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ORIGINAL PAPER

The Impact of Artificial Intelligence on the Quality and Transparency of Corporate Reporting

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Abstract:
The transition to the digital economy has generated an unprecedented volume of financial data, making traditional audit methods, based on statistical sampling, partially obsolete. We aim to investigate the disruptive impact of artificial intelligence (AI) technologies on corporate audit processes, analyzing how automation and machine learning algorithms recalibrate standards of accuracy and rigor.
It is important to understand that there is a shift from retrospective auditing to continuous auditing, an innovation that allows us to monitor transactions in real time. Specific AI capabilities are analyzed, such as natural language processing (NLP) for automated contract review and anomaly detection algorithms, capable of identifying fraud attempts or human errors that conventional methods might miss. By analyzing datasets, artificial intelligence manages to eliminate sampling risk, providing superior assurance on the integrity of financial statements, but as a tool used by the human factor.
We also try to address the challenges related to the implementation of these technologies. Particular attention is paid to the interpretability problem (the Black Box concept), where the complexity of algorithms can make it difficult to logically explain audit conclusions to regulators. The implications for human capital are also discussed, arguing that the role of the auditor is transforming from that of data processor to that of risk interpreter and strategic consultant.
Although artificial intelligence exponentially enhances the efficiency of corporate auditing, the success of its integration depends on the creation of a new ethical and normative framework. Thus, we argue that a synergy between human professional judgment and algorithmic precision represents the sustainable future of corporate governance, ensuring increased transparency in an increasingly complex global business environment.
Keywords: *Machine Learning, Continuous Auditing, Artificial Intelligence, Anomaly Detection.*
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1. Introduction

AI technology has moved from a future technology into being an essential part of auditing. It is becoming an intrinsic part of the actual environment within which financial information is prepared, reviewed, analyzed and communicated to various stakeholders such as investors, regulators, creditors among others. The more businesses prepare more data that is either structured or unstructured, the greater the pressure for change that the current audit practice faces. No longer is the debate about whether technology will impact auditing; it is rather how auditors, businesses and regulators can use it without compromising professional judgment, responsibility and integrity.

Corporate reporting requires credibility. Financial reporting becomes useful based on the ability to ensure that it accurately reflects the position and performance of the entity. This is made possible through auditing that provides assurance on the information prepared by companies. However, given the complexity of the transactions, digital platforms, operations in different countries and real-time data flow within the business environment, conventional audit practices are not sufficient in being able to review all data available at the same pace as they become available. While sampling remains an important aspect of most audits, it raises the probability of missing exceptions and errors.

Artificial intelligence (AI) could have considerable influence in the field of auditing. AI-equipped tools can help auditors process vast sets of data, spot anomalies in transactions, examine journal entries, analyze unstructured data, and point out areas which require additional attention of auditors. Machine learning techniques could be used for anomaly detection and natural language processing could facilitate the examination of contracts, reports of management, accounting policies, documents of the board, and other documents which would normally take considerable effort of an auditor. These new opportunities do not imply only acceleration of some routine operations but the change in the very nature of the auditing activity, moving its focus from the verification to risk assessment, interpretation, investigation, and professional judgement.

One of the most important implications of such a shift in approach is the growing importance of the continuous auditing. Instead of the examination of evidence at the end of the reporting period, organizations will increasingly use data-based tools for monitoring which detect exceptions almost immediately after they happen. In theory, it allows getting a proactive and timely kind of assurance. This approach could help detect problems with internal controls, unusual transactions, and make the reporting process more transparent. Such a value is especially high for industries characterized by high volume of transactions, short reporting periods, and costly undetected mistakes or frauds.

The digital transformation of financial functions is not limited to the automation of accounting and reporting procedures. It is also connected to broader changes in corporate decision-making, risk management, and value creation. Spulbar and Mitrache (2023) argue that corporate finance has evolved beyond a purely technical function, becoming a strategic mechanism through which organisations allocate resources, integrate sustainability-related risks, and support long-term resilience.

Nonetheless, technological capability should not be mistaken for automatic reliability. While an AI system can identify patterns, evaluate the risk level, or issue alerts, it cannot interpret the business environment, materiality of the event, ethics, and professional ramifications of the auditor's conclusion. Anomaly does not mean misstatement, while an algorithm-generated recommendation is not sufficient evidence by itself. It is up to the auditor to assess the appropriateness of the information generated, raise questions about atypical conclusions reached, be aware of limitations of the

technology used, and make a professionally sound conclusion. In that sense, the best scenario for the future is not a situation when human auditors will be substituted by algorithms, but when both elements complement each other.

It is necessary to note that this interrelationship also carries certain risks. The quality of the AI-assisted auditing process will depend on the quality, completeness, and integrity of the source data. It will be impacted by design of the algorithm, risks of bias in it, cybersecurity measures related to the confidential information, and understanding of how the tool works on the part of the users. Black box problem is especially relevant in the case of audits since the conclusions reached need to be explainable not only to the members of the engagement team, but also to the client and audit committee, regulators, and other parties where necessary. If the auditor cannot adequately explain the reasons why the system flagged the transaction as being of high risk or why an AI-generated output affected the audit procedure performed, the use of such technology will do more harm than good.

The broader financial-services sector already demonstrates that AI can improve data-driven decision-making by supporting the interpretation of large information flows, customer insights, and more personalised service strategies. Popescu et al., (2024) examine how AI technology is reshaping marketing strategies in financial services, illustrating that the value of AI increasingly derives from its capacity to transform raw data into operationally relevant insights.

There have been changes in the regulatory regime. In Europe, the Artificial Intelligence Act creates a risk-based regime for regulating AI systems that includes transparency, human supervision, risk assessment, data management, technical documentation, accuracy, robustness, and cybersecurity of AI. Some provisions of the act have been phased in already, and others are coming into effect progressively. Although the AI tools used in auditing have to be considered in terms of their particular uses and associated risks, it is important that the principles suggested by the EU regulation are highly relevant to using the technology responsibly in the course of audits and assurances. The technological development must be paired with protective mechanisms ensuring the safety of individuals, organizations, and public interests.

