ARTIFICIAL INTELLIGENCE APPLICATIONS IN AUDITING PROCESSES IN THE BANKING SECTOR

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Abstract

This research provides an in-depth examination of the role artificial intelligence (AI) plays in revolutionizing bank auditing and quality control processes. By integrating AI technologies, the banking industry stands on the edge of a transformative era where the efficiency, accuracy, and security of auditing operations are significantly enhanced. This systematic mapping study (SMS) explores the extent of AI's adoption in bank audits, specific areas of its application, its impact on auditing processes, challenges, and the dynamics of human-AI collaboration in auditing. The findings reveal AI's pivotal roles in enhancing credit risk analysis, operational efficiency, fraud detection, cybersecurity, and bankruptcy prediction, through analyzing complex data, identifying patterns, and ensuring financial stability, which leads to streamlining operations, detecting fraudulent activities through advanced pattern recognition, boosting cybersecurity measures, and accurately forecasting bankruptcy risks, thereby offering a robust tool for risk management and decision-making in the banking sector. By filling a critical gap in the literature, the study advances our understanding of AI's capabilities, limitations, ethical considerations of AI integration, and the need for further research to overcome technological challenges and ethical dilemmas. The comprehensive analysis offers valuable insights for academic debate, businesses, and regulators to enhance the quality, efficiency, and security of financial auditing practices in the digital age.

Keywords: Systematic Mapping Study, Artificial Intelligence, Bank Auditing, Fraud Detection, Risk Assessment

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1. INTRODUCTION

The emergence of artificial intelligence (AI) has marked a new era in various sectors, with the banking industry being one of the most significantly impacted. The integration of AI into banking operations, particularly in auditing and quality control, is not just an enhancement but a revolutionary transformation that will redefine the landscape of bank services. Structured to provide a cohesive and thorough exploration of AI's role in bank auditing, the research unfolds across several key sections (Cavus et al., 2021; Met et al., 2023).

This research explores the fine details of how AI technologies are being employed to elevate auditing practices within banks, focusing on the multifaceted roles AI plays in augmenting efficiency, accuracy, and overall quality of auditing processes. With the banking sector at the forefront of adopting digital innovations, the application of AI in auditing represents a critical intersection of technology and financial oversight. The mechanisms through which AI technologies contribute to the enhancement of auditing quality, risk assessment (Mehta et al., 2021; Milojević & Redzepagic, 2021), fraud detection (Kitchenham & Charters, 2007), and operational efficiency (Han et al., 2023; Mhlanga, 2020) within banks are examined. The significance and timeliness of this research are highlighted by its focus on AI's capability to navigate the complexities introduced by the digitalization of financial transactions. Through the automation of routine tasks, in-depth analysis of extensive datasets, and identification of obscure patterns, AI technologies offer a robust response to emerging cybersecurity threats and escalating regulatory requirements (Amzile & Habachi, 2022; Cai et al., 2022; Shahbazi & Byun, 2022).

The research embarks on a thorough exploration of the integration of AI in bank auditing processes, guided by a series of research questions (RQs) aimed at understanding AI's application in this crucial financial sector. These questions are pivotal for identifying the scope and trajectory of AI within banking audits, thereby shaping the study's direction and objectives. The first RQ (*RQ1*) probes the extent of the current level of AI adoption and integration in auditing practices within banks. This inquiry is foundational, offering a baseline to assess the adoption rate and readiness of the banking sector towards embracing AI for auditing purposes and identifying gaps and opportunities for enhancing auditing efficiency and effectiveness. The second RQ (*RQ2*) aims to identify specific areas utilizing AI in bank auditing where AI technologies are applied. The significance of this question lies in its ability to pinpoint where AI is making the most impact, thereby allowing for a targeted analysis of AI's contributions to auditing practices. The third RQ (*RQ3*) aims to assess the impact of AI on auditing processes, particularly how AI integration influences the efficiency, accuracy, and overall effectiveness of auditing practices. This aspect is important for quantifying AI's value proposition, providing concrete evidence of the benefits and potential drawbacks of AI adoption in bank auditing. The fourth RQ (*RQ4*) aims to recognize the obstacles and limitations associated with deploying AI in bank auditing essential for a balanced understanding of AI's practicality in this domain surfacing technical, ethical, and operational challenges, offering insights into the complexities of AI integration in a highly regulated environment. The fifth and final RQ (*RQ5*) aims to explore the dynamics of human-AI collaboration in ensuring ethical and responsible auditing practices. By addressing these questions, the research strives to offer valuable insights into the strategic integration of AI in bank auditing, thereby informing both academic and practical developments in the field. These insights include a few themes. First, risk assessment where AI's role in enhancing credit risk analysis and scoring accuracy demonstrates its ability to improve financial stability and access. Advanced AI techniques, including neural networks and machine learning algorithms, have shown superior performance in forecasting financial defaults and assessing creditworthiness, thereby bolstering the banking sector's risk management capabilities. Second, is operational efficiency where the study highlights AI's contribution to streamlining bank operations through automation and data analytics. By identifying inefficiencies and optimizing resource allocation, AI technologies enable banks to focus on strategic growth areas, thereby enhancing overall service quality and profitability. Third, fraud detection demonstrates AI's advanced pattern recognition capabilities as a pivotal role in detecting and preventing fraudulent activities. By analyzing big volumes of transactional data in real-time, AI algorithms can instantly identify anomalies indicative of fraud, significantly reducing potential financial losses and enhancing the security of banking transactions. Fourth cybersecurity, the research points to AI's critical role in fortifying cybersecurity measures within the banking sector. Through predictive analytics and machine learning, banks can proactively identify and mitigate cyber threats, safeguarding sensitive financial information and ensuring customer trust. Fifth bankruptcy prediction, AI's predictive modeling capabilities extend to forecasting bankruptcy risks with greater accuracy. By leveraging logistic regression and neural networks, AI provides banks with valuable insights into financial stability, enabling more informed decision-making and risk management.

