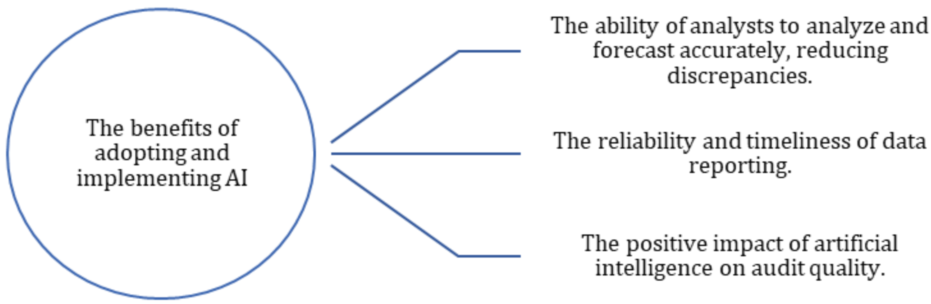


Figure 7: Benefits of adopting and implementing artificial intelligence[11]

[11] Source: Abdollahi, A., Pitenoei, Y.R., & Gerayli, M.S. (2020). Auditor's report, auditor's size and value relevance of accounting information. *Journal of Applied Accounting Research*, 21(4), 721-739. https://doi.org/10.1108/JAAR-11-2019-0153 ; Greenman, C. (2017). Exploring the impact of artificial intelligence on the accounting profession. *Journal of Research in Business, Economics and Management*, *8*(3).

The successful application of AI can facilitate the understanding of historical data and the prediction of data processing outcomes, avoiding information overload and ensuring the accuracy and timeliness of financial reporting. Lee & Tajudeen (2020) [33] highlighted a positive correlation between audit quality and the quality of financial reporting. While numerous studies, including those by Chukwuani & Egiyi (2020) [1], have examined the quality of the audit process from various perspectives, there is still a gap in the literature regarding the investigation of AI's effect on audit quality, particularly concerning the implications for accountants, highlighting the need for further research due to inconsistencies and the lack of clear conclusions in existing studies (***Table no. 1).***

Author	Positive effects	Negative effects	Comments
Hasan (2021)	Positive impact of information technology on audit qualityi		AI is versatile and flexible, contributing to the increased reliability and accuracy of financial and audit reports.
Hemin (2017)	Rezultate favorabile privind efectul tehnologiei informației asupra calității auditului		
Lee & Tajudeen (2020)		Contradictory results regarding the impact of information technology on audit quality.	
Greenman (2017)		Negative impact of disruptive technologies on the credibility of audited financial statements.	
Balios & colaboratorii (2020)		The increase in errors due to the complexity of IT systems, difficulties in verifying data, and excessive reliance on technology that may compromise the professional judgment of auditors.	
Albawwat & Frijat (2021)	AI recognized as a factor that can improve audit quality.		

Table no. 1: Positive and negative effects of using information technology in performing the audit.

Regarding financial reporting, AI represents a tool for the logical and structured extraction of data, providing accurate and reliable forecasts. It contributes to improving the processing and automation of document authorization to optimize internal accounting processes and reporting. More specifically, AI uses computerized algorithms and programming to identify and understand patterns and anomalies in datasets, allowing auditors to detect specific risk areas more effectively and perform a variety of other audit and accounting processing tasks at an unprecedented speed.

Disruptive technologies such as AI have revolutionized financial reporting processes, replacing some of the conventional methods of financial reporting. New technologies have brought clear benefits and profits to organizations that have adopted them over traditional methods. Hasan (2021) [19] investigated the impact and implications of using AI in audits on audit quality. The study used a structured questionnaire and an exploratory analysis of the relevant literature to examine multiple aspects of audit activities in which artificial intelligence has been beneficial. The study concluded by highlighting benefits such as accurate financial reporting, increased productivity, and auditor efficiency, compared to traditional audit methods.