Standard setters are also responding to the growing intersection between technology and assurance. Specifically, the International Auditing and Assurance Standards Board has established its Technology Position that is aimed at making sure that the auditing and assurance standards continue to be relevant in light of the rapid development of technologies. It is clear that responsible use of technology is to be ensured while maintaining the quality, integrity, and public interest nature of the audit engagement. According to the current professional literature, artificial intelligence, data analytics, automation, and cloud technologies have changed the work of an auditor, but have not made it redundant. It is important now to possess knowledge about technologies along with skepticism, ethics, and risk communication skills.

The study examines the effect of artificial intelligence on the quality and transparency of corporate reporting by virtue of its application in corporate auditing. It analyzes the possibilities for enhancing anomaly detection capabilities, expanding the reach of transaction population sampling, facilitating continuous auditing, and ensuring timely and traceable execution of audit processes. In addition, it takes into account the problems associated with explainability, data security, accountability, professional expertise, and continued human supervision.

The mixed method is used in the research. To begin with, a set of case studies involving selected documentation is studied to examine real-world applications of AI-based technologies in auditing, control, detection of fraudulent activities, and processing financial information. Then a survey and interviews of professionals who deal with auditing, accounting, financial management, internal control, and corporate reporting are conducted. Attention is given to the opinions of financial auditors, accountants, relevant professional associations' members, and financial directors of public and private enterprises. Participation in the study is voluntary, and anonymity of the respondents is protected.

Through a combination of theoretical, regulatory, and empirical approaches, this paper seeks to provide a balanced view of AI in corporate auditing. This research does not intend to portray AI as a cure-all for every problem in auditing. Instead, the intention here is to determine the situation where the use of AI would result in a significant improvement in audit quality and information disclosure. The point here is that there are situations where the application of AI will be of great benefit because the use of AI becomes valuable only when it operates under a governance system that provides reliable data, clear procedures, strong controls, ethical assurances, and clear human accountability.

2. Conceptual and Regulatory Framework for Artificial Intelligence in Corporate Auditing

The importance of artificial intelligence in auditing has increased due to the practical challenge facing the auditors as companies generate a much larger volume of data than can effectively be reviewed using the traditional manual approaches. The transactions are recorded in enterprise resource planning systems, electronic payment systems, cloud computing applications, client databases, and more complex supply chains. In this regard, the key question has shifted from the issue of the amount of available information to the way this information can be turned into meaningful and understandable audit evidence.

Artificial intelligence is an umbrella term for the suite of computational techniques allowing machines to complete tasks that traditionally involved human cognitive abilities, including pattern recognition, prediction, classification, natural language processing, and learning from the data. As claimed by Brynjolfsson and McAfee (2014), the intelligence of machines affects the economic nature of technology by augmenting the tasks requiring cognition rather than manual work. In auditing, the issue is important in that AI is not only capable of speeding up the process but also helps auditors detect connections that are invisible through other techniques.

Machine learning is one of the applications of artificial intelligence in the audit practice due to the possibility of using it to analyze historical and contemporary data and detect patterns related to normal and abnormal behavior. Unlike a process based on following a specific chain of actions, a machine learning algorithm can be used to find correlations between different variables and classify different observations depending on the level of their riskiness. According to Issa et al., (2016), AI technology can help with audit procedures because of the ability of this approach to analyze large and complicated datasets that cannot be analyzed using traditional approaches. The mentioned capabilities are very helpful in conducting journal entry tests, transactions monitoring, evaluating the risk of fraud, as well as recognizing accounting entries that need further analysis by professionals.

Natural language processing is another important application of AI in the auditing process because a significant amount of information that can be helpful for auditors is not represented in numerical form. Auditors often have to analyze various contracts, accounting policies, minutes of the meetings of the board of directors, management reports, internal communications, legal materials, and explanations to the financial statement provided by the management. Zhang (2019) shows how intelligent process automation can help audit teams extract, classify and process the information obtained from structured and unstructured sources. If used properly, NLP can help in saving time during document analysis and finding unusual clauses, contradictions, lack of information, or risky language.

The deployment of artificial intelligence makes anomaly detection more relevant in auditing. An anomaly does not imply either fraud or mistake but refers to a certain observation, transaction, pattern or relationship that deviates substantially from the expected normal state and requires further investigation. According to Appelbaum et al., (2017), through the employment of sophisticated analytics, audit teams can break free from the limited sampling since it allows performing broader transactions population analysis and identification of exceptions requiring testing. The importance of this is reflected in the statement about the possibility of better investigating of risky transactions through the application of data-driven solutions to prioritize abnormal transactions based on their amount, timing, frequency, counterparties, account combinations, and behaviors.

Additionally, the transition from periodic auditing to continuous auditing is regarded as one of the most common consequences of the advancement of technology in the field of assurance. Periodic audits typically are carried out near the end of the reporting period and may result in discovering of mistakes, deficiencies or abnormalities after they occur or affect the financial statements. Continuous auditing is described by Vasarhelyi et al, (2004) as a technologically enabled process when audit-related evaluations and controls are performed more frequently or continuously. By combining AI-assisted analytics with sound information systems and appropriate internal controls, the audit process gains timeliness and allows companies to detect potentially material exceptions sooner.

While the advantages of continuous auditing go beyond increased efficiency in terms of speed, they include, among others, improving the quality of reporting. With the ability to detect risks earlier and strengthen the audit trail for critical conclusions, continuous auditing could improve the overall integrity of reporting. According to Chan and Vasarhelyi (2018), continuous auditing may be described as the approach that helps in continuously evaluating data and controls and allows reporting the relevant exceptions within a relatively short period. In case of the corporation's stakeholders, the potential advantage consists in the creation of the more responsive assurance environment in which any deficiencies of controls or unusual activities can be explored before they become material issues in terms of reporting.

Digital transformation may also strengthen the informational foundations of corporate accountability when it is aligned with transparent governance structures and sustainability-related objectives. Spulbar et al., (2024) emphasise that the synergies between digitalisation and ESG practices can support corporate growth, responsible innovation, environmental sustainability, and regional development. In the audit context, this relationship is relevant because higher-quality data infrastructures and more transparent digital processes may create better conditions for reliable reporting, risk monitoring, and assurance activities.

