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Artificial intelligence's use in external auditing: Evidence from systematic literature review

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Abstract: This study examines artificial intelligence (AI) in external auditing by synthesizing existing evidence, clarifying key concepts, identifying theoretical and methodological gaps, and outlining future research directions. A systematic literature review and bibliometric analysis were conducted on 130 peer-reviewed articles retrieved from Scopus and Web of Science databases. The review followed the PRISMA 2020 guidelines, while VOSviewer was used to map research trends, and thematic clusters. Research on AI in auditing has grown substantially, with the United States, China, and the United Kingdom leading scholarly contributions. The analysis identified three dominant research streams: machine learning and fraud detection, audit analytics and big data, and AI adoption and governance. Commonly applied AI techniques include machine learning, neural networks, natural language processing, robotic process automation, and expert systems. The study suggested that AI enhances fraud detection, risk assessment, and audit quality, while raising concerns regarding algorithmic bias, transparency, and professional skepticism. The study develops an integrated framework linking AI applications to audit quality and provides a research agenda to guide future inquiry. The findings offer practical insights for auditors, regulators, and organizations seeking to implement AI responsibly and effectively in audit processes.
Keywords: *Artificial intelligence, Audit quality, External auditing, Independent audit, Machine learning.*

1. Introduction

The last ten years have seen the development of machine learning, natural language processing, and big data analytics change the ways of conducting an audit considerably by allowing auditors to leave the traditional sampling methods behind and adopt the practices of full population testing and continuous auditing. This is because the ever-increasing rate at which artificial intelligence (AI) is being diffused into auditing is an indicator of a larger change brought about by digitalization in the accounting, governance, and assurance systems. Large international accounting companies, such as Deloitte, PwC, KPMG, and EY, have been investing in home-built AI systems that are expected to help make audits more efficient, capable of detecting anomalies, and better able to assess risks [1, 2]. All these technological advances are happening in a world where there is growing regulatory oversight and pressure on the quality of audits, transparency and accountability, which are being placed on the stakeholders. As such, the introduction of AI into auditing is not just an improvement in the operation but a paradigm shift in the manner in which audit evidence can be produced, analyzed, and verified [3, 4].

The growing academic interest in AI within auditing can be seen in the high rate of scholarly publications, which, in turn, look at various applications of it based on their fraud detection to audit judgment supplementation. The bibliometric graph created using the VOSviewer analysis demonstrates that AI is the focal organizing concept that is closely connected with machine learning, auditing, and audit quality [5]. Nevertheless, the network also shows how the related constructs are spread among

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separate clusters, such as governance, ethical AI, internal controls, big data, and audit independence. This trend indicates that the field has acquired a significant breadth, but its conceptual structure is disjointed [6, 7] instead of cumulative, and the two fields remain disconnected, with the literature focusing on either technology functions or auditing results without sufficiently incorporating the other.

The quality of audits is one of the foundations of the auditing profession and a key factor that defines the credibility of financial reporting. It is usually understood as the likelihood of an auditor to detect and report material misstatements, and it involves such dimensions as auditor competence, independence, and professional skepticism [8]. The development of AI has been perceived as a possible tool to improve the quality of auditing by virtue of data processing and more advanced analytics. Some empirical evidence indicates that AI may improve the work of auditors by increasing their readiness to detect anomalies and evaluate risks with greater accuracy [9, 10]. Nevertheless, the adoption of AI and its relation to the quality of the audit is not unanimously positive. The issue of algorithmic opacity, bias, and an extreme dependence on automated systems has been raised and is considered to deteriorate the critical audit opinion and professional skepticism [11]. These conflicting views highlight the issue of the intricacy of determining the effect of artificial intelligence on audit quality.

The underlying weakness of the available literature is that it is disjointed. In a large percentage of studies, the use of technology has a technology-centric approach, meaning research that is preoccupied with creating and implementing AI tools without adequately addressing the outcomes of such tools in terms of quality and functioning of the audit. Based on the bibliometric clusters, the research on machine learning and big data analytics is not necessarily related to those studies that consider the issues of governance, ethics, and audit quality. Such a lack of connection restricts the possibility of creating a holistic view of artificial intelligence and the rest of the auditing ecosystem. Moreover, the theme of the literature is rather descriptive and exploratory with little reference to theory-based analysis. Even though the implicit reference to the theoretical perspectives, such as agency theory or institutional theory, is used by Zhang and Zhou [12], these theoretical perspectives are not applied in a systematic way to explain the mechanisms of how AI affects the audit practices and audit outcomes.

These observations are synthesized to create a critical research gap. Although the literature on the topic of AI in auditing is developing fast, rigorous empirical research that specifically links the adoption of AI to audit quality is unavailable. Zhang et al. [13] focus on technological innovation as opposed to the implications of the innovation on the effectiveness, independence, and reliability of the auditing. Furthermore, the theoretical bases of the field are still not developed, and there are few attempts to combine the views of several perspectives into a single system. This is of utmost relevance considering the multidimensional attribute of audit quality which incorporates technical accuracy, ethical factors and trust of stakeholders. It is hard to evaluate the circumstances when AI is threatening audit quality without a solid theoretical base.

