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Research Article

A Bibliometric Analysis On The Use Of Machine Learning In Auditing

Denetimde Makine Öğreniminin Kullanımına Yönelik Bibliyometrik Bir Analiz

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Abstract

This study aims to identify the most appropriate machine learning methods used in the field of auditing and to reveal the contributions of these methods to the field of auditing. In this context, a bibliometric analysis method was used. Within the scope of this analysis, 246 studies were examined, including 147 from the Scopus database and 99 from the Web of Science database. Following the combination of data, 160 studies were selected for comprehensive analysis. The analysis of bibliometric data was conducted using the Bibliometrix package in the R-Studio program with the help of Biblioshiny. The findings show that logistic regression and linear regression analysis continue to be widely used machine applications in auditing since the 1980s. In addition, the analyses show that in recent years, advanced applications such as deep learning, Long Short-Term Memory, Beetle Antennae Search, random forests, and XGBoost are more preferred. This study provides valuable insights for future researchers aiming to develop a comprehensive roadmap for conducting research on machine learning in the field of auditing. The study also emphasizes the necessity of approaching auditing within the discipline of accounting but from an interdisciplinary perspective, thereby contributing new perspectives to the literature in this context.

Keywords: Accounting, auditing, Machine learning, R-Studio, bibliometrix

Öz

Bu çalışmanın amacı denetim alanında kullanılan en uygun makine öğrenmesi yöntemlerini belirlemek ve bu yöntemlerin denetim alanına katkılarını ortaya koymaktır. Bu bağlamda bibliyometrik analiz yöntemi kullanılmıştır. Bu analiz kapsamında, Scopus veri tabanından 147, Web of Science veri tabanından ise 99 olmak üzere toplam 246 çalışma incelenmiştir. Verilerin birleştirilmesinin ardından analiz için 160 çalışma seçilmiştir. Bibliyometrik verilerin analizi Biblioshiny yardımıyla R-Studio programında Bibliometrix paketi kullanılarak yapılmıştır. Bulgular, lojistik regresyon ve doğrusal regresyon analizinin 1980'lerden bu yana denetimde yaygın olarak kullanılan makine uygulamaları olmaya devam ettiğini göstermektedir. Ayrıca analizler son yıllarda derin öğrenme, Uzun-Kısa Süreli Bellek, Beetle Antennae Search, Rastgele Orman ve XGBoost gibi ileri uygulamaların daha fazla tercih edildiğini göstermektedir. Bu çalışma, denetim alanında makine öğrenimi üzerine araştırma yapmak için kapsamlı bir yol haritası geliştirmeyi amaçlayan gelecekteki araştırmacılar için değerli içgörüler sunmaktadır. Çalışma ayrıca, denetimin muhasebe disiplini içinde, ancak

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disiplinler arası bir bakış açısıyla ele alınmasının gerekliliğini vurgulamakta ve bu çerçevede literatüre yeni bakış açıları kazandırmaktadır.

Anahtar Kelimeler: Muhasebe, denetim, makine öğrenmesi, R-Studio, bibliometrix

1. INTRODUCTION

Recently, AI technologies have been discussed in the audit literature as a way to further improve both the efficiency and effectiveness of audits (Krieger et al., 2021). Automated solutions like machine learning are required for the timely discovery of abnormalities because it is difficult to manually assess the vast volumes of data produced by information systems (Barta, 2018). Especially, machine learning-based models have been triumphantly implemented to detect anomalies in accounting data, prevent financial fraud, and promote the accuracy of the audit process (Oala et al., 2021; Bakumenko & Elragal, 2022). While traditional audit techniques frequently rely on sample-based analyses, machine learning offers a more comprehensive and trustworthy evaluation by examining all of the data (Chen et al., 2022; Chen & Wu, 2022). This technology, which makes audit processes more efficient, both saves time and increases the predictive potential of audit work by lowering the workload of auditors (Oala et al., 2021). Nowadays machine learning, which is more and more adopted in the field of accounting and auditing, is effectively used in a variety of tasks such as reviewing source documents, analyzing business processes, and risk assessment (Cho et al., 2020). Furthermore, it provides the chance to identify and manage audit risks instantly by optimizing risk management processes (Kang, 2024).

Machine learning (ML) and deep learning (DL) are the two primary components of artificial intelligence, which is a broad notion (Ever & Demircioğlu, 2022). Machine learning is a computer technique that creates models from vast and intricate data (Cho et al., 2020). The increasing use of machine learning, which enables the automation of processes based on the real-time analysis of enormous amounts of data, is transforming our lives in a variety of ways (Biczyk & Wawrowski, 2023). Machine learning has the potential to carry out tasks such as anomaly detection, risk analysis, and error prediction more quickly and efficiently by automating in audit processes (Shapovalova et al., 2023). Machine learning is used in many fields, such as biology, education, health, accounting, and finance (Ucoglu, 2020).

