Artificial Intelligence and Big Data Analytics in Financial and Administrative Auditing: Toward a Smart and Predictive Control System

Sirine Sabah [1]

[1] Abou bekr Belkaid university, Tlemcen, Algeria.
Sabah.sirine@univ-tlemcen.dz.

Abstract. The integration of Artificial Intelligence (AI) and Big Data Analytics into financial and administrative auditing is fundamentally transforming traditional control systems. This paper explores how these technologies enhance audit accuracy, efficiency, and transparency through the use of machine learning algorithms, anomaly detection, and predictive analytics. By enabling real-time identification of irregularities and improving risk assessment, AI reduces human error and strengthens decision-making processes. Meanwhile, Big Data allows auditors to process vast and unstructured datasets, providing more comprehensive insights into organizational performance and regulatory compliance. Based on international case studies, the study demonstrates that AI-driven auditing improves fraud detection and optimizes resource management, yet raises ethical and regulatory challenges concerning data protection and accountability. The findings emphasize that while AI and Big Data do not replace professional judgment, their integration represents a strategic evolution toward more resilient, transparent, and adaptive audit system.

Keywords: Artificial Intelligence (AI); Big Data Analytics; Financial and Administrative Auditing; Predictive Control Systems.

1 Introduction

The rapid evolution of digital technologies has profoundly transformed organizational ecosystems, with Artificial Intelligence (AI) and Big Data Analytics (BDA) standing out as two of the most disruptive forces. In the realm of financial and administrative auditing, these technologies offer opportunities to overcome long-standing limitations of traditional methods, such as reliance on retrospective evaluations, manual sampling, and static control mechanisms. Traditional auditing systems, while essential for ensuring accountability and compliance, are increasingly insufficient when confronted with the unprecedented complexity, heterogeneity, and velocity of data generated in contemporary financial and administrative environments [1] .

The volume of financial data produced daily by organizations, coupled with the proliferation of administrative records, e-government platforms, and digital transactions,

D. Agti et al. (eds.), *Proceedings of the International Conference on Artificial Intelligence Applications in Business Administration in MENA Region (ICAIABA 2026)*, Advances in Economics, Business and Management Research 393,
https://doi.org/10.2991/978-94-6239-711-8_12

has created a landscape where auditors must deal not only with structured financial statements but also with unstructured data sources, including emails, reports, and even social media indicators of organizational activity. This transformation aligns with the broader paradigm of the Fourth Industrial Revolution, in which automation, connectivity, and intelligent systems redefine how monitoring and control functions are performed [2]. Within this context, financial and administrative auditing must evolve toward methods that are not only more efficient and reliable but also more predictive and adaptive to emerging risks.

Artificial Intelligence plays a central role in this transformation. Machine learning algorithms are capable of identifying hidden patterns in large datasets, enabling auditors to detect anomalies and fraudulent activities with greater accuracy than conventional approaches [3]. Natural language processing (NLP) supports the automated analysis of unstructured administrative texts, such as contracts or policy documents, while robotic process automation (RPA) can replicate repetitive audit tasks, freeing auditors to focus on strategic and interpretative aspects of their work. Big Data Analytics complements these capabilities by allowing real-time examination of diverse datasets, thereby facilitating continuous auditing and proactive risk assessment [4].

The convergence of AI and BDA leads to what can be conceptualized as "smart and predictive auditing systems." Unlike traditional audit systems that primarily verify past compliance, predictive systems aim to forecast risks, anticipate irregularities, and provide decision-makers with actionable insights before problems escalate. This transition is particularly crucial in an era marked by financial crises, regulatory complexity, and increased public demand for transparency in both the private and public sectors [5]. In administrative auditing, predictive systems can improve oversight of public resources, enhance accountability, and reduce the risk of mismanagement or corruption.