The study's significance lies in its contribution to filling a critical gap in the literature by providing an in-depth examination of AI's multifaceted roles in bank auditing. It not only demonstrates the practical benefits and challenges associated with AI's implementation in this domain, but also highlights the need for further research to address technological limitations, such as data privacy, model transparency, and integration with existing banking systems. By advancing our understanding of AI's capabilities and constraints, this research plays a vital role in guiding future technological adoption, ethical considerations, and regulatory frameworks within the banking industry, thereby enhancing the robustness, efficiency, and security of financial auditing practices.

Furthermore, the study sheds light on the technological limitations and challenges that accompany AI implementation, offering a balanced perspective on the path forward and a conceptual framework. AI offers a solution to these challenges, providing tools that can automate repetitive tasks, analyze big datasets with unprecedented speed, depth, and accuracy, and identify patterns and anomalies that human auditors might overlook. This research is particularly relevant in the context of growing cybersecurity threats and regulatory demands, where the capabilities of AI can significantly enhance the resilience and compliance of banking institutions.

In summary, this research offers valuable insights into the integration of AI in bank auditing, illustrating both the immense potential and the challenges of leveraging AI in financial oversight. By highlighting specific applications, outcomes, and future directions, this study contributes to the broader understanding of AI's role in enhancing the quality and efficiency of banking services, paving the way for more informed and innovative approaches to auditing in the digital age.

The research is structured as follows. Section 2 provides a review of the literature. Section 3 presents an overview of the methodology used in the study. Section 4 illustrates the results. Finally, Section 5 concludes and suggests future research directions.

2. LITERATURE REVIEW

The integration of AI into the banking sector has become a central focus of research, presenting a landscape rich with both opportunities and challenges (Anshari et al., 2020; Ghandour, 2021; Kaur et al., 2020; Talwar et al., 2017; Vijai, 2019). This transformative era is significantly impacting various aspects of the banking industry, including the field of bank auditing which reveals several interconnected opportunities that are particularly relevant to bank auditing. One of the most prominent opportunities AI presents in banking is automation. AI's ability to automate repetitive and time-intensive tasks through intelligent robotic assistants holds great promise for bank auditing. The auditing process often involves examining through vast volumes of financial data to identify discrepancies or fraudulent activities. AI-driven automation can efficiently streamline this process, significantly reducing the time and effort required for audits. This, in turn, leads to substantial cost savings and increased productivity for auditors (Königstorfer & Thalmann, 2020; Vijai, 2019) it not only increases efficiency but also enables auditors to allocate their time and resources more effectively to focus on more complex and value-added aspects of their work.

Cybersecurity is a paramount concern in banking, AI can play a crucial role in fortifying the security of financial transactions. The application of AI technologies, such as machine learning and predictive analytics, empowers banks and, by extension, auditors, to proactively detect and prevent suspicious financial activities. This enhanced cybersecurity is indispensable for identifying and preventing fraudulent transactions (Ghandour, 2021). For auditors, AI-driven security measures provide an added layer of protection in their efforts to ensure the integrity of financial records and transactions (Kaur et al., 2020; Königstorfer & Thalmann, 2020; Mhlanga, 2021). As auditors rely on accurate and secure financial data, AI's role in enhancing cybersecurity is vital to their work. Moreover, AI has a mediating role in enhancing the perceived usefulness of forensic auditing services (FAS) for tracking down financial fraud and scams within the banking sector. Auditors are the frontline defense against financial fraud, and AI provides them with advanced tools to effectively identify and combat fraudulent activities. The insights derived from this research can empower auditors (Mehta et al., 2021). AI assists auditors in identifying red flags and streamlining the often meticulous and comprehensive transaction analysis required in forensic audits, thereby reducing the risk of errors stemming from the extensive data involved in accounting processes.

The accounting information systems (AIS) within the banking sector have been reshaped using AI. Conducted in the context of quality and control in Jordanian banks found that AI dimensions positively influence various aspects of AIS excellence, including customer information control, security levels, automated banking information integration, quality of accounting information integration, and customer account information protection. For auditors, this means that AI empowers them with AIS systems that provide enhanced control, aid in decision-making, and facilitate error management. These systems seamlessly adapt to their knowledge environments, which is helpful for auditors responsible for ensuring the accuracy and reliability of financial information for their audit procedures. The ability of AI to autonomously address issues and generate financial statements in accordance with international reporting standards contributes to the overall excellence of AIS in the financial sector (Ali et al., 2022; Haddad, 2021).