8. Case study regarding the application of specific AI mechanisms in internal auditing.
The quality of the activity carried out by the auditor can be measured by the product of their work, the audit report, which is an essential element for supporting managerial decision-making. In this sense, the case study conducted using the Orange Data Mining application (Orange) aims to identify a relationship between input variables (number of internal auditors/department, number of audit missions per year, number of recommendations per total audit missions) and the output variable (the level of appreciation of the recommendation) based on a regression equation and to identify the machine learning technique that allows the best classification of test data. In this regard, a comparative analysis will be made between logistic regression and the decision tree (DT) technique. DT allows the division of a vast and heterogeneous collection of records into a series of increasingly smaller and more homogeneous collections relative to a target attribute. The mathematical foundation of logistic regression is represented by the Order Logit Model with the following structure:

$$Prob\ (y_i = j|x, b, c) = F(c_{j+1} - x_i b) - F(c_j - x_i b)$$
$$Prob\ (y_i = j|x, b, c) = \frac{\exp(c_{j+1} - x_i b)}{1 + \exp(c_{j+1} - x_i b)} - \frac{\exp(c_j - x_i b)}{1 + \exp(c_j - x_i b)}$$

where:
• Xi = is the vector of explanatory variables (number of internal auditors/departments, number of audit missions per year, number of recommendations per total audit missions);
• Yj = 1 ..... 4 represents the four alternatives for choosing the endogenous variable, the level of appreciation of the audit recommendation.
• b = the vector of regression coefficients.
• c = the technical coefficients
In this case study, logistic regression is of the multinomial type due to the fact that the dependent variable, Level of Appreciation, has three response options: level to be improved, functional appreciation level, and critical appreciation level. The overall scheme of the widget-type elements leading to the testing of classification methods is shown in (***Figure no. 8).***

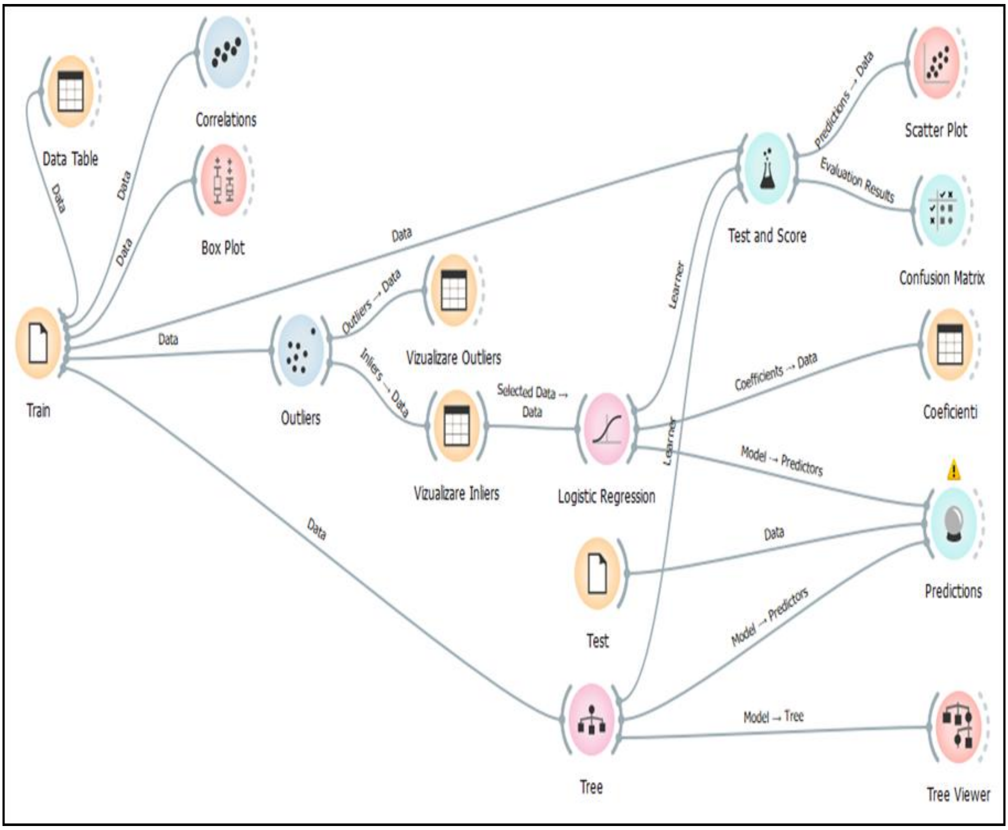


Figure 8: Classification testing in the Orange Data Mining application[12]