Nevertheless, the adoption of AI-driven auditing raises critical challenges. Data governance remains a pressing issue, as auditors must ensure data quality, integrity, and compliance with privacy regulations such as the General Data Protection Regulation (GDPR). Furthermore, algorithmic decision-making is not immune to biases, which may lead to unfair or inaccurate audit outcomes if not properly monitored [6]. Cybersecurity concerns also loom large, as the reliance on interconnected systems and large-scale data processing increases exposure to digital vulnerabilities. Additionally, the integration of AI and Big Data into auditing requires a fundamental rethinking of auditors' skills: beyond financial and regulatory expertise, auditors must develop competencies in data science, algorithmic logic, and digital ethics.

Given these opportunities and challenges, the research problem addressed in this article is: "How can Artificial Intelligence and Big Data Analytics transform financial and administrative auditing into a smart and predictive control system, while ensuring reliability, transparency, and ethical compliance?"

The objectives of this research are threefold:
- To review the state of the art in AI and BDA applications within auditing practices.
- To propose a conceptual framework for the development of a smart and predictive control system in financial and administrative auditing.
- To discuss the benefits, limitations, and future directions of implementing such systems, with particular attention to governance, ethics, and professional practice.

The article contributes to both academic literature and professional debates by situating auditing within the digital transformation agenda. For scholars, it provides an integrative perspective on how emerging technologies reshape auditing theory and methodologies. For practitioners and policymakers, it highlights the practical implications of deploying AI and Big Data tools in audit processes, including risk management, regulatory compliance, and organizational efficiency.

In line with these objectives, the paper is structured as follows. Section 2 presents a literature review of AI and Big Data applications in auditing, emphasizing both achievements and gaps in current research. Section 3 outlines the methodological framework and technological tools that underpin smart auditing systems. Section 4 develops a conceptual model of a predictive control system and illustrates its potential functionalities through case-based insights. Section 5 discusses the broader implications of adopting such systems, including benefits, challenges, and ethical considerations. Finally, Section 6 concludes the article by summarizing the findings and identifying avenues for future research. Sample Heading (Third Level). Only two levels of headings should be numbered. Lower-level headings remain unnumbered; they are formatted as run-in heading

2 Literature review

The literature on Artificial Intelligence (AI) and Big Data Analytics (BDA) in auditing has expanded considerably over the past decade, reflecting the growing importance of technological innovation in assurance and control functions. This section reviews key theoretical contributions, practical applications, and identified research gaps. It is structured into four subsections: AI applications in auditing, Big Data Analytics in auditing, integration of AI and Big Data for smart auditing, and limitations and challenges of existing approaches.

The literature on Artificial Intelligence (AI) and Big Data Analytics (BDA) in auditing has expanded considerably over the past decade, reflecting the growing importance of technological innovation in assurance and control functions. This section reviews key theoretical contributions, practical applications, and identified research gaps. It is structured into four subsections: AI applications in auditing, Big Data Analytics in auditing, integration of AI and Big Data for smart auditing, and limitations and challenges of existing approaches.

2.1 Artificial Intelligence in Auditing

Artificial Intelligence encompasses a range of technologies—including machine learning (ML), natural language processing (NLP), expert systems, and robotic process automation (RPA)—that can mimic human reasoning, learn from data, and make predictions or decisions. In auditing, AI technologies are primarily used to enhance anomaly detection, automate repetitive processes, and provide predictive insights.

Machine learning models are particularly relevant for detecting fraudulent transactions and irregular accounting patterns. According to Issa, Sun, and Vasarhelyi (2016), ML techniques outperform traditional rule-based approaches by identifying subtle and non-linear relationships in financial data. For example, supervised learning algorithms can be trained on historical fraud cases to predict the likelihood of fraud in new transactions, while unsupervised methods such as clustering can reveal anomalous patterns that deviate from normal business activity.