Today, there is an increasing demand for the application of machine learning technologies in financial auditing (Bakumenko & Elragal, 2022). The widespread use of machine learning applications in auditing has led to an important trend in scientific research on this subject (Cho et al., 2020; Lamboglia et al., 2021; Agustí & Orta-Pérez, 2023; Hezam et al., 2023). Although bibliometric studies have been conducted in different subfields of accounting, such as financial accounting (Yang, 2024; Liaras et al., 2024), management accounting (Nielsen, 2022; Ranta et al., 2023), and fraud auditing (Ramzan & Lokanan, 2024; Cardona et al., 2024; Dewayanto, 2021), a comprehensive bibliometric analysis on the use of machine learning in auditing has not yet been conducted. In literature, there are various studies on the use of machine learning in auditing. For example, academic research has been conducted on topics such as financial report fraud detection (Soltani et al., 2023), the role of machine learning in financial reporting and auditing processes (Khorsheed et al., 2024), and machine learning strategies of large audit firms (Ucoglu, 2020). However, existing studies generally focus on specific subfields, and there is no holistic analysis that comprehensively addresses the most widely used machine learning methods in auditing.

The main purpose of this research is to identify the most appropriate machine learning methods in auditing and to reveal their contributions to the field of auditing. To this end, we analyzed the existing scientific literature on the use of machine learning technologies in auditing through bibliometric analysis using Web of Science and Scopus databases and identified the machine learning approaches used in auditing. Overall, the scope of this study is to provide an appropriate explanation for the following research questions (RQs):

RQ1: What are the trends in publications related to machine learning technology in the field of auditing?

RQ2: Which are the main sources, publications, authors, organizations, and countries contributing to machine learning technologies in the field of auditing?

RQ3: What are the top trending topics and major themes of machine learning technologies in auditing?

RQ4: What are the most widely used machine learning technologies in auditing?

The paper also presents various machine learning methods and summarizes these methods. In the introduction of the article, the need for machine learning in auditing, which is a subfield of accounting, is discussed, and the benefits of machine learning technologies to the related field are discussed. Then, the existing scientific literature on the use of machine learning technologies in auditing is analyzed through bibliometric analysis by taking into account the Web of Science databases and Scopus. As a result of the bibliometric analysis, the most commonly used machine learning methods in the field of auditing were revealed. Finally, the article concludes with a general conclusion.

2. MACHINE LEARNING

Via the use of mathematical and statistical methods, machine learning analyzes data samples to provide primary outputs, allowing computers to learn without programming (Ahsan et al., 2022). A branch of computer science called "machine learning" involves the development of computer algorithms that use statistics to identify patterns in large amounts of data and make very accurate predictions about the future (Ucoglu, 2020). Creating learning algorithms that can operate vehicles, understand spoken language, and find hidden patterns in massive volumes of data is the large field of machine learning (Bertomeu et al., 2021).

In machine learning, the basic goal is to learn from data to make predictions or judgments based on the task at hand (Ahsan et al., 2022). In general, there are two types of machine learning algorithms: ensemble classifiers and conventional single classifiers (Chen & Wu, 2022). Specifically, a single classifier is a technique for classifying or forecasting samples. On the other hand, an ensemble classifier combines the predictions made by several single classifiers using a single classification to produce a final prediction (Chen & Wu, 2022). Thanks to machine learning algorithms, many laborious tasks can now be completed quickly and with minimal effort (Ahsan et al., 2022). Furthermore, machine learning allows us to predict future events (Cho et al., 2020). The most frequently used machine learning algorithms are Logistic Regression, Linear Regression, Support Vector Machines (SVM), Random Forests, Decision Trees, and Naive Bayes in the literature (Ahsan et al., 2022). Nevertheless, machine learning algorithms that have been employed in the literature include Extreme Ridge Regression, Gradient Boosting, Ordinary Least Squares, Generalized Linear Models, Gradient Boosting, Multilayer Perceptron, Convolutional Neural Networks, Adaboost, Long Short-Term Memory, and Recurrent Neural Networks (Ferris, 1982; Fukas et al., 2022; Zhou et al., 2024; Westland, 2017; Saeedi, 2023; Dai & Zhu, 2022; Wasito et al., 2023).