AI ensures that financial data is secure, shared, verified, and consensus driven, through technologies like blockchain and machine learning, thus enhancing the quality control of this data. This is paramount for auditors who rely on the accuracy and reliability of financial information for their audit procedures (Han et al., 2023). The role of AI in promoting data accuracy and compliance within financial statements is indispensable for auditors who seek to provide assurance about the financial health of the institutions they audit (Kaur et al., 2020; Kumar et al., 2020; Lui & Lamb, 2018). Although AI does not replace the human touch in auditing, it complements the work of auditors by summarizing red flags and simplifying forensic audits. It aids in handling extensive data involved in accounting processes, making auditing more efficient. Auditors continue to provide the analytical and judgmental decisions necessary for accurate financial assessments. The collaboration between humans and AI systems is becoming a key element in improving the quality of audits and ensuring that all financial irregularities are addressed (Ali et al., 2022; Cavus, 2021). The adoption of AI-based systems in the banking sector, including in audit processes, enhances client trust. Clients benefit from the convenience and transparency of AI-based services, which can lead to a positive perception of the bank's auditing practices. On the other hand, clients are more likely to trust a bank that employs advanced AI systems to ensure the accuracy and security of their financial transactions. This trust is essential for the long-term success of banks and auditors who play a crucial role in maintaining trust in the industry (Abusalma, 2021; Ali et al., 2022; Kaur et al., 2020; Malali & Gopalakrishnan, 2020).

Accordingly, the integration of AI into the banking sector has far-reaching implications for various aspects of bank auditing. Researchers have extensively explored the role of AI in improving efficiency, enhancing cybersecurity, and reshaping the practices of auditors (Königstorfer & Thalmann, 2020; Vijai, 2019). Furthermore, AI's impact on AIS excellence and its mediating role in FAS are emerging areas of interest in the literature (Mehta et al., 2021). The collaborative relationship between AI and auditors is positioned as a key element in improving the quality of audits and building client trust industry (Ali et al., 2022). These interconnected themes underscore the significance of AI in reshaping bank auditing practices and lay the foundation for further research in this domain. The adoption of AI in banking has the potential to revolutionize the auditing profession and significantly enhance its ability to protect the integrity of financial transactions and records, thereby contributing to the overall health and stability of the banking sector. As banking institutions and auditors continue to embrace AI, it is likely that the auditing landscape will continue to evolve, providing new opportunities and challenges for the industry (Anshari et al., 2020; Cai et al, 2022; Kaur et al., 2020; Talwar et al., 2017; Vijai, 2019). This dynamic interplay between AI and banking auditing will undoubtedly be a subject of ongoing research and practical application in the coming years.

In conclusion, while the application of AI in bank auditing has been discussed in terms of efficiency, cybersecurity, and transformative auditing practices, there remains a critical gap in understanding the precise effects of AI on the auditor's decision-making process and the ethical implications thereof. Despite significant advancements, the differential impact of AI across various scales of banking operations and its integration with traditional auditing tools are not well-documented. Moreover, the evolving regulatory landscape and its response to rapid AI adoption presents a fertile ground for further empirical studies. Thus, this research aims to not only fill these gaps by exploring under-researched areas such as the influence of AI on auditing ethics and decision-making but also to assess the consistency of AI application in differing regulatory environments. This exploration is vital for developing a comprehensive framework that can guide the integration of AI in bank auditing practices effectively and ethically.

3. METHODOLOGY

In this study, we employed a systematic mapping study (SMS) methodology, a variant of systematic literature review (SLR) introduced by Kitchenham and Charters (2007), to assess the current understanding of AI applications within the realms of banks and bank auditing. This methodology was chosen for its efficacy in critically and comprehensively evaluating and categorizing themes and revealing the evolutionary path of the topic as it identifies themes, trends, relationships, or patterns that emerge from the literature. This research generally aims to discern trends and suggest potential research gaps for future directions and exploration.

Aligned with the systematic mapping process SMP advocated by Petersen et al. (2008) and Petersen et al. (2015), the study adhered to specific steps. It commenced with the formulation of RQs to guide the investigation, followed by a pilot search for primary studies to refine the search string. Subsequently, a thorough search collected all pertinent papers and then applied keywording of the abstracts to do the systematic analyses. This systematic approach ensures a comprehensive overview of the researched area and serves to identify avenues for future research, in line with the methodology's objectives.

3.1. Research questions

The first step of the SMP is to define RQs and to overview a wide range of available topics related to AI applications in auditing in banks. The RQs outlined below aim to analyze all peer-reviewed research available on the intersection of AI applications in banks and auditing in the banks:

RQ1: What is the current level of adoption of AI in auditing practices within the banking sector?

Understanding the current state of AI adoption is crucial for providing a baseline assessment. It helps identify the extent to which banks are integrating AI into their auditing processes, setting the stage for further exploration of specific areas and impacts.

RQ2: Which specific areas within auditing for banks are utilizing AI technologies?

This question aims to identify the key focus areas where AI is being applied in auditing within the banking sector (themes).

RQ3: How does the integration of AI impact the efficiency, accuracy, and effectiveness of auditing processes in the banking sector?