Natural language processing has also gained prominence in auditing research. NLP facilitates the automated analysis of unstructured data, such as contracts, financial disclosures, and regulatory reports [7].This capability is crucial given the growing role of textual information in both financial and administrative auditing. Robotic process automation further enhances audit efficiency by replicating routine tasks such as data extraction, reconciliation, and reporting [6].

Despite these advances, AI applications in auditing remain in their early stages, with many organizations experimenting through pilot projects rather than full-scale adoption. Concerns about transparency, interpretability, and ethical implications of AI-driven decisions persist [8] **(see fig. 1).**

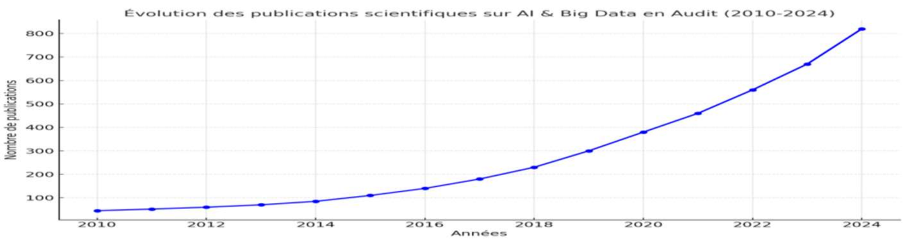

Fig.1. *Evolution of Scientific Publications on AI and Big Data in Auditing (*2010–2024)
Source: *Authors' elaboration based on Scopus database data (2010–2024).*

2.2 Big Data Analytics in Auditing

Big Data Analytics refers to techniques that process massive volumes of data characterized by the "four Vs": volume, velocity, variety, and veracity [9]. In auditing, BDA enables the continuous monitoring of vast and heterogeneous datasets, moving beyond sample-based audits toward population-wide analysis.

Yoon, Hoogduin, and Zhang (2015) argue that BDA represents a paradigm shift in auditing, allowing auditors to test 100% of transactions rather than relying on statistical sampling. This approach reduces the risk of undetected anomalies and increases the reliability of audit outcomes. Real-time analytics further allows auditors to detect irregularities as they occur, rather than months after financial closure.

Applications of BDA include fraud detection, compliance monitoring, and risk assessment. For instance, case studies show that banks and financial institutions have successfully implemented BDA tools to identify suspicious patterns of transactions indicative of money laundering [10]. In the public sector, BDA has been used to enhance administrative audits by analyzing expenditure patterns, procurement records, and tax compliance data [5].

However, Big Data auditing faces limitations related to data integration, quality assurance, and the challenge of analyzing unstructured data sources. While structured transactional data is relatively easy to process, unstructured sources such as policy documents or multimedia evidence remain underutilized in audit practices.

2.3 Toward Smart and Predictive Auditing Systems

The convergence of AI and BDA opens the path to what scholars describe as "smart auditing" or "cognitive auditing" [1]. These systems combine predictive analytics, continuous monitoring, and automated decision-making to create a proactive audit environment.

Smart auditing systems can perform several key functions:

- Predictive risk assessment: By analyzing historical and real-time data, systems can forecast the likelihood of fraud, financial distress, or compliance breaches [11].
- Continuous auditing: Unlike periodic audits, continuous auditing allows real-time verification of transactions and controls, significantly reducing the audit lag [12].
- Anomaly detection: AI algorithms can highlight outliers in financial records that may not be apparent through traditional audit sampling.
- Automated reporting: Advanced systems can generate dynamic dashboards and real-time audit reports for decision-makers, improving transparency and responsiveness [13].

Such systems are increasingly being explored in both private and public organizations. Professional service firms such as PwC, Deloitte, and KPMG have invested heavily in AI-driven audit tools, including predictive analytics platforms and blockchain-integrated solutions [14]. In the public sector, governments are exploring predictive auditing to combat corruption and enhance fiscal oversight.