More so, the literature fails to effectively define the multi-dimensional interaction between the various aspects of AI and the different elements of the auditing process. The bibliometric mapping displays these issues because such constructs as algorithmic justice, ethical AI, and governance are included in it, but not systematically combined with audit quality results. This conceptual deficit constrains the process of creating in-depth models that can explain the multidimensional impacts of artificial intelligence in auditing [14, 15].

To overcome these shortcomings, the current research will assume an integrative and holistic method, which integrates bibliometric mapping with a qualitative systematic review of the literature. With this two-fold approach, one can have precise comprehension of the research context, not only determining the structural patterns, but also the substantive content of the literature. The bibliometric analysis gives information on the intellectual organization of the discipline and identifies general themes, groups, and connections. Simultaneously, the systematic review helps to evaluate the theoretical background, methodological, and empirical results of the studies included in a critical way. The combination of these approaches allows the study to go beyond the descriptive synthesis to an in-depth theory-based framework that interrelates the methods of AI and audit quality.

This study helps to fill these gaps and, therefore, leads to the development of knowledge in the field of the intersection of AI and auditing. It provides a theoretically based and methodologically sound point of view that supplements the knowledge about the leveraging of AI to improve the quality of audits and reduce the risks involved. Moreover, it determines a definite research agenda that requires interdisciplinary methodology, a deeper integration of theory, and a more rigorous methodology. By so doing, the study is in line with the changing needs of the auditing profession and offers informative findings to researchers, practitioners, and policymakers who would be attempting to manoeuvre the challenges of auditing in the digital age.

Objectives of the study

i. To systematically map and synthesize existing empirical and theoretical research on the use of AI in external auditing.
ii. To categorize and critically evaluate the specific AI techniques applied in external audit processes.
iii. To identify the prevailing theoretical frameworks underpinning research on AI adoption in external auditing.
iv. To assess the impacts of AI implementation on external auditing quality.

2. Methodology

The methodology used in this research is aimed at guaranteeing the ability to achieve the analytical rigor, transparency, and reproducibility of the study in accordance with the academic standards. The study combines systematic literature review and bibliometric analysis to offer both content and formative understanding of the changing arena of AI in external auditing. This two-way methodological design allows identifying patterns of concepts, theoretical gaps, and methodological inconsistencies [16] and at the same time tracing the intellectual organization of the discipline.

Figure 1 below is a systematic review that complies with the PRISMA and meta-analyses 2020 protocol, which offers a standardized guideline in identifying, screening, and synthesizing studies of interest. To reduce selection bias and increase methodological transparency, the review protocol was put in place before the data were collected [17, 18]. The protocol stipulates the research objectives, inclusion and exclusion criteria, search strategy, and procedures of analysis. Two large academic databases, Scopus and Web of Science, were selected to do the literature search because of their extensive representation of high-quality peer-reviewed journals in the accounting and auditing field and information systems. These databases have been known to have reliability and indexing standards that make them the right sources of systematic reviews in interdisciplinary areas.