A special element of the entire process of establishing a mathematical relationship to characterize the historical data set and enable the prediction of the audit opinion is the adherence to the conditions for applying the tests related to logistic regression and decision trees. These preliminary conditions for applying the tests refer to verifying the existence of extreme values (outliers) among the data for the independent variables (number of internal auditors/departments, number of audit missions per year, number of recommendations per total audit missions).

Outlier values are considered values greater than Q3 + 1.5 x IQR or values smaller than Q1 - 1.5 x IQR and can be visualized using a BoxPlot diagram. Below, the Boxplot diagrams for the predictor-type variables used in the analysis are shown ***(Figures no. 9.1-9.3)***

[12] Source: Own design in defining the workflow.

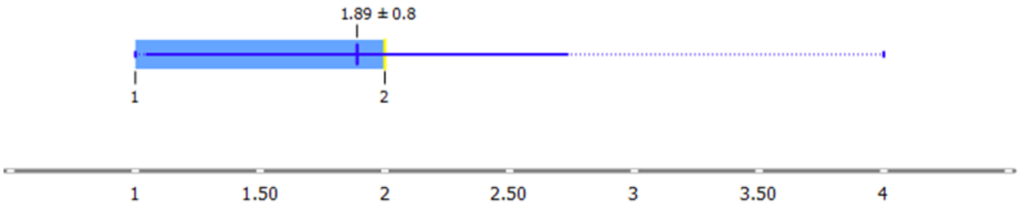


Figure no. 9.1: BoxPlot diagram for the independent variable Number of auditors.

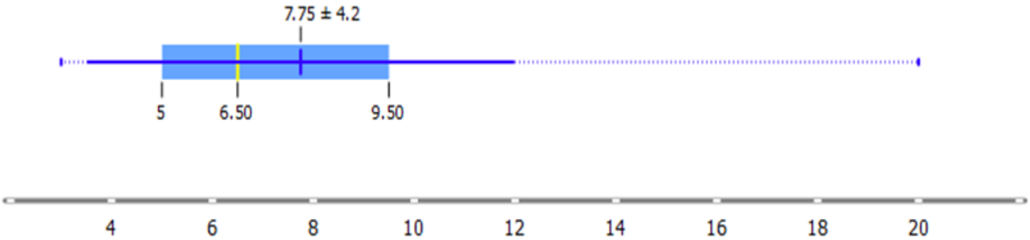


Figure no. 9.2: BoxPlot diagram for the independent variable Number of missions.

It can be observed that all the predictor variables have outlier values. In this situation, these values must be removed in order to avoid distorting the statistical determinations related to logistic regression. The removal of outlier values was performed using the Outliers component, which allows for the determination and visualization of these values ***(Table no. 2)***. By removing these values, the data set is prepared for the application of specific ML techniques.

	NivelApreciere	NrAuditori	NrObiectiveAuditate	NrRecomandari
1	Critic	4	20	85
2	Critic	3	12	63
3	Critic	3	18	67

Table no. 2: Visualization of outlier values.

The algorithm for constructing a decision tree using ID3 (Iterative Dichotomizer) starts from a classified data set. Assuming that the elements (instances) of the data set have a series of attributes whose values are known, the decision tree is generated in such a way that, by traversing it for a new instance with a new set of attribute values, the class in which that instance falls can be determined. The application of the decision tree construction algorithm to the existing data set provides the following graphical representation ***(Figure no. 10)***.