2.4 Limitations and Challenges in the Literature

Although the literature highlights significant benefits of AI and BDA in auditing, several challenges remain underexplored. First, data governance and quality are critical issues. Poor data integrity can undermine the effectiveness of predictive models, leading to unreliable audit outcomes [15]. Second, the black-box nature of AI algorithms raises concerns about interpretability and accountability. Auditors, regulators, and stakeholders may be reluctant to rely on decisions that cannot be easily explained or justified [16]. This challenge underscores the need for explainable AI in auditing.

Third, ethical and legal concerns arise from the use of personal and sensitive data in audit processes. Compliance with privacy regulations such as GDPR in Europe or CCPA in California is a major constraint on the use of large-scale analytics.

Fourth, the skills gap is a recurring theme. Auditors traditionally trained in accounting and finance must now acquire competencies in data science, programming, and algorithmic thinking [6]. This raises questions about how auditing education and professional certifications should evolve to keep pace with technological transformation.

Finally, there is a limited number of empirical studies that measure the effectiveness of AI- and BDA-driven auditing in practice. Much of the literature remains conceptual or exploratory, with case studies often limited to large multinational firms. The application in small and medium enterprises (SMEs) and public administrations is less documented, representing a gap in current research.

2.5 Synthesis of the Literature

The literature converges on the idea that AI and Big Data have the potential to transform auditing from a retrospective, sample-based process into a proactive, predictive, and continuous control system. While theoretical and technical foundations are well established, practical implementation remains uneven across sectors and regions. Challenges of data governance, algorithmic transparency, and professional readiness continue to hinder large-scale adoption.

This synthesis highlights the need for research that bridges theory and practice by proposing integrative frameworks for smart auditing systems, particularly in contexts where both financial accountability and administrative transparency are critical. The following section builds on these insights to develop a methodological framework for designing and implementing predictive auditing models.

3 Methodological Framework

The development of a smart and predictive auditing system requires a robust methodological framework that integrates conceptual, technological, and practical perspectives. This section outlines the methodological underpinnings of the study, focusing on research approach, data sources, analytical tools and techniques, and the proposed conceptual model for predictive auditing.

The research adopts a conceptual and exploratory approach, complemented by insights from case studies and empirical findings in existing literature. Unlike purely empirical studies that rely on proprietary organizational data, this research focuses on synthesizing theoretical frameworks and technological applications to design a holistic model for predictive auditing.

The methodological approach is twofold:

Descriptive analysis: reviewing how AI and BDA have been applied in financial and administrative auditing.

Prescriptive modeling: proposing an integrative framework that can guide practitioners and policymakers in the implementation of smart audit systems.

This dual approach is consistent with the paradigm of **design science research**, which emphasizes the creation of artifacts (frameworks, models, systems) to address complex organizational problems [17].

Predictive auditing relies on multi-source data, including financial records, administrative information, and external sources such as media communications and whistleblowing reports. The integration of these heterogeneous datasets, combined with preprocessing techniques (cleaning, normalization, anonymization), ensures data quality and compliance with privacy regulations. The framework leverages AI and Big Data tools such as Machine Learning for fraud detection, Natural Language Processing for text analysis, and Big Data Analytics for real-time and predictive insights. Additionally, Robotic Process Automation enhances efficiency by automating repetitive tasks, enabling continuous and predictive auditing.

The study proposes a four-layer model (data, processing, intelligence, and decision) integrating AI, Big Data, and human expertise to enable predictive, continuous, and reliable auditing systems. This framework emphasizes transparency, reliability, scalability, and ethical compliance, and is validated through case studies and simulations to provide real-time, forward-looking insights for decision-makers.

4 Toward a Smart and Predictive Control System

The integration of Artificial Intelligence (AI) and Big Data Analytics (BDA) in auditing enables the transition from traditional retrospective approaches to **smart and predictive control systems**. Such systems are designed not only to verify past compliance but also to forecast risks, identify anomalies in real time [18], and enhance decision-making through intelligent automation. This section develops a conceptual architecture of the proposed system, highlights its key functionalities, and illustrates practical applications through international examples.