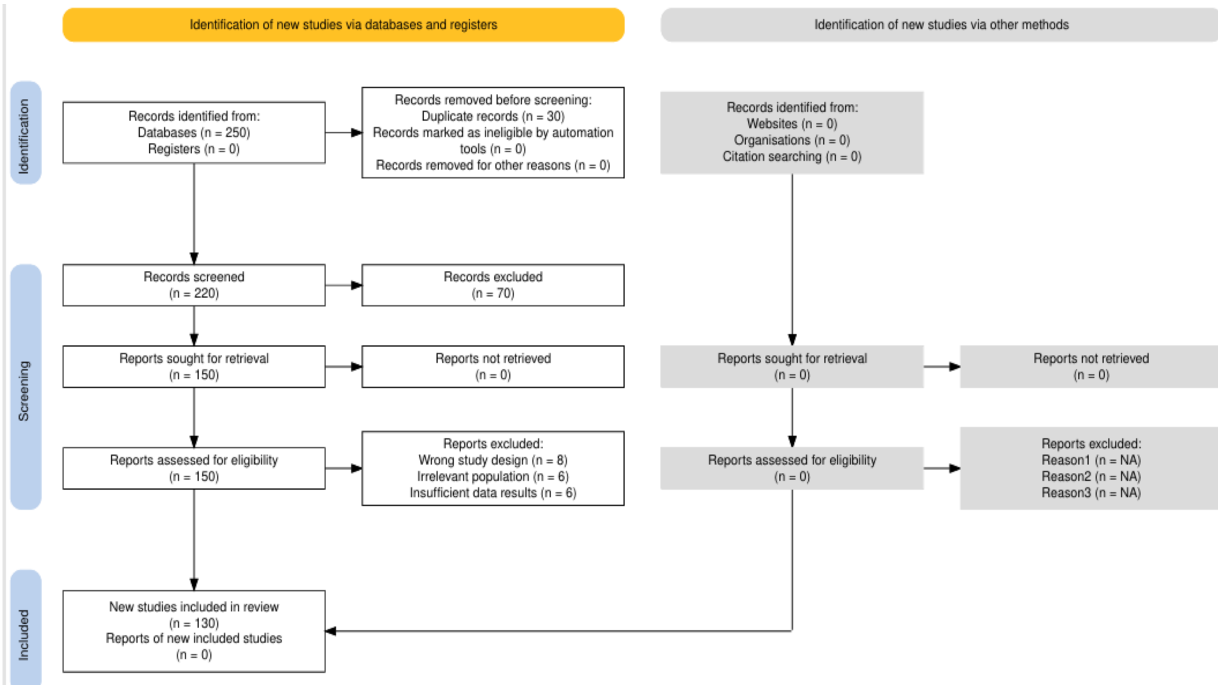

Figure 1.
PRISMA flow diagram.
Source: Generated from the PRISMA software.

The search timeframe will be between the years 2005 and 2025 and will include the beginning and the swift development of artificial intelligence applications in auditing. The beginning is the initial progress of machine learning and data analytics in accounting studies, and the end point guarantees the incorporation of the latest contributions. Only articles in English were included in order to be consistent and to be able to interpret them. Additionally, only peer-reviewed journal articles were included in the review but not conference proceedings, editorials, book chapters, and short notes. Such limitation improves the quality and reliability of the synthesized evidence as it focuses on rigorously reviewed research products.

The search strategy was developed clearly and was replicable with a Boolean search query containing the essential dimensions of AI and external auditing. The search query was developed in the following manner: (Artificial Intelligence OR Machine Learning OR Deep Learning OR Expert Systems OR Natural Language Processing) AND (External Audit OR Audit Quality OR independent audit). Such formulation guarantees that all the studies relating to the topic are covered by addressing both general and specific terms related to artificial intelligence and core audit constructs. The wildcard operators enable one to vary the terminology, and thus the chances of missing the studies are minimized. The search was done under the titles, abstracts, and keywords to ensure that maximum retrieval was made whilst being relevant.

Inclusion and exclusion criteria were established to keep the research goals and methodology in check. The studies were to be included in case they clearly analyzed the use, implications, or effects of AI in relation to external auditing. Empirical and theoretical studies have been taken into account, though they have to provide material information about the connection between AI and audit processes or outcomes. The studies that only dealt with the area of internal auditing unrelated to external audit situations were screened out. Likewise, non-peer-reviewed publications, lack of English studies, as well as insufficient methodological description or outcome data were omitted. This is a controlled filtering process that will ensure that the end sample is of high quality and contributes to the field.

The screening was done in several phases in order to be accurate and consistent. First, redundant records were detected and eliminated, leaving refined data to screen. Titles and abstracts were then checked so as to eliminate studies that failed to pass the inclusion criteria. Final eligibility was then carried out by carrying out full-text assessments. The procedure led to 130 studies in the final review after the elimination of studies that had inappropriate research design, irrelevant population, and lack of outcome data. To increase reliability, two independent reviewers were used in the screening process by comparing each study with the predefined criteria. Any discrepancies between the reviewers were decided by discussion and consensus, and in cases where it was felt appropriate, a third reviewer was consulted. To measure inter-rater reliability, the Cohen Kappa coefficient was used, and the result showed a great degree of agreement, hence validating the selection process.

Bibliometric analysis was done in parallel to the systematic review to map the intellectual structure and development of the field in terms of themes. The bibliometric data were collected using Scopus in a comma-separated values format that is supported by bibliometric software. VOSviewer, which is a popular tool for constructing and visualizing bibliometric networks, was used to conduct the analysis [19]. Keywords co-occurrence, patterns of co-citation, and co-authorship network were the units of analysis, which made it possible to use a multi-dimensional analysis of the literature. The analysis of the co-occurrence of keywords was given special focus because it gives information on the conceptual framework of the field as well as on the thematic associations.

The keywords had a minimum occurrence threshold of five to make sure that only meaningful and non-repetitive keywords were used in the analysis. It is a balance that is comprehensive and yet clear, as it eliminates relatively rare or peripheral terms that can bring noise into the network. The subsequent visualization shows some specific clusters, which represent the thematic areas in the overall area. As an example, one group is based on AI and machine learning methods, the other group is based on audit quality and governance, and the other group is based on ethical considerations, internal controls, and big data analytics. The clustering was produced by the association strength normalization method that calculates the strength of the items' relationship using the frequency of their co-occurrence. The process is especially appropriate when meaningful relationships are sought in complex bibliometric networks where differences in the frequency of terms are taken into consideration, and where items that have strong relationships are pooled.