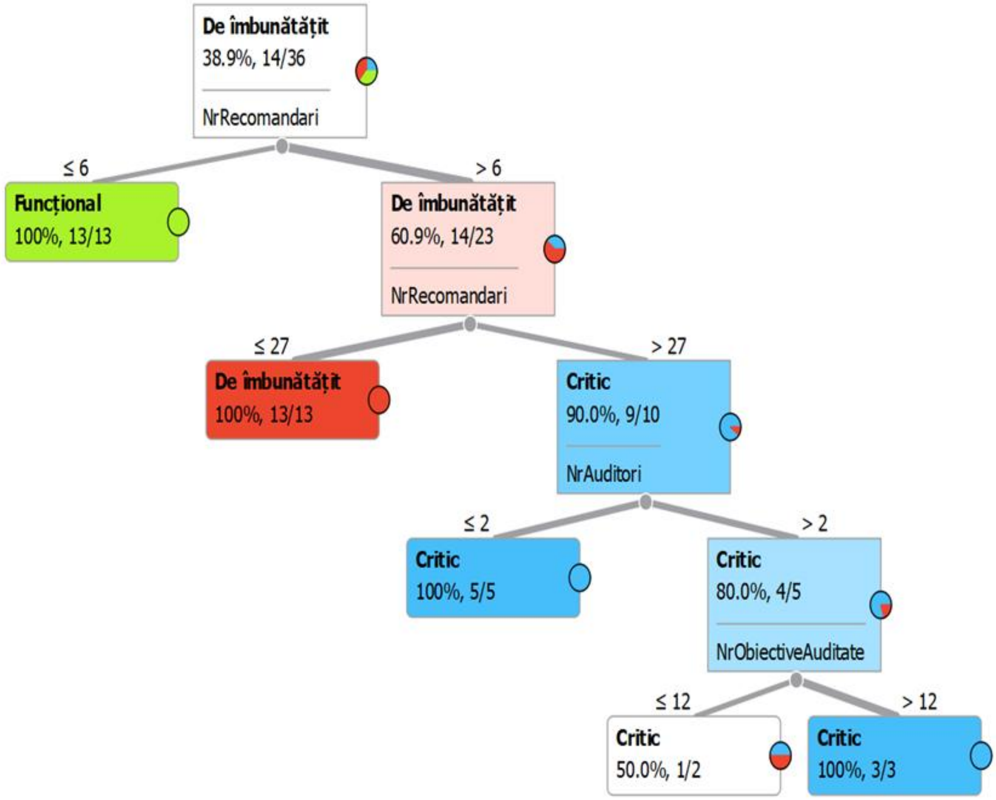


Figure no. 10: The decision tree related to the internal audit opinion.[13]

Traversal of the decision tree is done from the root to the leaf-type nodes and stops when all filtering criteria have been analyzed. In our example, all analyses of the predictor-type variables have been exhausted. The algorithm used to generate the decision tree stops IF the number of audit missions > 12, the number of auditors > 2, and the number of recommendations > 27, THEN the level of appreciation of the audit opinion is critical. This algorithm allows us to classify a new set of data into a specific label related to the level of appreciation of the audit opinion. By applying the specific logistic regression calculation algorithm, the regression coefficients were determined, as presented in (***Table no. 3)***.

[13] Source: Own design.

	name	Critic	De îmbunătățit	Funcțional
1	intercept	-3.57301	-0.75766	4.33067
2	NrAuditori	-0.218367	-0.0216826	0.240049
3	NrObiectiveAu...	-0.440187	0.0230806	0.417107
4	NrRecomandari	0.569663	0.349044	-0.918708

Table no. 3: Coefficients of the logistic regression equation.

The logistic regression equations that allow labeling new instances as medium or low class are the following:

CRITICAL level of appreciation of the recommendations = - 3.57 - 0.21 * Number of auditors - 0.44 * Number of audited objectives + 0.54 * Number of recommendations (1)

LEVEL TO BE IMPROVED of the recommendation appreciation = - 0.75 - 0.21 * Number of auditors + 0.02 * Number of audited objectives + 0.34 * Number of recommendations (2)