Evaluating the impact of AI on auditing processes is essential for understanding its practical implications. This question examines the specific aspects of efficiency, accuracy, and overall effectiveness, providing insights into the tangible benefits or challenges associated with AI implementation.

RQ4: What challenges and limitations are associated with the implementation of AI in auditing for banks?

This question explores the obstacles and constraints that may hinder the effective use of AI in banking audits, contributing to a more comprehensive understanding of the technology's real-world application.

RQ5: How do human auditors collaborate with AI technologies to ensure ethical and responsible auditing practices?

Exploring the role of human auditors in conjunction with AI emphasizes the importance of human-machine collaboration ensuring that ethical considerations and responsible practices are maintained in the auditing process.

3.2. Primary study search and search string

Following the formulation of RQs and the pilot search, the next step of the SMP involved conducting a comprehensive search for all relevant papers. This search was executed on February 8, 2024, covering the period from 2000 to 2023. Utilizing database and manual search strategies (Petersen et al., 2008; Petersen et al., 2015) the study primarily accessed the Scopus database to gather pertinent literature for analysis.

The study utilized data from Scopus, a comprehensive multidisciplinary database renowned for its extensive collection of peer-reviewed academic literature. Scopus is highly regarded for its accessibility, advanced search capabilities, and customizable bibliometric analysis features (Alshater et al., 2021; Goodell et al, 2021). Furthermore, Scopus versus Web of Science (WOS) offers broader coverage in terms of volume and diversity of sources, which is crucial for a comprehensive review of interdisciplinary studies that intersect technology and finance. This depth and breadth in content significantly enhance the comprehensiveness of the literature review, enabling a more robust meta-analysis and synthesis of current knowledge and trends. Additionally, Scopus's user interface and bibliometric tools are exceptionally suited for tracking citation patterns and analyzing the impact of seminal works, facilitating a deep understanding of the evolution of AI in bank auditing. This rationale aligns with the study's aim to map out a detailed landscape of the field and identify emergent research trajectories.

3.3. Search for relevant papers

After the initial identification of papers, a crucial step involved assessing their relevance to the research topic. Rigorous inclusion and exclusion criteria were defined to systematically evaluate the alignment of obtained articles with the scope of the study. This evaluation extended to titles, abstracts, and keywords, aiming to distinguish papers within or beyond the scope of the mapping study. Considering the research domain focusing on the development, application, and evaluation of AI technologies for bank audits, the study recognized the importance of incorporating additional literature to broaden the understanding and context of AI's impact on auditing practices, thus enhancing the robustness and comprehensiveness of the analysis.

The inclusion criteria for paper selection encompassed English scientific peer-reviewed articles and conference papers published between 2000 and 2023, specifically focusing on AI applications in banks' activities related to auditing. Conversely, exclusion criteria were applied to filter out papers without full-text availability, non-English publications, duplicates, and papers from other subject areas where the study was more technically oriented toward general applications of AI in the banks.

The final database search string including automated or manual application of inclusion/ exclusion criteria on title, keywords, and abstract are provided in Table 1.

During the screening process of papers for relevance, borderline cases were identified based on the title, abstract, and keywords. For such papers, a thorough examination involving reading the introduction, conclusion, and, if necessary, the full text was undertaken to ascertain their pertinence to the RQs (Ben Dhaou & Rohman, 2018). Borderline papers that were excluded primarily centered on next: 1) AI applications for the broader financial sector beyond banks, including central banks, financial trading, and/or exchanges, as well as the general economy; and 2) broader topics emphasizing regulations and legal issues as the primary focus, which deviated significantly from applications in banks related to auditing.

Additionally, a forward snowballing sampling technique was employed on the most cited papers, resulting in the inclusion of six more studies (Wohlin, 2014). The decision to implement forward snowballing was driven by the desire to focus on recent and innovative publications and to facilitate an evaluation of theoretical validity. The final quality assessment was conducted on the consolidated set of 49 primary studies.

3.4. Keywording of abstracts

In the subsequent phase of the SMP, the abstracts of the final set of pertinent papers were subjected to keywording. Keywording is an efficient method for expediting the development of a classification schema and ensuring its alignment with the existing scope of studies. The construction of the current classification schema adhered to the guidelines outlined by Petersen et al. (2008), and involved the following steps:

First, thoroughly reading abstracts to identify keywords and concepts that encapsulated the paper's contribution. In cases where abstracts did not offer meaningful keywords, the introduction and conclusion of the paper were also examined.

Second, combining sets of keywords from different papers to form a high-level comprehension of the nature and contribution of the published research. This step resulted in a set of categories representative of the encompassed studies.

Third, reading the selected papers. If a paper introduced new crucial keywords in its text, existing categories were revised Petersen et al. (2015).

Lastly, a final compilation of keywords was then organized into clusters, forming the basis for the categories in the current SMS (Petersen et al., 2008).