4.1 Conceptual Foundations of Smart Auditing

A smart and predictive auditing system builds on the premise that auditing should be continuous, proactive, and risk-oriented [9]**.**Unlike traditional audits that rely on periodic reviews, predictive auditing emphasizes:

- **Timeliness** – real-time analysis of transactions and administrative activities.
- **Predictive intelligence** – use of AI algorithms to forecast irregularities and fraud.
- **Automation** – reduction of human intervention in repetitive and mechanical tasks.
- **Decision support** – dynamic dashboards and scenario-based insights for auditors and policymakers.

These principles align with the broader movement toward **continuous assurance** in auditing [12], which is now empowered by the scalability of Big Data and the intelligence of AI-driven models.

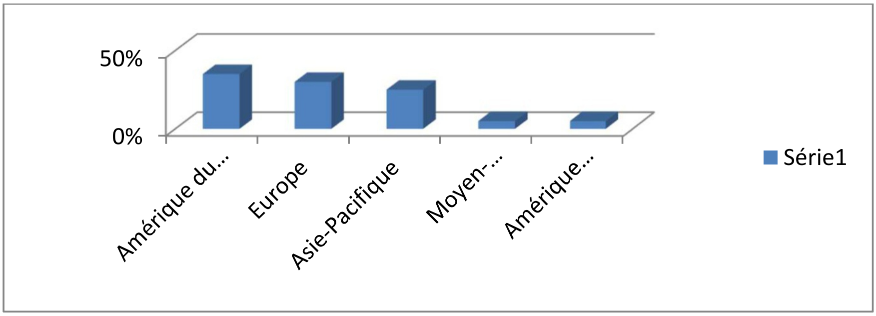

Fig.2. Geographical Distribution of AI Use in Auditing (2024)

Source: Authors' elaboration based on Scopus database data (2024).

North America and Europe dominate the adoption of AI in auditing, together accounting for 65% of total use, followed by the Asia-Pacific region. Emerging regions show slower adoption but are expected to experience significant growth prospects **(see fig. 2).**

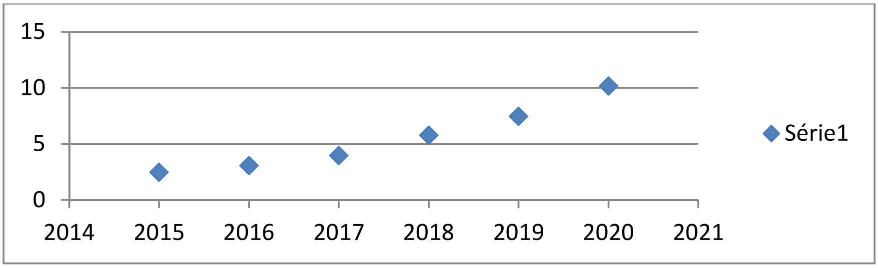

Fig.3. Investissements mondiaux en Big Data & IA pour l'audit (2015–2020)

Source: Authors' elaboration based on bibliometric data extracted from the Scopus database on AI and auditing research publications (2015–2020).

Investments have increased more than twelvefold in less than a decade, confirming the growing strategic importance of AI and Big Data in control and auditing functions **(see fig. 3).**

4.2 System Architecture

The proposed smart auditing system is structured around five integrated components: data acquisition and integration, an analytical engine, risk prediction and scoring, a visualization and decision-support interface, and a feedback and learning module. These components collectively enable real-time data processing, anomaly detection, predictive risk assessment, and interactive reporting. This modular architecture ensures scalability, adaptability, and transparency across different organizational and regulatory environments.