However, it is important to note that the use of AI in auditing does not mean that professional auditors will cease to exist. The core value of auditing consists not only in data processing but also in demonstrating professional skepticism, considering materiality, understanding the business environment, testing the managers' explanations, and making conclusions where professionals should still take responsibility. As Spulbar and Mitrache (2025) explain, it is crucial that the use of AI should be based on the combination of human experience and technical capabilities, rather than on the idea that AI would substitute the professional activities of people. It is particularly true for the field of auditing, where an algorithm could discover the risk but would be unable to evaluate its relevance, reliability, materiality, and so forth.

Changes in the role of the auditor need to be viewed as changes in professional roles and not as displacements of roles. As the automation of data processing continues to advance, auditors can focus their efforts on identifying signs of risk, analysis of AI model output, evaluation of internal control environment, and communication with management and governance organizations. The model of AI co-piloted auditing by Gu et al. (2024) is the most appropriate in the situation because it incorporates the enhanced analytical capabilities provided by the AI while leaving human judgement crucial in the auditing process. Explainability is the key problem of using AI-supported methods of auditing.

Explainability is one of the most challenging theoretical and practical issues associated with the use of AI in audit procedures. Sophisticated machine learning models might provide very high accuracy when classifying transactions and providing other kinds of predictions but still be difficult to understand. In auditing, this problem becomes particularly acute since it would not be enough to call a conclusion valid because it was derived using some complicated algorithm. Explainable artificial intelligence is necessary for the proper performance of the audit according to Jones and Free (2026). It is impossible to rely on results of any system that has identified a transaction as an anomaly until it is clear what variables and data were used to come up with such a decision.

The black-box problem also has implications for transparency and accountability. A reporting environment cannot be considered more transparent if the systems used to analyse financial information produce outputs that no professional can adequately interpret or challenge. Spulbar (2025) observes that the broader use of AI in economic activities creates persistent legal concerns linked to responsibility, algorithmic bias, transparency, compliance, and market integrity. Within auditing, these concerns require organisations to establish clear lines of responsibility for the selection, validation, deployment, monitoring, and review of AI-supported tools. Technology may facilitate decision-making, but it should not create uncertainty regarding who remains accountable when the technology produces incomplete, misleading, or biased results.

The quality of data is equally important. AI systems are trained, configured, and operated using data; therefore, incomplete, inaccurate, outdated, biased, or poorly governed data can undermine even a technically sophisticated model. Katyal (2019) underline that accountable algorithmic systems require mechanisms capable of supporting meaningful review, validation, and contestability. In an audit setting, this means that firms should not rely on an AI tool merely because it has been acquired from a reputable provider or because it produces visually convincing outputs. They need to understand the origin of the data, the logic of the model, the limitations of its use, the mechanisms for documenting results, and the controls through which human reviewers can challenge its recommendations.

However, the regulatory environment is slowly adapting to the changes mentioned above. The Artificial Intelligence Act of the European Union, Regulation (EU) 2024/1689, sets up a risk-based system of regulation for AI systems, whose declared purpose is promoting trustworthy AI and protecting safety and fundamental rights of people. According to the European Commission (2026), the new regulation differentiates between four types of AI activities - prohibited, high-risk, transparency-risk and minimal-risk. This means that more strict regulation is applied when there is a risk that the consequences of using the AI technology will be higher for people and societies. Even though the specifics of applying any AI tool in auditing have to be taken into account in the particular context, the principles set forth in the Artificial Intelligence Act are directly applicable to auditing, as they connect technological use with risk management, data governance, documentation, traceability, transparency, human oversight, accuracy, robustness and cybersecurity.

Thus, some of the requirements for high-risk AI systems include the following: risk assessment and mitigation procedure, quality of datasets used, logging of activities for traceability, technical documentation, human oversight and high levels of accuracy, robustness and cybersecurity. As per the implementation plan, these requirements will be gradually applied starting with the rules for certain types of high-risk AI systems being introduced on 2 December 2027. However, even though an audit firm may not deal with high-risk AI tools, the above principles can be used as a standard for governance: the AI-enabled audit process has to be explainable, documented, secure, monitored and controlled.

In the context of applying AI in auditing, the General Data Protection Regulation continues to play an important role, as auditors may have access to the personal data of employees, clients, suppliers, shareholders, management and other parties related to the audit process. According to Regulation (EU) 2016/679, processing of personal data must be lawful, fair and transparent, pursued for specified, explicit and legitimate purposes, in line with the data minimisation, accuracy, storage limitation, integrity, confidentiality and accountability principles. Hence, the European Parliament and Council (2016) offer the basis for the responsible processing of data used in the AI-assisted audit process. As concerns the empirical part of the current research, these principles provide the guideline for the protection of participants' identity, their voluntary participation and informed consent, safe storage of the data collected during the research and presentation of the results in the form of aggregation or pseudonymisation.

Finally, standard-setting bodies respond to the technological revolution in audit and assurance processes. The IAASB adopted the Technology Position to make sure that the standards stay relevant and effective in light of increasing use of technologies in the auditing field. IAASB (2024) notes that the goal of this position is to facilitate and support responsible use of technology by practitioners and audit firms and to find possibilities for development of standards and non-authoritative guidance as well as monitoring technological developments. It is very important for audit innovations to be assessed not only in terms of efficiency but also quality, reliability, consistency and public interest orientation.

In regard to the Romanian professional setting, the process of adopting AI technologies in auditing is going to be conditioned by more than just the existence of the technological means. It would also rely on the ability of the financial auditors, professional accountants, finance directors, internal control professionals, and organization managers to acquire proper digital competencies and governance processes. CAFR provides its members with training and obliges them to continue developing their professional

competencies, which constitutes one of the characteristics of the institution, conducive to the adoption of innovations associated with technology. As a result, the empirical part of the research would focus on the assessment of the opportunities and limitations of AI in terms of the effect on audit quality, anomaly detection, continuous auditing, reporting quality and transparency, professional competence, data privacy, explainability, and human accountability.

In general, the theoretical and regulatory framework shows that AI can improve auditing not through the elimination of professional judgment, but through the extension of the analytical capabilities of the auditor. In other words, it can help professionals analyze large amounts of data, find the signals worth investigating, and create new opportunities for investigation. However, it would help to improve the quality and transparency of the corporate reporting only under the condition of good data, good model governance, secure technological environment, relevant professional competencies, compliance with applicable regulations, and the availability of the auditor himself who would interpret the evidence and make a final decision..