Bibliometric analysis and systematic review combine the quantitative and qualitative methods in the integration of both approaches, which makes the methodology stronger. Whereas the systematic review helps to provide the study with the detailed analysis of the specific studies, bibliometric analysis offers a macro-level view on the organization and development of the research area. This complementary strategy allows the research clusters, emerging trends, and gaps to be identified, and may not be clear when the traditional literature review methods are used alone. Moreover, it helps to build a theory-based framework as it helps to connect empirical evidence to more general patterns of concepts. The given methodological rigor is an excellent basis that allows addressing the research goals and is a contribution to the development of academic knowledge on AI in external auditing.

3. Results

VOSviewer model can be used to obtain a visual representation of the intellectual structure of AI in auditing through mapping the co-occurrence and co-citation relationships of keywords, authors, and publications. The model, with the help of the association strength normalization technique, detects clusters disclosing thematic concentrations, such as machine learning and fraud detection, audit analytics with big data, and AI adoption with governance in mind. The conceptual relationships and fragmentation made by this mapping demonstrate how the technical, organizational, and ethical dimensions are spread throughout the literature. The visualization enables researchers to find out the prevalent topics as well as influential research and gaps, thus enabling researchers to get in depth on the research scope.

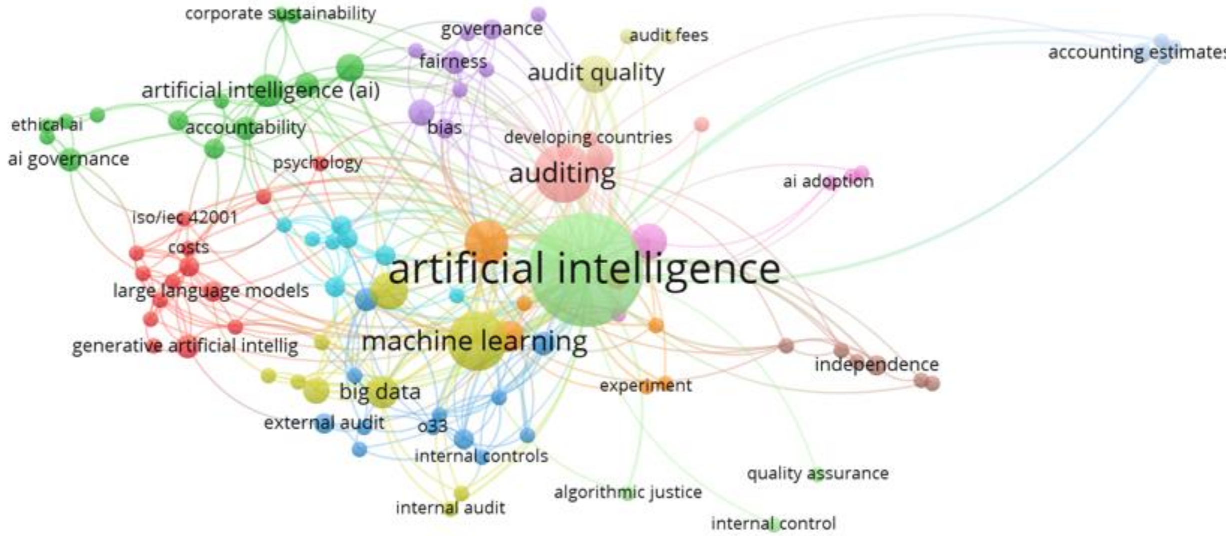

Figure 2.
Research model.
Source: Generated from VOSviewer software.

3.1. Descriptive Statistics

The descriptive review of the 130 identified papers demonstrates a sharp increase in academic interest in AI in external auditing, specifically in the post-2018 era. Such growth is consistent with the increasing institutionalization of data analytics and AI applications in the auditing practice and the regulatory support of assurance processes based on technology. The prior studies were more conceptual compared to the recent studies, which exhibit a higher empirical orientation but still lack methodological rigour.

The journal distribution portrays that the publications are centralized in the quality journals like Accounting Horizons, Journal of Emerging Technologies in Accounting, and International Journal of Accounting Information Systems. This focus indicates the field is becoming legitimate in mainstream accounting studies. The United States is the leading producer of research by geographical region, followed by China and the United Kingdom, which is attributed to both the technological capability and attention to audit innovation by regulatory bodies. Also, citation analysis further recognizes seminal contributions that define the field. The initial literature supports the revolutionary purpose of big data and artificial intelligence in auditing, especially audit effectiveness and decision-making procedures [20]. Nevertheless, the intellectual concentration implied by the prevalence of a few studies with a high number of citations also indicates the limitation of diversity in theories.

Table 1.
Annual distribution of publications.

Year Range	Frequency	Percentage (%)
2005–2010	8	6.2
2011–2015	22	16.9
2016–2020	45	34.6
2021–2025	55	42.3
Total	130	100

3.2. Bibliometric Mapping Results

3.2.1. Keyword Co-Occurrence Analysis

The VOSviewer analysis reveals three dominant clusters that structure the intellectual scope of AI in auditing.