4.3 Key Functionalities

The smart system performs several interrelated functions [8]:

- **Anomaly Detection**: AI algorithms identify deviations from expected financial or administrative patterns, flagging potentially fraudulent or erroneous activities [3].
- **Predictive Risk Forecasting**: Models project potential compliance breaches, fraud, or financial distress, enabling proactive intervention [11].
- **Continuous Auditing and Monitoring**: Automated routines verify transactions in real time, minimizing audit lag and improving oversight [1].
- **Automated Reporting**: The system generates dynamic, customized audit reports for stakeholders, ensuring timely communication and transparency.
- **Decision Support**: Dashboards provide actionable insights to guide auditors, managers, and policymakers in risk management and resource allocation.

Criterion	Traditional Auditing	AI-Based Auditing
Average Duration (days)	**30**	**7**
Average Cost (USD)	**120,000**	**60,000**
Accuracy (%)	**70%**	**92%**
Fraud Detection (%)	**55%**	**85%**

Table.1. Comparison Between Traditional Auditing and AI-Based Auditing (2024)
Source: Authors' synthesis based on findings reported in the auditing and artificial intelligence literature.

AI significantly reduces the time and cost of audits while improving accuracy and fraud detection, supporting its widespread adoption (see table 1).

4.4 Practical Applications and Case Studies

Several international cases illustrate the feasibility and impact of predictive audit systems:

- **Private Sector: PwC and Deloitte**
  Major audit firms have developed AI-powered platforms, such as PwC's *Halo* and Deloitte's *Argus*, which analyze vast amounts of transactional data to detect anomalies and predict risks. These systems demonstrate the shift from manual sampling to population-wide, continuous auditing [14].
- **Public Sector: U.S. Government Accountability Office (GAO)**
  The GAO has piloted the use of data analytics to monitor federal spending programs, identifying suspicious procurement patterns and predicting areas prone to mismanagement [19].
- **Banking Sector: Anti-Money Laundering (AML)**
  Financial institutions globally use predictive analytics and AI models to detect money laundering and terrorist financing activities. By scoring transactions based on suspicious patterns, banks improve compliance with international regulations [10].
- **Emerging Economies: Brazil and India**
  In Brazil, AI-enabled auditing systems monitor public procurement contracts to de-

tect irregularities, while India's tax authorities employ machine learning to predict fraudulent claims in the Goods and Services Tax (GST) system [5] .These examples highlight the versatility of predictive auditing systems across private, public, and financial domains.

4.5 Benefits of the Smart System

The advantages of predictive auditing include [20]:

- Efficiency: Automation reduces audit costs and resource requirements.
- Accuracy: AI algorithms improve fraud detection and minimize false negatives.
- Proactivity: Predictive models anticipate risks before they materialize.
- Transparency: Continuous reporting enhances accountability to stakeholders.
- Scalability: Systems can be applied across sectors and adapted to different regulatory frameworks

4.6 Challenges and Constraints

Despite its benefits, the adoption of predictive auditing systems faces several challenges:

- **Data Governance**: Ensuring accuracy, privacy, and ethical use of sensitive information.
- **Algorithmic Transparency**: Addressing the "black box" problem of AI decision-making.
- **Cybersecurity Risks**: Protecting audit systems from external threats and data breaches.
- **Human Factors**: Training auditors to interpret and validate AI-driven insights.
- **Regulatory Adaptation**: Updating audit standards and legal frameworks to incorporate predictive technologies.

These challenges underscore the need for a balanced approach that combines technological innovation with strong governance and ethical safeguards.

5 Conclusion

The smart and predictive control system marks a major shift in auditing, moving from retrospective analysis to proactive and forward-looking oversight through AI and Big Data. These technologies enhance audit quality by improving efficiency, detecting fraud more accurately, and providing strategic insights for decision-making. They also transform the auditor's role into that of a data-driven advisor, requiring new digital and analytical skills. However, successful implementation depends on addressing challenges such as data governance, transparency, and ethical concerns. Ultimately, AI-driven auditing represents a strategic evolution toward more transparent, efficient, and accountable governance system.