3. Research Methodology

This study uses a mixed-methods research design for exploring the consequences of artificial intelligence for corporate auditing at both organizational and professional levels. A mixed-methods design is needed since the implementation of AI technologies in auditing cannot be evaluated only on the basis of quantitative measures or on an individual perspective. Such an evaluation requires a consideration of practical application of new technologies, their pros and cons, as well as the professional reasoning behind the application of new technologies. Creswell and Plano Clark (2023) define mixed methods designs as the inclusion of both quantitative and qualitative data within the same research process so that the researcher could use the strengths of each method.

The first part of the research involves case studies based on selected documents. These cases will be chosen among reports, publications in professional literature, company disclosure reports, scientific evidence, as well as documents produced by audit firms or any other regulator. The purpose of this step is to demonstrate actual applications of AI technologies in such spheres as data analytics, anomaly detection, fraud risk assessment, document review, control, and continuous auditing. All cases will be analyzed using a unified set of analytical questions related to the AI technology being used, the area of audit or control affected, the expected advantages, the existing limitations, as well as control and accountability mechanisms.

The qualitative part will be based on a questionnaire administered online to individuals holding appropriate qualifications and experience in financial auditing, accounting, financial management, internal control, corporate reporting, risk management, and digitalization. Potential participants can include financial auditors or members of professional associations such as CAFR, CECCAR, and ACCA, as well as the finance directors or financial experts working in both public and private sector organizations. Closed-ended questions and Likert scale statements will be used to examine (a) the level of knowledge about AI, (b) its usefulness for audit practices and audit-related tools, (c) the potential influence on audit quality and transparency, and (d) the most significant barriers for implementation. Possible barriers can include lack of access to credible information, insufficient digital literacy, cost of implementation, cybersecurity issues, lack of explainability, regulation problems, and professional accountability concerns.

Statistical methods for the interpretation of quantitative data will include descriptive statistics (frequencies, percentages, means, and standard deviations). In case multi-item constructs are used, their internal consistency can be tested with the help of Cronbach's alpha coefficient. The relationship between respondents' professional background, level of AI knowledge, and perceptions of benefits and risks can be examined using non-parametric tests or Spearman correlation analysis. This study remains exploratory in nature, and therefore results obtained from statistical analyses will be interpreted carefully and will not serve as proof of general causal links.

The qualitative part will include semi-structured interviews with a reduced sample of professionals working in the fields of audit, accounting, finance, internal control, or compliance. Interviews will cover aspects that cannot be easily addressed using surveys, namely, practical constraints of AI implementation, reliability of risks signaled by artificial intelligence, the explainability of models' output, changing role of an auditor, and necessary security measures to maintain professionals' responsibility and independence. The advantage of semi-structured interviews is the combination of consistency in design required for comparison of participants and flexibility needed to allow each participant to speak about his or her experience and concerns in professional language. Analysis of the data will be based on thematic coding and will pay special attention to recurring themes such as efficiency, anomaly detection, data quality, transparency, human involvement, ethical risk, digital literacy, and regulatory compliance.

Evidence obtained from case studies, questionnaire, and interviews will be combined using triangulation. Specifically, the study will compare documentary evidence of actual usage of AI with information about it given by professionals in the questionnaire and during interviews. Such an approach will improve interpretation of the results by highlighting convergences, divergences, and context specifics. In the course of empirical research, all participants will act voluntarily and with their informed consent. No unnecessary personal or organizational information will be gathered, and participants of the interviews will be referred to using pseudonyms or generic titles. Results will be presented in aggregate form; however, all documents gathered during the research will be secured and accessible exclusively for research purposes. These precautions are compliant with the GDPR requirements related to processing of personal data for scientific research.

4. Analysis and Results

The empirical investigation combined three complementary sources of evidence: documentary case studies, an online questionnaire survey, and semi-structured interviews. This mixed-methods design was intended to provide a more comprehensive understanding of the potential contribution of artificial intelligence to audit quality and the transparency of corporate reporting. Documentary evidence was used to examine concrete applications of AI-enabled technologies, while the questionnaire captured the perceptions of professionals involved in audit-related and financial-reporting activities. The interviews were used to explore the practical conditions, professional concerns, and governance requirements that may influence the responsible adoption of AI.

The analysis includes three documentary case studies, 186 valid questionnaire responses, and 12 semi-structured interviews. The survey was distributed electronically to professionals working in financial audit, accounting, financial management, internal audit, risk management, and corporate reporting. A total of 204 questionnaires were received, of which 18 were excluded because they were substantially incomplete or did not meet the eligibility criteria. The final sample therefore comprised 186 valid responses. Interview

participants were selected to provide a diversity of professional perspectives. Furthermore, to ensure confidentiality in accordance with ethical codes and GDPR regulations, neither participant names nor company names are used; instead, all interviewees and their organizations are referred to using pseudonyms or generic titles.

Table 1. Overview of the empirical material

Data source	*Initial material*	*Included material*	*Analytical purpose*
Documentary sources	7 potential cases screened	3 case studies	To identify concrete AI applications in audit and control processes
Questionnaire survey	204 responses received	186 valid responses	To assess professional perceptions of benefits, barriers, and governance conditions
Semi-structured interviews	14 interviews initiated	12 interviews included	To explore practical experiences, conditions, and concerns in greater depth

Source: Made by the authors based on research methodology

The selected documentary cases represented three complementary areas of AI application: anomaly detection in transaction testing, natural language processing for the review of unstructured documents, and continuous monitoring of internal controls. The three sources of evidence were subsequently integrated through a triangulation process in order to identify convergent findings, contextual differences, and complementary insights.

4.1. Documentary Case-Study Findings

The first documentary case deals with a large audit and advisory firm in western Romania, namely in the city of Timisoara, that has applied machine-learning-based analytics in their journal entry testing and transaction risk assessment. The tool was designed for processing large amounts of accounting entries and for identifying observations with unusual features such as unusual posting times, account pairs never observed before, unusual user profiles, transaction value anomalies and reversal entry behavior. The main advantage stated in the case is the ability to help auditors to focus on the transactions that need professional evaluation and analysis without using traditional random or judgmental sampling.