3.2.1.1. Cluster 1: Machine Learning and Fraud Detection

This cluster is focused on machine learning, AI, and fraud detection. It is highly technical in its orientation, and research activities have been centered on predictive modeling and anomaly detection. The focus on fraud detection conforms to the historical purpose of the audit with regard to detecting material misstatements and indicates that AI is mainly used to improve detection capabilities. The effectiveness of machine learning models in enhancing the accuracy of fraud detection on the basis of empirical evidence is supported by the fact that machine learning models outperform traditional statistical methods.

3.2.1.2. Cluster 2: Audit Analytics and Big Data

The second group brings into the spotlight the adoption of big data and audit analytics into the audit. In this stream, the focus of attention is on continuous auditing, data mining, and real-time assurance. The results imply that the use of AI is becoming entrenched in the larger data analytics systems that allow auditors to handle large amounts of structured and unstructured data. But issues like data quality, integration, and governance remain, which stifle the full utilization of these technologies.

3.2.1.3. Cluster 3: AI Adoption and Governance

The third cluster is concerned with governance, ethical matters, and the quality of the audit. It is an indication of the increasing worry over the institutional and ethical aspects of the use of AI. Research in this cluster focuses on the problems of accountability, transparency, and compliance with the regulations. The similar distance between this cluster and technical clusters implies that technology innovation and governance systems do not integrate, and this argument supports the conceptual fragmentation argument.

3.2.2. Co-citation Analysis

The co-citation analysis demonstrates that there are three streams of theory that are dominant. To start with, there is the adoption of the theory of technology, especially the Technology Acceptance Model, which is often utilized to explain the adoption of AI tools. Second, the agency theory is used to investigate the implications of AI on audit quality and independence. Third, resource-based theory views AI as a strategic potential to improve audit performance. Although these theoretical streams are relevant, they are not often combined, so the explanation of the adoption and impact of AI is fragmented.

3.3. Artificial Intelligence Techniques in External Auditing

The literature is dominated by machine learning because it is diversified and predictive. Nevertheless, its performance is based on the quality of data and its model, which must be transparent. Neural networks provide enhanced analytical features but a lack of interpretability, which is a major issue in audit scenarios that require elucidation. The relevance of natural language processing is increasing with the size of textual disclosures whereas robotic process automation is adding to operational efficiency. Expert systems are less common and are more structured decision support, and are not adaptable to dynamic audit environments.

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Table 2.
Artificial intelligence techniques in external auditing.

Technique	Primary Application	Strengths	Limitations
Machine Learning	Fraud detection, risk assessment	High predictive accuracy, scalability	Data dependency, potential bias
Neural Networks	Pattern recognition, anomaly detection	Captures complex relationships	Lack of interpretability
Natural Language Processing	Text analysis, audit documentation	Handles unstructured data efficiently	Context sensitivity, ambiguity
Robotic Process Automation	Routine audit procedures	Efficiency, cost reduction	Limited analytical capability
Expert Systems	Decision support	Consistency, knowledge codification	Rigidity, limited adaptability

3.4. Theoretical Frameworks Identified

According to the review, the theoretical background of the discipline is not developed and dispersed. The theories that have been mentioned most are the technology acceptance model, institutional theory, resource-based view, and agency theory. Nevertheless, they are used superficially. The results show that the majority of studies refer to theories without further empirical testing. As an example, the technology acceptance model is very often applied to describe the adoption of users, but it cannot describe the complexity of the auditing environment. Equally, the agency theory is called upon to comment on the quality of audit but has not been empirically proved in the case of artificial intelligence. Such a trend indicates that the gap between theoretical citation and theoretical contribution is present, which restricts the building of a coherent body of knowledge.

Table 3.
Theoretical frameworks in artificial intelligence auditing research.

Theory	Frequency	Application Focus	Evaluation
Technology Acceptance Model	High	AI adoption behavior	Limited extension
Agency Theory	Moderate	Audit quality, independence	Rarely empirically tested
Resource Based View	Moderate	AI as a strategic capability	Conceptual focus
Institutional Theory	Low	Regulatory and normative pressures	Underutilized

3.5. Artificial Intelligence and Audit Quality

Analysis of the results provides that AI has both adverse and beneficial implications on audit quality. It has been demonstrated empirically that AI contributes to the accuracy of fraud detection and better processing of risk assessment because it allows significant data to be analyzed [21]. There is also the benefit of efficiency achieved as a result of the automation of routine tasks, and this enables the auditors to concentrate on activities that generate higher value to them. Nevertheless, the risks are also pointed out in the literature. Audit reliability may be compromised by algorithmic bias and lack of transparency, especially when opaque models are used by the auditors. More so, overtrust in AI can lead to a decline in professional skepticism, which is an important element of audit quality [22]. These risks are highlighted by conceptual studies, and empirical validation is limited; thus, there is a disjuncture between theoretical concerns and empirical evidence.