Table 1. Steps and results of the query

No.	*Steps of query*	*Results*
1	Applying search string on the database: (TITLE-ABS-KEY (bank*) AND TITLE-ABS-KEY ({artificial intelligence}) OR TITLE-ABS-KEY (AI))	4,181
2	Applying inclusion/exclusion criteria on the database: (TITLE-ABS-KEY (bank*) AND TITLE-ABS-KEY ({artificial intelligence}) OR TITLE-ABS-KEY (AI)) AND PUBYEAR > 2000 AND PUBYEAR < 2024 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp")) AND (LIMIT-TO (PUBSTAGE, "final")) AND (LIMIT-TO (SRCTYPE, "j") OR LIMIT-TO (SRCTYPE, "p")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "ECON"))	385
3	Applying the inclusion and exclusion criteria and treating boarder line papers.	43
4	Manual search and forward snowballing on the most cited papers.	49
5	Quality assessment.	49

4. RESULTS

In this section, we present a detailed synthesis drawn from a comprehensive SMS of forty-nine articles that studied various applications of AI in bank auditing, as explained in the methodology section. Several themes were identified from the SMS of which five main themes are presented in Table 2 with brief descriptions of each theme highlights, and the percentages of its occurrence within the 49 reviewed research, whereas Table 3 highlights the yearly trends of research themes. Moreover, Figure 1 depicts a conceptual framework for the identified themes related to AI applications in bank auditing with specific AI technologies applied. The framework and themes highlight the important roles AI plays in refining risk assessment processes, boosting operational efficiency, improving fraud detection methods, enhancing cybersecurity measures, and predicting bankruptcy with greater accuracy as related to auditing in banks. Furthermore, Table 2 shows brief details of the application of AI technologies in banks for the identified themes, supported by the relevant references, and furnishes descriptions that tie these diverse AI applications into the broader context of banking operations and strategy.

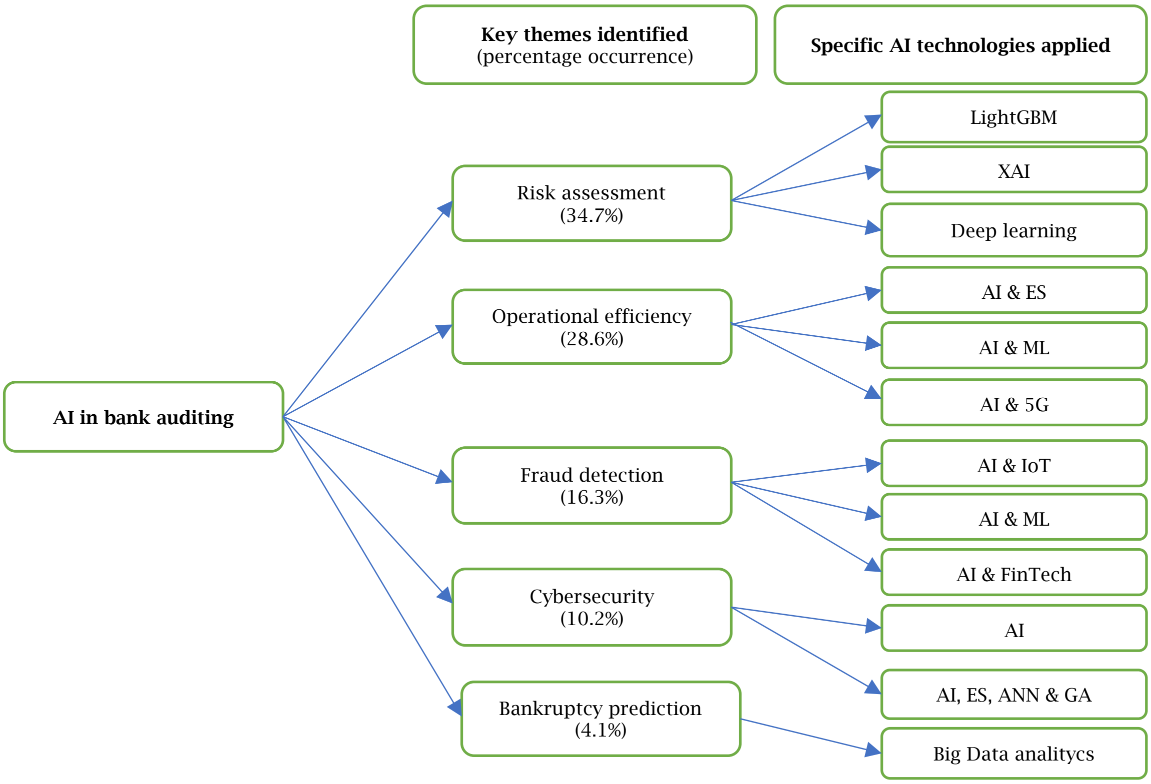
The results underscore the dynamic intersection of AI advancements and their transformative impacts on banking practices, particularly considering the challenges and opportunities that accompany the adoption of such technologies particularly in bank auditing.