The second documentary case is related to an AI-powered tool for analyzing contracts, policies, management reports and selected financial-reporting disclosures of an organization based in Bucharest. The tool was designed to extract the important parts of those documents, identify the terms associated with accounting risks, and highlight any anomalies or gaps that require manual review. The second case shows the potential of AI to help with the analysis of unstructured information that is often time-consuming and difficult to analyze by hand. On the other hand, this case highlights the importance of the expert review since the understanding of contractual provisions depends on the commercial, legal and materiality aspects that cannot be determined through automated analysis only.

The third documentary case relates to continuous control monitoring in a digital business environment of an organization also based in Bucharest. AI-based analytics were

used to detect unusual payments, duplicate vendor information, abnormal deviations from the approval processes and potential segregation of duties problems. The software generated the alerts for internal control and audit professionals who could review the possible anomalies. The most significant advantage of this case is the potential for transitioning from the verification of risks and controls to their continuous monitoring. However, this case also demonstrates that requires complete and standardized data and a clear escalation procedure.

Table 2. Comparative analysis of documentary case studies

Analytical dimension	***Case 1: Transaction analytics***	***Case 2: NLP document review***	***Case 3: Continuous control monitoring***
Primary AI capability	Machine learning and anomaly detection	Natural language processing	Predictive analytics and automated alerts
Audit/control area	Journal-entry testing and fraud-risk assessment	Contract and disclosure review	Internal controls and transaction monitoring
Main benefit	Prioritisation of potentially high-risk transactions	Faster review of extensive unstructured documentation	Earlier identification of control exceptions
Contribution to audit quality	Broader review of transaction populations	Improved consistency and coverage of document analysis	More timely investigation of unusual patterns
Main implementation risk	False positives and limited model explainability	Contextual misunderstanding of textual information	Data integration, alert fatigue, and cybersecurity
Human oversight mechanism	Auditor validates flagged transactions	Auditor or legal/accounting specialist reviews clauses	Control owner and auditor assess alerts and corrective action
Governance requirement	Model documentation and audit trail	Transparency of extraction and classification criteria	Data governance, access controls, and escalation protocols

Source: Made by the authors based on research methodology

The comparative assessment suggests that AI creates value at different stages of the audit and control process. Machine learning appears particularly relevant for identifying unusual transactions within large datasets, NLP supports the examination of textual evidence, while continuous monitoring can improve the timeliness of control-related information. Across all three cases, however, the main conclusion is consistent: AI contributes to audit quality when it helps professionals focus their attention more

effectively, but it does not eliminate the need for professional judgement, adequate documentation, or clear responsibility.

4.2. Questionnaire Results

The output of the questionnaire presents a picture of professionals' perception of the prospects and limitations of AI-assisted auditing. The total number of 186 respondents involved in the study included the highest number of financial auditors, then accountants, and finally finance managers. The sample also consisted of professionals working in areas such as internal auditing, risk management, controls, consulting, and digital transformation. The majority of respondents had more than five years of professional experience, which means that the data present perceptions of people with significant practical knowledge of accounting/auditing/financial management/related procedures.

Table 3. Respondent profile

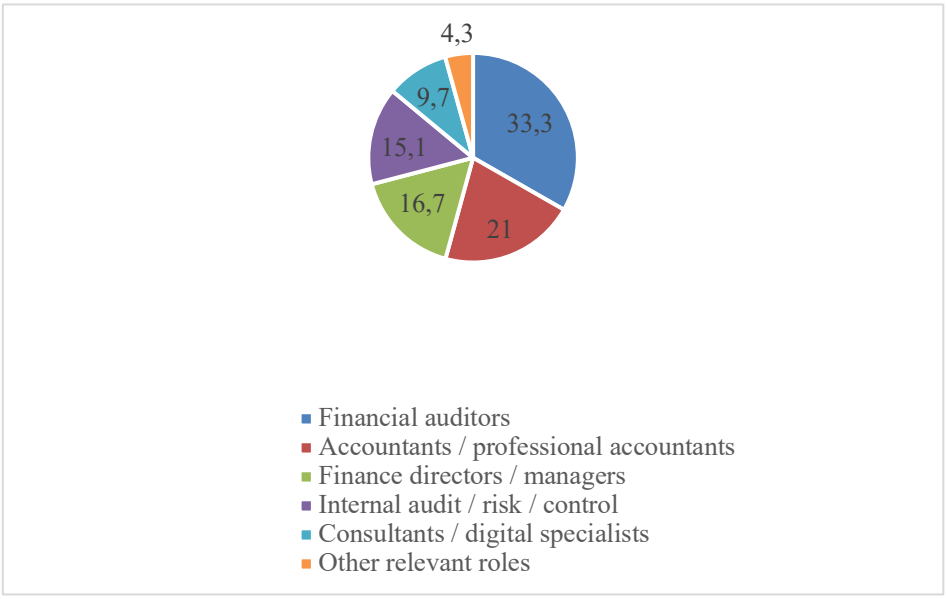
Variable	*Category*	*Frequency*	*Percentage*
Professional role	Financial auditor	62	33.3
	Accountant / professional accountant	39	21.0
	Finance director / finance manager	31	16.7
	Internal audit, risk, or control professional	28	15.1
	Consultant / digital transformation specialist	18	9.7
	Other relevant role	8	4.3
Sector	Private sector	112	60.2
	Public sector	47	25.3
	Both public and private sector	27	14.5
Professional experience	Under 5 years	24	12.9
	5–10 years	52	28.0
	11–15 years	46	24.7
	More than 15 years	64	34.4
Familiarity with AI	Very low or low	29	15.6
	Moderate	71	38.2
	High or very high	86	46.2
Current use of AI	No current use	37	19.9
	Exploratory or experimental use	61	32.8
	Limited operational use	53	28.5
	Regular or advanced use	35	18.8

Source: Made by the authors based on research methodology

From the results, it can be seen that although knowledge of AI was rather common, the use of AI at a high level was not that common among organizations. This can be seen by the fact that 18.8% of those interviewed had regular or advanced use of AI technology in their organization, compared to the 32.8% who felt that their organizations