The results indicate that the role of AI in the quality of auditing depends on several aspects such as technology design, organizational environment, and regulation. Although AI can be used to improve the effectiveness of auditors, it does not have an automatic beneficial effect and needs to be carefully implemented and governed. The absence of combined systems connecting the methods of AI with the quality of the audit also reduces the possibility of making conclusive decisions. The findings point to a market with a high growth rate but high fragmentation. These simultaneous high-level technical developments and low-level theoretical integration are also good reasons to consider more comprehensive and interdisciplinary research approaches. The limitations should be tackled to further the understanding and practice of AI in external auditing.

4. Contributions of the Study

4.1. Theoretical Contributions

The results of this research have an important theoretical contribution since it makes the conceptual fragmentation that has always dominated the study of AI in external auditing. One of the main contributions is that it consolidates the streams of research that were hitherto separate into a more coherent and integrative picture. The bibliometric evidence shows that previous research has been developed in parallel lines, and technical research on machine learning and data analytics did not have much connection to the discussion of governance, ethics, and audit quality. The synthesis of these streams, which has been done in this study in a systematic manner, gives a cohesive view of AI as not a technological instrument but as a multidimensional phenomenon found in organizational, institutional, and regulatory realms. This unification moves the literature forward as it facilitates the building of cumulative knowledge as opposed to individual theoretical gains.

A second significant theoretical contribution is the identification and critical analysis of theoretical frameworks that are predominant and under-utilized. The review indicates that theories like the Technology Acceptance Model, agency theory, and the resource-based view are common and are often mentioned, but their implementation is superficial and not sound enough empirically. As an example, the adoption of AI tools by the auditors has been extensively explained using the Technology Acceptance Model, which does not accommodate the complexity of professional judgment, regulatory pressures, and ethics issues within auditing backgrounds. Equally, agency theory has been called to provide the explanation of audit quality; nonetheless, in most cases, the empirical studies do not attempt to test the assumptions of the agency theory against the possible implications of algorithmic decision-making. Institutional theory, which might offer useful information on regulatory and normative factors that may affect AI adoption, is underutilized, in contrast. The mapping of these theoretical applications allows identifying that further theoretical involvement is essential and that several perspectives should be consolidated, which can enhance the explanatory capabilities of the multidimensionality of AI in auditing.

The third and most important theoretical contribution is the creation of a comprehensive conceptual model in which AI techniques are associated with audit quality. Such a model addresses the gap between the technical features of technology and the effectiveness of auditing by defining the most important mechanisms by which AI impacts audit processes. In particular, this model conceptualizes the AI as a facilitating power that increases data processing, anomaly detection, and risk assessment, which subsequently influence audit quality dimensions, including accuracy, reliability, and independence. Meanwhile, the model takes into account moderating factors, including the nature of governance, ethical considerations, and the expertise of an auditor that impact the degree to which AI is helpful or harmful to the quality of the audit. Such an integrative approach does not rely on linear cause-effect relationships; rather, it considers the complexity of the interaction between technology, human judgment, and institutional context.

Notably, the dual character of AI in auditing is also covered by the proposed framework. Although previous studies have tended to reduce the importance of the other side, the current project incorporates the two schools of thought in one theoretical framework. It is possible to better balance the perspective on the way AI can both increase efficiency and bring new risks, including algorithmic bias and a lack of professional skepticism. The framework is more representative and detailed by including these dynamics in artificial intelligence adoption in the practice of auditing. The theoretical implications of the research are based on the possibility of synthesizing the scattered pieces of knowledge, critically assessing the current theoretical background, and developing a unified model that would contribute to deeper insights into the connection between AI and the quality of audits. These contributions offer the basis for future research to develop stronger and integrative theories that represent the dynamics of the digital era of auditing.

4.2. Methodological Contributions

The current study is a considerable contribution to methodological studies in terms of the practical application of systematic literature review methods, along with bibliometric analysis and theory synthesis techniques, as it enhances the methodological rigor of the accounting and auditing research. This combination of methods overcomes critical weaknesses of previous research that has tended to be either narrative reviews of the literature or empirical studies iso-celebrative without offering a synthesis of literature that can be replicated.

The PRISMA framework is used to provide a clear and methodological process of literature identification, screening, and selection. The study is high in reproducibility through clear documentation of every step of the review process, including inclusion and exclusion criteria, which will minimize the chances of selection bias. PRISMA is specifically significant when it comes to a rapidly developing area like AI in auditing because the number of publications grows rapidly, and the quality of studies significantly varies. The screening process is structured with the help of inter-rater reliability assessment, thus making sure that only pertinent and methodologically sound studies are included in the analysis. This rigor is what separates the current study from the previous reviews, which, in many cases, lack transparency in the selection process.