Table 2. Themes related to AI applications in bank auditing

No.	*Related themes*	*Application in banks (brief details)*	*References*
1	Risk assessment (34.7%)	AI's role in credit risk analysis. AI, particularly neural networks, and decision trees, enhances credit scoring accuracy. It's pivotal for those with limited banking access, although AI's use in credit analysis invites bias concerns. The use of Light Gradient Boosting Machine (LightGBM), a type of machine learning algorithm, in conjunction with explainable artificial intelligence (XAI). This combination is used to make the process and outcomes of AI-driven credit risk predictions more understandable and transparent. XAI aims to clarify the decision-making of AI models, so integrating it with LightGBM helps users and stakeholders see why and how particular credit predictions are made. While advanced AI, including deep learning, excels in default forecasting. Deep learning outperforms standard models in predicting credit delinquency, suggesting a blend of sentiment analysis for improved risk evaluation.	Amzile and Habachi (2022), Chen and Shih (2006), de Lange et al. (2022), Heuver and Triepels (2019), Ince and Aktan (2009), Maeno et al. (2013), Mhlanga (2021), Milojević and Redzepagic (2021), Pons et al. (2023), Prisznyák (2022), Sadok et al. (2022), Shahbazi and Byun (2022), Sun and Vasarhelyi (2018), Tsakonas et al. (2006), Zang (2022), Zhou et al. (2019), Zhou (2022)
2	Operational efficiency (28.6%)	Highlighting machine learning for bank performance prediction and target setting, revealing a novel approach that increases target success and addresses seasonality issues. It details AI's impact on enhancing banking services and client trust, emphasizing AI's pivotal role in risk management and cost reduction. Service quality in Jordanian banks, improving customer satisfaction through intelligent systems. It analyzes technologies such as machine learning, and the internet of things (IoT) impact on bank service quality and profitability, highlighting the shift towards technology acceptance in the financial sector. Lastly, AI technologies can automate the tracking of regulatory changes and ensure that bank operations remain within the legal framework.	Al-Araj et al. (2022), Ali et al. (2022), Chew (2020), Cho et al. (2023), Ciampi et al. (2021), Grout (2021), Haddad (2021), Helm (2022), Hughes et al. (2022), Met et al. (2023), Sánchez-Medina et al. (2019), Song and Huang (2010), Srinadi et al. (2023), Wu et al. (2023)
3	Fraud detection (16.3%)	Machine learning techniques for detecting credit card cyber fraud were analyzed with respect to their efficiency over traditional methods. Online banking fraud, which personalizes fraud detection. Hybrid approaches for fraud detection in online transactions were explored, emphasizing the importance of machine learning models. The application of AI in criminal investigations, particularly for ATM fraud in Nigeria, and the development of secure systems in digitized economies. Additionally, it addresses the growing influence of AI and machine learning in banking risk management the financial crisis and the role of mobile banking in Islamic finance, with a focus on ethical and halal considerations in e-commerce and m-commerce.	Attigeri et al. (2018), Ayofe et al. (2010), Marazqah Btoush et al. (2023), Carminati et al. (2015), Carminati et al. (2018), Jovanovic et al. (2022), Vilar et al. (2015), Yazid et al. (2023)
4	Cybersecurity (10.2%)	The pivotal role of AI, particularly machine learning, expert systems (ES), artificial neural network (ANN), genetic algorithms (GA), and deep learning, in proactively detecting and preventing cybercrimes and financial fraud within the banking sector. The literature underscores the urgency for policymakers to adopt regulations to leverage AI and emerging technologies effectively for cybersecurity.	Al-Tahat and Moneim, (2020), Marazqah Btoush et al. (2023), Chitimira and Ncube (2021), Maeno et al. (2012), Salameh and Lutfi (2021)
5	Bankruptcy prediction (4.1%)	Corporate bankruptcy prediction models, highlighting an increasing interest post-2008 crisis, with little co-authorship among influential researchers. It focuses on Logistic Regression and Neural Networks as prevalent models, noting a rise in machine learning applications. Another study improves bankruptcy prediction using audit report data, achieving 80% accuracy with simplified methods and AI techniques, offering practical implications for users. This underscores the evolving relationship between bankruptcy prediction and external audit information.	Muñoz-Izquierdo et al. (2019), Shi and Li (2019)

Note: Numbers in parentheses in the second column are the percentages among the 49 reviewed articles. Details are in Table 3.

Figure 1. A conceptual framework for the themes related to AI applications in bank auditing with specific AI technologies applied



Note: ML — machine learning.

The review of the 49 articles resulted in a synthesis of AI in bank auditing. It highlights the following synthesis citing the related references:

- *Similarities and differences in AI utilization.* AI is used across banks for credit risk assessment and customer service, but methodologies vary, ranging from machine learning to advanced neural networks, for example (Marazqah Btoush et al., 2023; Chitimira & Ncube, 2021; Shi & Li, 2019; Votintseva et al., 2019).
- *AI and technology patterns.* AI integration with big data analytics is common, emphasizing AI's ability to process large datasets for accurate predictions and efficient operations, for example (Al-Araj et al., 2022; Cho et al., 2023; Milojević & Redzepagic, 2021; Sadok et al., 2022; Wu et al., 2023; Zhou et al., 2019).
- *Challenges and limitations.* Issues include AI model complexity, data quality needs, interpretability concerns, and regulatory hurdles. The complexity of AI models, data quality and quantity requirements, interpretability, and regulatory challenges are major concerns, for example (Desrousseaux et al., 2019; Grout, 2021; Helm, 2022; Sadok et al., 2022).
- *State of current AI adoption.* AI use is growing, especially in risk assessment, operational efficiencies, and customer service, but full integration across all functions is still evolving for example (Srinadi et al., 2023; Cho et al., 2023).
- *Benefits and threats to auditing.* AI can enhance auditing efficiency, quality, and accuracy but also raises concerns about over-reliance, biases in algorithms, and cybersecurity risk, for example (Al-Tahat & Moneim, 2020; Hughes et al., 2022; Song & Huang, 2010; Votintseva et al., 2019).