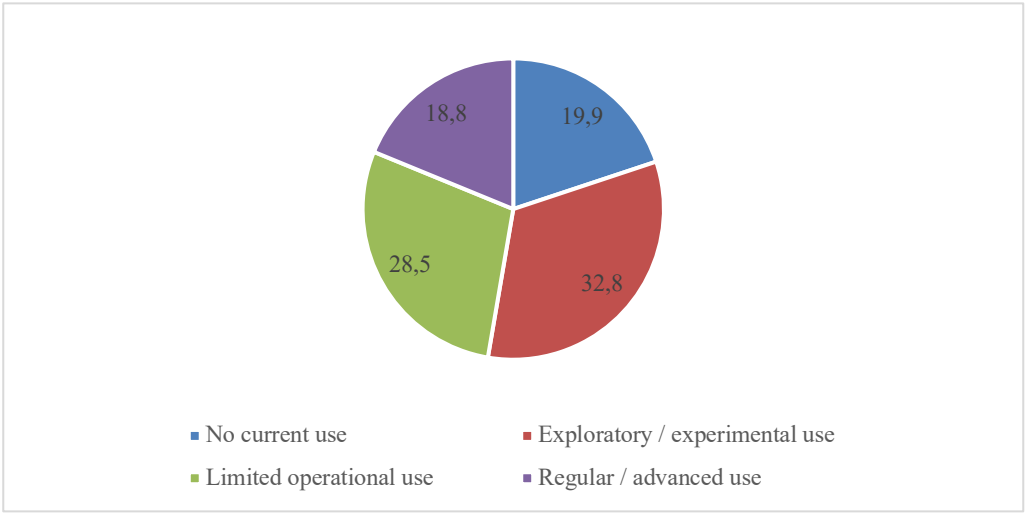
were still in a trial stage. This indicates that although the professional knowledge of AI is increasing faster than AI adoption.

Figure 1. Distribution of respondents by professional role (%)



Source: Made by the authors based on research methodology

Figure 2. Current organisational use of AI (%)



Source: Made by the authors based on research methodology

However, the results suggest an overall positive evaluation of the use of artificial intelligence as a technology which may improve the quality of audits, their efficiency, and the transparency of reporting. The most substantial level of consensus was reached concerning the ability of AI to increase the chances of detecting anomalies and suspicious

cases, then comes the belief in its ability to reduce the time spent on performing repetitive tasks. Also, there is an overwhelming level of consensus concerning the ability of AI to perform a comprehensive analysis of transactions.

Table 4. Perceived benefits of AI in auditing

Code	*Statement*	*Mean*	*Standard deviation*	*Agreement rate (%)*	*Rank*
BEN1	AI can improve the identification of unusual transactions and potential anomalies.	4.38	0.71	87.6	1
BEN2	AI can reduce the time required for repetitive audit procedures.	4.29	0.76	84.9	2
BEN3	AI can enable broader examination of transaction populations than traditional sampling methods.	4.21	0.80	81.7	3
BEN4	AI can support more timely audit procedures and continuous monitoring.	4.16	0.82	79.6	4
BEN5	AI can improve the transparency and traceability of corporate reporting processes.	4.02	0.86	74.7	5

Source: Made by the authors based on research methodology

The composite score for the perceived-benefits scale was 4.21, indicating a high level of overall agreement. The internal consistency of the five-item scale was good, with a Cronbach's alpha coefficient of 0.86. This value suggests that the items measured a coherent construct related to the expected contribution of AI to auditing and reporting processes.

Table 5. Reliability analysis of the questionnaire constructs

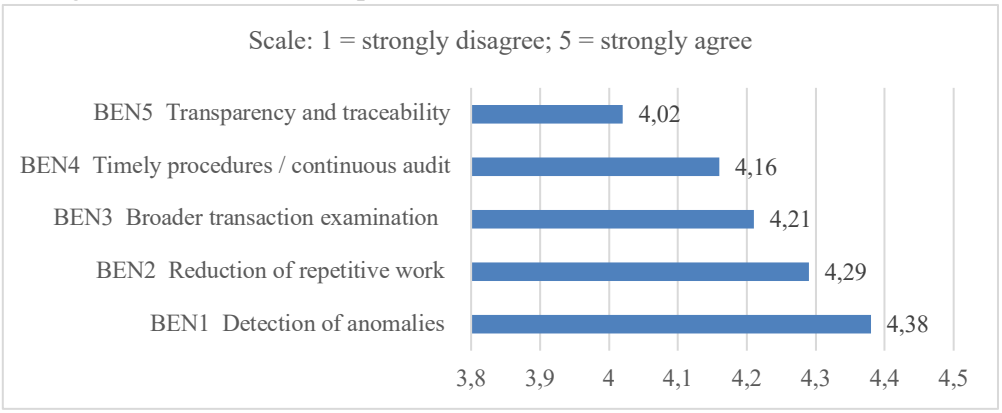
Construct	*Number of items*	*Cronbach's alpha*	*Interpretation*
Perceived AI benefits	5	0.86	Good internal consistency
Perceived risks and barriers	5	0.82	Good internal consistency
Human oversight and governance	5	0.89	Good internal consistency

Source: Made by the authors based on research methodology

The findings support the proposition that professionals perceive AI not primarily as a replacement for audit work, but as an analytical tool that can improve the capacity to

identify exceptions, process large data volumes, and focus audit effort on higher-risk areas. The results are particularly relevant for the transition towards continuous auditing, as respondents recognised the potential of AI to provide more timely information and to support ongoing monitoring of transactions and controls.

Figure 3. Mean scores for perceived benefits of AI



Source: Made by the authors based on research methodology

While the participants recognized the benefits that come with AI, they also highlighted various worries pertaining to the requirements for the proper use of AI. The highest average rating was obtained on the requirement that involved evaluating the outputs generated by AI through the professional judgement of experts. Other requirements highlighted were explainability, quality of data, cybersecurity, and appropriate governance.