The study engages a systematic review and bibliometric mapping based on VOSviewer to understand the intellectual structure of the field, in addition to the systematic review. With this quantitative approach, clusters of research, thematic relationships, and patterns of citation that are difficult to observe using conventional qualitative methods can be readily discovered. Resorting to the analysis of keyword co-occurrence and co-citation gives a macro-view of the development of the literature, showing the trends of conceptual growth and dislocation. The study is important as it normalizes the strength of associations and uses a minimum occurrence threshold to make sure that the clusters that do come out are meaningful and interpretable. Such a methodological integration can be more fully used to understand the field, combining breadth and depth within one model of analysis.

Another methodological addition is the synthesis of theory with the empirical and bibliometric results. Although most systematic reviews are mainly based on summarizing the literature findings, the current research goes further than that as it critically analyzes the theoretical basis of the literature. This not only entails determining the theories applied, but also evaluating their application, and determining whether they add to knowledge development. The connection between theoretical analysis and bibliometric mapping results in a more holistic study, which relates the conceptual, empirical, and structural aspects of the research domain.

The uniqueness of the approach is that it allows triangulating results of various sources, thus contributing to validity and strength. The systematic review offers comprehensive information on each of the studies, the bibliometric analysis helps to see the general tendencies, and the synthesis of the theories helps to relate the findings to a logical framework. Such a triangulation helps minimize the constraints of single-method studies and allows for conducting a more in-depth and credible analysis. Moreover, the method is flexible and can be used on other emerging research areas, so it can be considered a worthy contribution to methodological practice in accounting and management research.

4.3. Practical Implications

This study has important practical implications for various stakeholders such as an audit firm, regulators, setters of the standards, and developers of technologies. Such implications are especially applicable in the light of the fact that the use of AI in auditing practice is growing, and that there is a need to make sure that such technologies improve but do not negatively affect the quality of audits.

In the case of audit firms, the research also shows the necessity to embrace AI in a way that would not jeopardize the professional judgment and skepticism but rather increase the efficiency. Although AI tools can greatly improve the ability to process data and detect fraud more accurately, their efficiency is related to proper implementation and control. To utilize AI in audit procedures, audit firms should not only invest in technology but also educate auditors on how and when to critically analyze the output of artificial intelligence. This involves nurturing skills in data analytics and interpretation of algorithms, and nurturing the culture that promotes critical thinking and skepticism. The results also imply that companies ought to incorporate governance systems to oversee how AI is used and curb the risks of bias and lack of transparency.

To regulators, the study highlights the importance of creating frameworks that will tackle the special challenges of AI to auditing. The conventional regulatory methods might not be adequate in capturing the complexities of algorithmic decision-making and data-driven audit. Regulators should then come up with guidelines that will make AI systems transparent, accountable, and auditable. This involves the establishment of documentation standards, validation, and explainability of algorithms applied in auditing. Also, governments and other regulatory agencies ought to promote the use of ethical AI to avoid unintended outcomes to preserve societal confidence in the auditing profession.

Standard setters are also instrumental in determining the future of AI in auditing. These results indicate that the current auditing standards might have to be revised to incorporate the use of new technologies. This way, they will be able to promote the effective and consistent application of AI in the profession. To technology developers, the paper shows the significance of ensuring AI systems are made based on particular requirements and limitations of auditing. This involves making sure that the algorithms are transparent, interpretable, and explainable in terms of their results. Black box models need not be as fit as more interpretable methods because of the high stakes that are attached to audit decisions. The developers must also have in mind the ethical aspects of AI and take precautions to avoid bias and to be fair. The cooperation of technology developers and auditors is necessary to help guarantee that AI tools are not only technically sound but also applicable to practice.

The implications of the present study in practice underline the necessity of a holistic approach toward the application of AI in auditing. Harmonizing technological innovation with professional standards, regulatory frameworks, and ethical concerns, the stakeholders will be able to gain the most benefits of AI without causing its negative effects. This is a comprehensive solution towards ensuring that the AI positively affects the quality of the audit and the long-term sustainability of the auditing profession.

4.4. Limitations and Direction for Future Studies

Although the methodological rigor and integrative approach used in the study were employed, it is necessary to note several limitations that, in turn, present a basis for developing future research. These shortcomings are mainly associated with the data scope, methodological provisions, and the dynamic aspects of artificial intelligence as part of auditing. It is crucial to address such problems in order to enhance the strength and generalizability of results in this field.

The main restriction is associated with the geographical concentration of reviewed studies. Descriptive analysis shows that most publications are made by the developed economies, especially the United States, the United Kingdom, and China. Although these regions are in the vanguard of technological innovation and auditing practice, their prominence creates a bias in the context of the findings that could restrict the extrapolation of findings to other regions. Literature on emerging and developing economies is still underrepresented, even though these economies present distinct institutional, regulatory, and technological challenges. As an illustration, regulatory enforcement, technological infrastructure, and professional capacity differences can have a profound effect on the adoption and effects of artificial intelligence in auditing. This means that future studies must focus more on unexplored areas and, in particular, those in Africa, Latin America, and a section of Asia in order to have a more detailed and global picture of artificial intelligence in auditing. This kind of research would also assist in putting theoretical frameworks into context and pinpointing region-specific drivers and barriers to adoption.