References

1. M. A.vasarhely, A. Kogan and B. Tuttle, "Big Data in acconting, an overview," *Accounting Horizons,* vol. 29, no. 2, pp. 381-396, 2015.
2. M. Shreyer, T. Sattarov, D. Borth, A. Dengel et B. Reimer, «Detection of anomalies in accounting data using deep autoencoders,» *arXiv,* vol. abs, n° 1https://doi.org/10.48550/arXiv.1709.05254, p. 15, 2017.
3. H. Issa, T. Sun and M. A.Vasarhelyi, "Research ideas for artificial intelligence in Auditing," *journal of Emerging technologies in Accounting,* vol. 13, no. 2, pp. 1-20, 2016.
4. Y. Kyunghee, L. Hoogduin and Z. Li, "Big data as complementary audit evidence," *AccountingHorizons,* vol. 29, no. 2, pp. 431-438, 2015.
5. World Bank, "World Development Report 2021: Data for Better Lives," World Bank, Washington, DC, 2021.
6. J. Kokina et T. H.Davenport, «The emergence of Artificial Intelligence in auditing,» *Journal of Emerging technologies in accounting,* vol. 14, n° 1, pp. 115-122, 2017.
7. H. Brown-Liburd, H. Issa and D. Lombardi, "Behavioral implications of big data's impact on Audit judgment and deccision making," *Accounting Horizons,* vol. 29, no. 2, pp. 451-468, 2015.
8. L. Qiang, M. A.Vasarhelyi and A. Kogan, "The impact of artificial intelligence on auditing," *International journal of digital accounting research,* vol. 20, no. 1, pp. 1-20, 2020.
9. A. Gandomi and M. Haider, "Beyond the: Big Data concepts, methods, and analitics.," *International journal of information Management,* vol. 35, no. 2, pp. 137-144, 2015.
10. S. Ting, Q. and W. Gang, "Data miningfor money launderingdetection," *journalof financial crime,* vol. 25, no. 2, pp. 373-389, 2018.
11. M. G.Alles, "Drivers of the Use and facilitators and obstacles of the evolution of big data by the audit profession," *Accounting Horizons,* vol. 29, no. 2, pp. 439-449, 2015.
12. M. A.Vasarhely and F. B.Halper, "The continuous audit of online systems," *Auditing: A journal of practice and theory,* vol. 10, no. 1, pp. 110-125, 1991.
13. Z. Juan , Y. Xiongsheng et D. Appelbaum, «Toward Effective Big Data Analysis in Continuous Auditing,» *Accounting Horizons,* vol. 29, n° 12, p. 469–476, 2015.
14. PwC, «The audit of the future: Harnessing AI and analytics,» PwC global report, ., 2021.
15. J. D.Warren, K. C.Moffitt and P. Byrnes, "How big data will change accounting," *Accounting Horizon,* vol. 29, no. 2, pp. 397-407, 2015.
16. . Q. Liu, M. A. Vasarhelyi et A. Kogan, «The Impact of Artificial Intelligence on Auditing,» *International Journal of Digital Accounting Research,* vol. 20, n°0 1, pp. 1-20, 2020.
17. A. R. Hevner, S. T. March, J. Park et S. Ram, «Design Science in information systems Research,» *MIS quarterly,* vol. 28, n°1, pp. 75-105, 2004.
18. . E. Bogdani, M. Causholli et . R. Rakipi, «Data Analytics Adoption, Social Support, and Internal Auditor Performance,» *Auditing: A Journal of Practice & Theory,* vol. 14, n° 01:110, p. ., 2024.
19. United states Governement accountability offie, "Using data analytics to adress oversight challenges in federal spending.," U.S Governement accountability office, Washington, DC, 2019.
20. E. Bogdani, M. causholli et R. Rakipi, «Data analytics adoption, social support, and internal auditor performance.,» *Auditing: a journal of practice and theory,* vol. 3, n° 11, pp. 158-230, 2024.