Table 6. Perceived risks and barriers

Code	*Statement*	*Mean*	*Standard deviation*	*Agreement rate (%)*	*Rank*
RISK 1	Limited data quality and data availability may reduce the reliability of AI-supported audit procedures.	4.31	0.73	85.5	1
RISK 2	The lack of explainability of AI outputs may limit their use in audit engagements.	4.27	0.78	83.9	2
RISK 3	Cybersecurity and confidentiality concerns represent major barriers to AI adoption in auditing.	4.19	0.82	79.0	3
RISK 5	Insufficient digital skills may hinder the effective use of AI in auditing.	4.12	0.85	76.9	4
RISK 4	Implementation and integration costs may limit adoption, particularly in smaller organisations.	3.94	0.91	68.8	5

Source: Made by the authors based on research methodology

The results demonstrate that respondents did not perceive AI adoption as a purely technical matter. Instead, the ability to obtain reliable data, understand AI-generated outputs, protect confidential information, and develop relevant skills appeared to be central

to the practical value of AI. The composite score for the perceived-risks-and-barriers scale was 4.17, while Cronbach's alpha was 0.82, indicating good internal consistency.

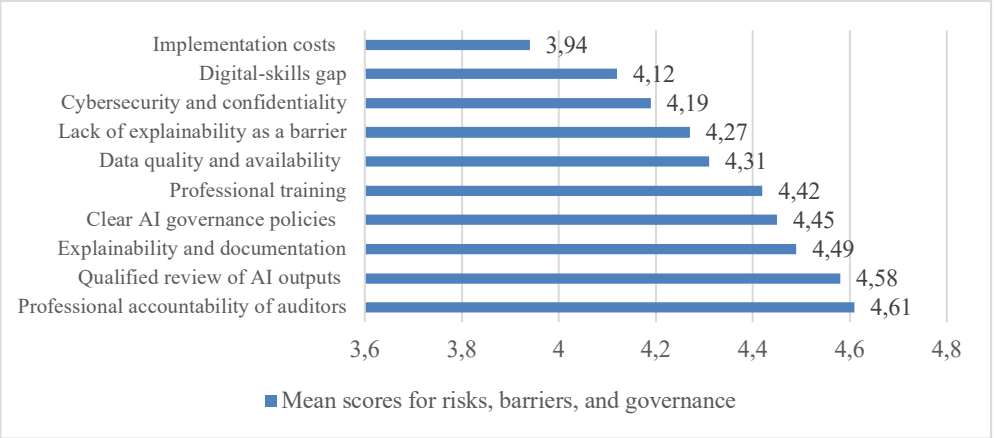
Table 7. Human oversight and governance conditions

Code	*Statement*	*Mean*	*Standard deviation*	*Agreement rate (%)*	*Rank*
GOV1	AI-generated alerts and recommendations should be reviewed by a qualified professional before audit decisions are made.	4.58	0.61	93.5	2
GOV2	Auditors should remain professionally accountable for conclusions reached with AI-supported tools.	4.61	0.58	94.6	1
GOV3	AI-supported audit procedures should be sufficiently explainable and documented.	4.49	0.65	90.9	3
GOV4	Organisations should establish clear policies for governance and monitoring of AI tools used in audit activities.	4.45	0.68	89.2	4
GOV5	Professional training in AI, data analytics, and digital ethics should become a priority.	4.42	0.70	88.7	5

Source: Made by the authors based on research methodology

The human-oversight-and-governance scale recorded the highest composite score, at 4.51, and the highest reliability coefficient, with Cronbach's alpha equal to 0.89. This result is important because it shows that the favourable attitude towards AI does not imply an acceptance of fully autonomous audit decision-making. On the contrary, the respondents strongly supported a human-in-the-loop approach in which AI assists the audit process, while qualified professionals remain responsible for reviewing evidence, interpreting results, and forming final conclusions.

Figure 4. Mean scores for risks, barriers, and governance



Source: Made by the authors based on research methodology

Spearman correlation analysis was used to explore whether familiarity with AI and current AI use were associated with respondents' perceptions of its benefits, risks, and governance requirements. The findings indicate a positive and statistically significant association between AI familiarity and perceived AI benefits. Respondents who reported a higher level of familiarity with AI were more likely to recognise its potential to improve anomaly detection, support broader transaction analysis, reduce repetitive work, and enable more timely audit procedures.

Table 8. Spearman correlations between AI exposure and perceptions

Variable pair	*Spearman's ρ*	*p-value*	*Interpretation*
AI familiarity – perceived AI benefits	0.46	<0.001	Moderate positive association
Current AI use – perceived AI benefits	0.41	<0.001	Moderate positive association
AI familiarity – perceived risks and barriers	0.24	0.001	Weak positive association
Current AI use – human oversight and governance	0.29	<0.001	Weak-to-moderate positive association
Professional experience – perceived risks and barriers	0.18	0.014	Weak positive association

Source: Made by the authors based on research methodology

The positive association between AI familiarity and perceived benefits should not be interpreted as proof that familiarity causes favourable perceptions. Nevertheless, it suggests that professionals who have greater exposure to AI may be better able to recognise both its practical opportunities and its limitations. The positive association between AI familiarity and perceived risks is also meaningful: more informed respondents did not appear to be uncritically optimistic. Instead, they were more likely to acknowledge the importance of data quality, explainability, cybersecurity, and appropriate governance.

A Kruskal–Wallis test was conducted to examine whether perceived AI benefits differed across the main professional categories. The results suggest that the differences between groups were statistically significant, $H(4) = 11.27$, $p = 0.024$. Finance directors and digital-transformation specialists reported slightly higher perceived-benefit scores than the other groups, whereas accountants reported the most cautious evaluations. However, all professional groups recorded composite scores above the neutral point of the scale, indicating broadly positive perceptions across the sample.

Table 9. Perceived AI benefits by professional role

Professional category	*Mean rank*	*Median composite benefit score*
Financial auditors	94.2	4.20
Accountants / professional accountants	78.6	4.00
Finance directors / managers	108.7	4.40
Internal audit, risk, or control professionals	95.5	4.20
Consultants / digital-transformation specialists	115.3	4.50

Source: Made by the authors based on research methodology

Such disparities in professional categories can be attributed to the unique responsibilities and exposure of each profession. The finance directors and experts in digital transformation are likely to have more direct involvement with decision-making concerning investments in data infrastructures and automation technology while accountants may be more concerned about the integrity and consistency of financial data. Financial auditors and controllers find themselves in a middle ground between having good expectations for analytics and strong concerns for validation and documentation.