The second weakness involves the predominance of the cross-sectional and exploratory research designs in the literature. The adoption of AI is captured in most of the studies at one point in time, hence limiting the capacity to determine the effects and dynamic changes in the auditing practices in the long run. Since AI technologies are developing at a very rapid pace and are actively introduced in the field of audit, cross-sectional analyses can only give a partial picture of the effect they have. Longitudinal studies are hence necessary to understand how AI impacts audit quality over time, its effects on auditor conduct, institutional practice, and compliance with regulations. This kind of research would help researchers document the learning effects, adaptation processes, and other unwanted outcomes that might occur with the long-term use of artificial intelligence.

Additionally, the adoption of experimental research designs is another significant gap. Conceptual and archival studies are very useful, although they do not always suffice to prove the causal relationships between the adoption of AI and audit results. Laboratory and field experiments are examples of experimental design, which provide the opportunity to isolate certain variables and investigate their impact in controlled conditions. Experimental research can be used to gain a better understanding of the mechanisms by which AI influences the practices of auditing by integrating behavioral and cognitive lenses. Future research, hence, should embrace more stringent experimental designs so as to complement the methods already in use and to enable causal inference.

The other essential constraint is associated with the lack of attention paid to ethical issues when using artificial intelligence in the auditing process. In spite of the fact that the bibliometric examination shows that there is a cluster that deals with governance and ethical AI, this sector is still underdeveloped in terms of technical and analytical research streams. The problems of algorithmic bias, transparency, accountability, and data privacy are especially relevant to auditing, as its decisions can be associated with major financial and societal consequences. The fact that empirical research has not been conducted on these issues constrains the possibility of evaluating the ethical risks of adopting AI. The next-generation study should focus on studying ethical aspects, such as the creation of frameworks for the responsible application of AI in auditing. This involves exploring ways to operationalize ethical guidelines, training auditors on how to detect and reduce bias, and ensuring accountability within algorithmic decision-making by organizations.

Lastly, the literature does not discuss any major studies on cross-country comparisons that can help in understanding the effect of various regulatory settings on the implementation and adoption of AI in auditing. Regulatory frameworks are important in the development of auditing practices, such as the level at which AI can be incorporated into the audit processes. Legal systems, enforcement mechanisms, and professional standards can be different, resulting in differences in the implementation of AI and its impact on the quality of the audit. The cross-jurisdictional comparative studies would offer important information on how regulation is contributing to or hindering technological innovation. These studies may also be used in the formulation of harmonized standards and best practices, especially with the growing globalization of auditing services.

Besides these particular guidelines, future studies must seek to combine various research strategies and theoretical frameworks in order to deal with the intricacy of AI in auditing. The interdisciplinary studies involving the integration of knowledge on accounting, information systems, ethics, and management are of particular interest in establishing holistic and effective frameworks. Additionally, academia and practice need to work together more to make sure that research is pertinent and receptive to the changing demands of the audit profession.

5. Conclusion

This study is a synthesis of the fast-developing literature on AI in external auditing that is both theory-informed and comprehensive in filling a significant gap in the context in which technological advances are integrated with audit quality performance. The integration of systematic review processes with bibliometric mapping and theoretical analysis has the advantage of going beyond the descriptive aggregation offered by such an approach to construct a systematic notion of the intellectual and empirical range of the field. The results show that although the study of AI in auditing has expanded tremendously, it continues to be marked by conceptual and theoretical fragmentation as well as methodological incongruencies.

This analysis shows that the current literature is mainly consolidated in three top areas, which are machine learning and fraud detection, audit analytics and big data, and AI adoption and governance. Despite the benefits of each area, it is their lack of integration that prevents the creation of a rich body of knowledge. Besides, the research points to the excessive dependence on a limited number of theoretical frameworks, which are frequently implemented on a thin layer with a lack of empirical support. Such theoretical deficiency compromises the capacity to completely understand how AI affects the quality of auditing.

Notably, the research also proves that AI has a massive potential to positively impact auditing by increasing its quality by detecting fraud, assessing risks, and optimizing processes. Nevertheless, there are major issues that are associated with these advantages, such as algorithmic bias, lack of transparency, and possible undermining of professional judgment. The future of the use of AI in auditing is thus dependent on how the three elements of technology, organizational, and regulatory practices interact.

This study helps improve research and practice as it suggests a conceptual framework that is integrated. It gives a basis to further research that is more theoretically sound, methodologically, and contextually. Finally, the research indicates that a balanced and interdisciplinary approach is necessary to make the implementation of AI reinforce the efficacy, credibility, and durability of the auditing profession in a digitalizing world.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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