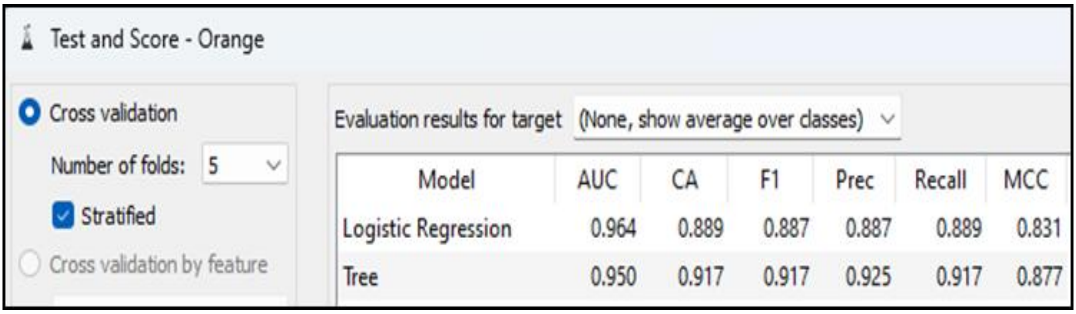
It should be noted that the reference category is the high level of appreciation of the audit opinion, in which case the regression equation does not need to be written. In this case, the goal was to determine the appreciation of the audit opinion for an unclassified data set consisting of three instances (**Table no. 4**), both through the decision tree algorithm and the logistic regression algorithm. The procedure for determining the label for each instance is automated and does not involve any calculations from the data analyst. In this case, the label options for the three instances, both for the DT algorithm and the logistic regression algorithm, are highlighted in ***(Table no. 5)***.

	NivelApreciere	NrAuditori	...rObiectiveAuditate	NrRecomandari
1	?	3	9	15
2	?	4	18	60
3	?	2	10	18

Table no. 4: The test data set

	Tree	Logistic Regression	NivelApreciere	NrAuditori	rObiectiveAudita...	NrRecomandari
1	De îmbunătățit	De îmbunătățit	?	3	9	15
2	Critic	Critic	?	4	18	60
3	De îmbunătățit	De îmbunătățit	?	2	10	18

Table no. 5: The result of applying the calculation algorithms for the decision tree vs. the logistic regression equation.


Test and Score - Orange

Cross validation
Number of folds: 5
Stratified
Cross validation by feature

Evaluation results for target (None, show average over classes)

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.964	0.889	0.887	0.887	0.889	0.831
Tree	0.950	0.917	0.917	0.925	0.917	0.877

Table no. 6: The Test and Score option to determine the overall performance of the classifiers

Number of Auditors	Number of audited objectives	Number of recommendations	Level of recommendation appreciation
3	9	15	To be improved
4	18	60	Critical
2	10	18	To be improved

Table no. 7: Classification of the internal audit opinion based on the logistic regression algorithm. Source: Own design.

The exemplified case study aims to apply specific AI mechanisms to automatically formulate assessments of the results of an internal audit mission when new information is available. The algorithm can serve as a tool for verifying the quality of the internal auditors' work, considering the similarities with audit missions conducted over time by internal auditors. Although the current capabilities of machine learning are limited, it excels at routine tasks. Due to the large amount of data involved and the complexity of the activities that need to be completed, machine learning has the potential to increase the efficiency and quality of the internal audit process, with direct consequences on the auditor's productivity, allowing more time for review and analysis, and a stronger focus on high-risk areas. The quality of internal audit services is a concept that cannot be measured solely by focusing on aspects such as incident/non-compliance reporting or strict adherence to procedures, but also by evaluating the efficiency and effectiveness of the recommendations provided, the impact on continuous improvement, and the added value that internal audit brings to the entity. In this case, the combination of human resources and technology was the factor leading to the qualitative assessment of internal audit services.

9. Conclusions

Regarding auditing, the use of artificial intelligence involves using technologies to improve audit processes. This implies modifying the audit process, reorganizing audit functions, and updating skills across the profession to remain relevant through investments in technology, training, and continuous professional development (CPD). AI can be applied in various functions of the audit profession, including performing analytical review procedures, risk assessment, applying algorithms, classification functions, evaluating significance, judgments related to assessing business continuity, projections regarding company failure, and evaluating internal controls. The application of AI in different audit functions is accompanied by controversies concerning ethical considerations and audit quality. It can be said that AI highlights advantages such as accuracy, objectivity, and speed, but it can also draw attention to challenges related to bias and fairness.

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