4.3. Interview Findings

Themes that emerged from the thematic analysis of twelve semi-structured interviews included the following: (1) efficiency improvement and analytical support through the use of AI technology; (2) anomaly detection and monitoring; (3) data quality, security and confidentiality; (4) explainability and professionalism; and (5) skillset, governance and readiness.

Table 10. Interview themes

Theme	*Interpretation*	*Frequency*
AI as efficiency and analytical support	AI is viewed as useful for automating repetitive work and directing attention to exceptions	11 of 12 participants
Anomaly detection and continuous monitoring	AI can improve prioritisation and timeliness, but alerts require contextual review	10 of 12 participants
Data quality, security, and confidentiality	Poor data and confidential information are considered major constraints	9 of 12 participants

Explainability and professional accountability	Auditors must understand, challenge, and remain accountable for AI-assisted outputs	12 of 12 participants
Skills, governance, and organisational readiness	Training, governance policies, and infrastructure are needed for responsible adoption	11 of 12 participants

Source: Made by the authors based on research methodology

Theme 1 deals with the ability of AI to increase efficiency and improve focus of analysis. Generally, participants did not see AI as something that could replace professional work. Instead, participants viewed AI as a tool for decreasing repetitive processing of information, organization of large datasets, and enabling professionals to pay attention to transactions or documents that need more scrutiny. As demonstrated in the interviews, an auditor highlighted the following value in using AI: *The biggest benefit is not that the system makes decisions for us; it is that it makes it easier to reduce the time spent figuring out where the risk really lies.* (Participant P03, financial auditor).

Theme 2 focuses on the issue of anomaly detection and continuous monitoring. Participants saw the value of AI in being able to find out transactions that diverge from the expected pattern and allow for faster monitoring of controls. However, participants stressed at all times that alert does not mean fraud or misstatement. As it was noted by one of the participants: *Unusual transaction is a trigger for investigating the transaction, not evidence of fraud.* (Participant P08, internal-control professional).

Theme 3 relates to issues of data quality, cybersecurity, and confidentiality. Participants agreed that the effectiveness of AI is dependent on the quality of source data. Besides, participants mentioned that auditors deal with commercially sensitive and personal information. One of the participants noted the following: *Before talking about fancy algorithm we should ensure that the data are complete, proper, authorised and protected.* (Participant P05, finance manager). This result proves the hypothesis of the paper that introduction of AI technologies requires proper data management practices and information security procedures to be introduced.

Theme 4 of explainability and professional accountability appeared to be the most emphasized issue in the interviews. Participants agreed that AI-supported output should be sufficiently clear to enable the auditor to understand what triggered the alert and recommendation. As it was said by one of the audit professionals: *I can use tool for making decision only if I am able to explain the rationale behind the decision and my actions.* (Participant P11, senior auditor). It can be seen that this result is consistent with the findings of the survey that showed very high agreement in relation to human review and continuing professional responsibility.

Theme 5 is about skills, governance and organizational readiness. Participants noted that effective adoption of AI is not simply a matter of acquiring or developing technology. Professionals have to possess necessary skills to interpret data, identify limitations of AI, critically assess output of the tool and apply ethical and regulatory standards. It is how one of the participants expressed this necessity: *The future auditor should know not only financial logic of the transaction but also digital logic of the tool that analyses it.* (Participant P02, accounting and compliance specialist). The above mentioned statement implies that artificial intelligence and data analytics, information security and digital ethics should become the subject of educational programs and further professional training of the specialists.

5. Conclusions

This study examined the potential contribution of artificial intelligence to corporate auditing and, consequently, to the quality and transparency of corporate reporting. The analysis indicates that AI should not be understood merely as a tool for accelerating routine tasks. Its more significant contribution lies in extending the auditor's analytical capacity: processing larger volumes of information, identifying unusual transactions, supporting the review of unstructured documentation, and enabling more timely monitoring of risks and internal controls.

The documentary case studies illustrated that machine learning, anomaly-detection techniques, natural language processing, and continuous-monitoring tools may be applied at different stages of audit and control processes. These technologies can help professionals direct attention towards transactions, documents, and control exceptions that require deeper examination. Their value is therefore linked to improved prioritisation and broader analytical coverage, rather than to the replacement of audit procedures or the automatic generation of reliable audit conclusions.

The survey results showed a generally positive perception of AI among among the surveyed professionals. Respondents particularly recognised its potential to improve anomaly detection, reduce time spent on repetitive procedures, extend the examination of transaction populations, and support more timely audit activities. At the same time, the analysis revealed that familiarity with AI was associated not only with stronger recognition of its benefits, but also with greater awareness of the risks connected to data quality, explainability, cybersecurity, and implementation complexity.

The interview-based analysis reinforced the idea that AI-generated outputs must be treated as decision-support signals rather than as final conclusions. Professionals may use AI to identify where attention should be directed, but they must still evaluate the business context, reliability of evidence, materiality of the issue, and plausibility of management explanations. This finding confirms that professional scepticism, ethical reasoning, and informed judgement remain essential to the public-interest role of the auditor.

A central conclusion of the study is that the responsible adoption of AI requires a clear human-in-the-loop governance model. Auditors must retain responsibility for conclusions reached through AI-supported procedures, while organisations need transparent policies for model selection, data management, validation, documentation, monitoring, and escalation. This conclusion is consistent with the European approach to trustworthy AI, which emphasises human oversight, privacy and data governance, technical robustness, transparency, and accountability.

The regulatory and professional framework is therefore not an external constraint on technological innovation; it is a necessary condition for making AI useful and credible in audit practice. The IAASB's Technology Position similarly recognises that audit and assurance standards need to evolve alongside technological change, while preserving their effectiveness, relevance, and public-interest purpose. In practice, AI adoption should be accompanied by secure data infrastructure, reliable audit trails, appropriate cybersecurity measures, explainable outputs, and professionals who possess both accounting knowledge and digital competence.

The study supports the view that artificial intelligence can strengthen corporate auditing when it is used as an instrument of professional augmentation rather than professional substitution. The future of auditing is unlikely to be defined by a choice

between human expertise and algorithmic capability. Instead, it will depend on their responsible integration: AI can provide speed, scale, and pattern-recognition capacity, while auditors provide scepticism, contextual understanding, ethical responsibility, and accountable judgement.

Authors' Contributions:
The authors contributed equally to this work.

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