The SMS reveals diverse technologies utilized in the realm of AI applications in bank auditing, highlighting a significant reliance on AI and machine learning across various fields. The integration of AI with Big Data (Al-Araj et al., 2022; Cho et al., 2023; Milojević & Redzepagic, 2021; Sadok et al., 2022; Wu et al., 2023; Zhou et al., 2019), the IoT (Al-Araj et al., 2022), and 5G indicates a trend towards combining AI with other cutting-edge technologies to enhance analytical and predictive capabilities (Chitimira & Ncube, 2021; Zang, 2022). Applications in finance, such as through FinTech innovations, and in cryptocurrency analysis using machine learning, showcase AI's expanding footprint. Notably, there's an exploration of specialized techniques like deep neural networks (DNN), support vector machines (SVM), and fuzzy models, pointing towards a tailored approach in leveraging AI for specific problem-solving (Chitimira & Ncube, 2021; Chen & Shih, 2006; Jovanovic et al., 2022; Salameh & Lutfi, 2021; Sun & Vasarhelyi, 2018; Wu et al., 2023). While not explicitly focused on the conjunction of human auditors and AI, the integration of human and AI technologies emerges as crucial for ethical and responsible auditing. This confluence underscores a synergistic approach where AI's analytical prowess is balanced with human insight and ethical guidance (Al-Araj et al., 2022; Al-Tahat & Moneim, 2020; Ayofe et al., 2010; Chew, 2020; Haddad, 2021; Helm et al., 2022; Salameh & Lutfi, 2021; Sánchez-Medina et al., 2019).

The synthesis of AI applications in bank auditing suggests an increasing trend toward integrating machine learning and AI to enhance the accuracy and efficiency of financial assessments

(Chew, 2020, Hughes et al., 2022; Met et al., 2023; Sánchez-Medina et al., 2019; Votintseva et al., 2019; Zhou, 2022). Notably, advancements in predictive modeling for bankruptcy and credit risk, as evidenced using logistic regression and neural networks, indicate a shift towards more sophisticated, data-driven methods (Al-Araj et al., 2022; Ciampi et al., 2021; Sadok et al., 2022; Salameh & Lutfi, 2021; Sun & Vasarhelyi, 2018; Zhou et al., 2019). The adoption of AI-driven systems, such as Carminati et al. (2015), and innovations in AI for risk management and fraud detection, reflect a broader movement toward technology-enhanced financial services (Al-Gasawneh et al., 2022). The use of deep learning for credit card delinquency prediction and the development of explainable AI models for credit default prediction underscores the potential of AI to improve interpretability and reliability in banking operations (Marazqah Btoush et al., 2023; Haddad, 2021; Helm et al., 2022; Milojević & Redzepagic, 2021; Sánchez-Medina et al., 2019; Sun & Vasarhelyi, 2018). These findings demonstrate the significant contribution of AI to risk assessment, operational efficiencies, customer service, and regulatory compliance in the banking sector.

The findings from the SMS on AI applications in bank auditing suggest several technological limitations. These include: 1) data privacy and security — with AI's reliance on big data, there are significant concerns about protecting sensitive financial information against cyber threats; 2) model transparency and explainability — there is a need for explainable AI models, especially in highly regulated sectors like banking, where stakeholders must understand how AI arrives at its conclusions; 3) data quality and availability — effective AI requires high-quality data. In some instances, the availability of comprehensive and unbiased datasets is a challenge; 4) algorithmic bias — AI systems can perpetuate biases present in their training data, leading to unfair or unethical outcomes; 5) complexity and resource requirements — advanced AI models often require significant computational resources, which can be a limitation for some institutions; 6) integration with existing systems — merging AI with legacy banking systems can be complex and costly; and 7) regulatory compliance — ensuring AI systems comply with all relevant financial regulations can be challenging and restricts some aspects of technology implementation.

Further analysis regarding the trends in related research, based on the 49 reviewed articles in this study, versus the year of publication, shown in Table 3 below, indicates an upward trajectory of the number of published articles started in 2019 onwards, where most of the research so far was published in 2022. However, the apparent drop in the number of related published research in 2020 could be attributed to the prevailing conditions during the COVID-19 pandemic. Risk assessment emerges as the dominant theme, accounting for just over one-third of the published research. This capability enables auditors to prioritize areas of higher risk, making the audit process more efficient and effective. Operational efficiency, which appears to be gaining attention in the last three years 2021–2023, represents almost 30% of the published research. This can be attributed to the ability of AI in analyzing internal processes to identify inefficiencies or control weaknesses thus allowing auditors to focus on more strategic aspects of the audit. This analysis aligns with the innovative and evolving nature of AI technology in serving the auditing process in banks. Other notable areas of focus include fraud detection and cyber security. AI algorithms can analyze vast amounts of transaction data in real-time to identify patterns indicative of fraudulent activities, non-compliance, and potential risks all imperative to auditing. This not only improves the accuracy of audits but also allows for real-time fraud detection, significantly reducing the financial losses associated with fraudulent activities. Moreover, AI technologies can automate the tracking of regulatory changes and ensure that bank operations remain within the legal framework, thereby streamlining the audit process. In summary, the analysis reflects AI's growing impact and potential in transforming the banking sector.

Table 3. Trends of research themes related to AI applications in bank auditing

Year of publication	*Cyber security*	*Risk management*	*Fraud detection*	*Operational efficiency*	*Bankruptcy prediction*	*Others*	*Grand total*
2006	0	2	0	0	0	0	2
2009	0	1	0	0	0	0	1
2010	0	0	1	1	0	0	2
2012	1	0	0	0	0	0	1
2013	0	1	0	0	0	0	1
2015	0	0	2	0	0	0	2
2018	0	1	2	0	0	0	3
2019	0	2	1	1	2	1	7
2020	1	0	0	1	0	0	2
2021	2	2	0	3	0	0	7
2022	0	7	2	4	0	1	14
2023	1	1	0	4	0	1	7
Grand total	5	17	8	14	2	3	49
Percentages	10.2%	34.7%	16.3%	28.6%	4.1%	6.1%	100.0%

5. CONCLUSION

The objective of this research is to explore the application and impact of AI in bank auditing, focusing on enhancing risk assessment, operational efficiency, fraud detection, cybersecurity, and bankruptcy prediction. The study conducted an SMS of 49 articles, revealing five main themes where AI significantly contributes to the auditing process. The findings highlight AI's transformative role in improving the accuracy, efficiency, and predictive capabilities of bank audits. However, challenges such as data privacy, model transparency, and integration with legacy systems were identified. Future research directions suggest focusing on developing transparent, explainable AI models, ensuring data quality and privacy, and exploring the ethical use of AI in auditing.

The integration of AI in bank auditing is progressively expanding, notably in areas such as risk assessment, operational efficiencies, customer service, and notably, the exploration into fraud detection and cybersecurity. This trend underscores the banking sector's adoption of AI to harness enhanced financial assessments and predictive analytics, leveraging advanced technologies like machine learning and deep learning. These applications not only improve the accuracy and efficiency of audits but also pave the way for innovative financial services, including FinTech and cryptocurrency analysis.

However, the implementation of AI in auditing faces several challenges, including concerns over data privacy and security, the need for transparent and explainable models, ensuring high-quality data, addressing algorithmic biases, and integrating AI with existing systems amidst regulatory complexities. Despite these obstacles, the potential for AI to revolutionize banking audits is evident, with a growing emphasis on combining AI's analytical strengths with human auditors' insights to foster ethical and responsible auditing practices. This collaborative approach aims to balance technological advancements with the imperative for integrity and accountability in the financial auditing process.

This section outlines the multifaceted contributions and implications of the research on AI in bank auditing to both academic fields and business practices. It aims to delineate how the findings not only advance scholarly discussions but also offer practical strategies for organizations seeking to implement AI technologies effectively. The study has the following implications:

First, in research, the study expands academic dialogue as it serves as a catalyst for further scholarly inquiry into AI's applications within financial auditing, encouraging the development of advanced AI models tailored to address specific challenges like data privacy and algorithmic bias. It also highlights the need for future research focused on improving AI model transparency and explainability, thereby fostering a deeper understanding and trust in AI's decision-making processes among stakeholders. Second, in businesses, the study offers a comprehensive framework for businesses to integrate AI into auditing processes, emphasizing operational efficiencies, accuracy improvements, and strategic benefits. Moreover, advises businesses on adopting AI with a focus on ethical considerations, data protection, and compliance with regulatory standards, promoting responsible and sustainable innovation. It proposes a collaborative approach between human auditors and AI technologies, highlighting the importance of education on new technologies and adaptation for a harmonious integration, enhancing the audit process through a blend of AI's analytical prowess and human insight.

The recommendations for future research and practice in the field of AI applications in bank auditing are as follows. First, the ethical use of AI in auditing cannot be overstated. Future studies should explore the ethical frameworks and guidelines that ensure AI applications in auditing adhere to high moral standards, focusing on fairness, accountability, and transparency. Second, the intersection of AI with other emerging technologies like blockchain could revolutionize bank auditing further. Research should investigate how these technologies can be synergistically applied to enhance auditing practices, focusing on aspects such as traceability, security, and efficiency. Third, high-quality, accessible data is the backbone of effective AI applications. Future initiatives should focus on the standardization of data collection and processing methods to ensure AI systems have access to accurate and comprehensive datasets.

These recommendations highlight the multi-dimensional approach needed to advance AI applications in bank auditing, emphasizing the balance between technological advancement, ethical considerations, and practical implementation challenges.

The SMS methodology, while valuable for broadly understanding a research field, does have some limitations. SMS focuses more on mapping out the extent of research and identifying trends and gaps rather than providing in-depth analysis on specific topics. Also, conducting an SMS can be time-consuming and requires extensive resources, as it involves screening many studies to create a comprehensive map of the field. Given the broad scope, updating an SMS can be challenging as new research can rapidly change the landscape, making it difficult to keep the mapping current.

These constraints indicate that while SMS is proficient at providing a general understanding and outlining research trajectories, the results derived from such studies should be approached cautiously.

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