3. METHODOLOGY AND DATA

Scientific databases like Web of Science (WoS) and Scopus have made it relatively simple to obtain large amounts of bibliometric data, and programs like Gephi, Leximancer, and VOSviewer allow for the practical analysis of such data (Donthu et al., 2021). As a result, bibliometric analysis has garnered more attention from academics recently (Donthu et al., 2021). The R Studio software package's bibliometric software has been extensively utilized in literature lately for bibliometric data analysis. Bibliometrix is an open-source application that is integrated into the R studio software and was created referring to Aria & Cuccurullo (2017). Bibliometrix is a software program integrated into the R Studio software program to do bibliometric analyses, and as it is programmed in R, the recommended tool is adaptable and simple to combine with other statistical R programs (Aria & Cuccurullo, 2017). By addressing research concerns about authors, sources, collaboration patterns, and publication trends, Bibliometrix facilitates a range of academic analyses (Sheela et al., 2023).

In this study, the WoS and Scopus databases are used to create a report on the studies on the use of machine learning methods in the field of auditing and to investigate the trends in the related field. The WoS and Scopus are databases widely used in academic literature. Biblioshiny for bibliometrix, an R Studio software, was used to analyze the bibliometric data obtained from both databases. The data were obtained by queries in the WoS and Scopus databases and combined through R programming. Bibliometrix was preferred because it is one of the software tools used for comprehensive analysis and visualization of academic studies.

3.1. Identification

Defining search terms plays an important role in conducting the research as it provides a comprehensive review of publications by various researchers using different terminologies within a given thematic area (Donthu et al., 2021). The WoS and Scopus databases are the most frequently used databases in the literature to access the highest quality articles in the academic field. Therefore, in this study, in order to effectively find publications on machine learning methods used in the field of auditing; firstly, the “WoS Advanced Search” interface was used in the Clarivate Web of Science database. Thus, search terms in the field of auditing were identified by using the words “auditing” AND “accounting” with the “TS=topic” option in the WoS Advanced Search database. Then, using the “AND” option, it was decided to use the machine learning methods that are widely used in the literature one by one to identify the machine learning methods used in the field of auditing. Otherwise, it was observed that machine learning was not mentioned as a word in every publication written in the field of machine learning (for example, the words “support vector machine” were used instead of “machine learning”). Accordingly, in order to reach more publications, machine learning methods were identified and these were searched as words. In summary, the search words in the “WoS Advanced Search” database were created as follows: TS=("auditing") AND TS=("accounting") AND TS=("Machine Learning" OR "Deep Learning" OR "Artificial Neural Network" OR "ANN" OR "Logistic Regression" OR "Linear Regression" OR "Support Vector Machine" OR "SVM" OR "Decision Tree" OR "Random Forest" OR "Naive Bayes" OR "Extreme Gradient boosting" OR "Ordinary Least Squares" OR "Generalized Linear Models" OR "Gradient boosting" OR "Multilayer Perceptron" OR "Adaboost" OR "Convolutional Neural Networks" OR "CNN" OR "Long Short-Term Memory" OR "LSTM" OR "Recurrent Neural Networks" OR "RNN" OR "Ridge Regression"). While performing this search, the "Exact Search" option in WoS is also selected to access documents that contain exactly the words related to machine learning in the field of auditing. When all documents were analyzed one by one, no article was found outside the related field. It was used “WoS Advanced Search” in the Clarivate Web of Science database.

Using the “Advanced Search” interface in the Scopus database, the search terms in the field of auditing were determined by using the words “auditing” AND “accounting” with the “TITLE-ABS-KEY” option. Then, using the “AND” option and the “TITLE-ABS-KEY” option, it was decided to use machine learning algorithms commonly used in the literature to identify machine learning methods used in the field of auditing. In summary, the research words in the “Scopus Advanced Search” database were created as follows: TITLE-ABS-KEY (“auditing”) AND TITLE-ABS-KEY (“accounting”) AND TITLE-ABS-KEY ("Machine Learning" OR "Deep Learning" OR "Artificial Neural Network" OR "ANN" OR "Logistic Regression" OR "Linear Regression" OR "Support Vector Machine" OR "SVM" OR "Decision Tree" OR "Random Forest" OR "Naive Bayes" OR "Extreme Gradient boosting" OR "Ordinary Least Squares" OR "Generalized Linear Models" OR "Gradient boosting" OR "Multilayer Perceptron" OR "Adaboost" OR "Convolutional Neural Networks" OR "CNN" OR "Long Short-Term Memory" OR "LSTM" OR "Recurrent Neural Networks" OR "RNN" OR "Ridge Regression"). During this search process, the “Advanced query” button was activated in order to access the documents in the Scopus database that contain the exact words related to machine learning in the field of auditing. The literature in the WoS and Scopus databases was searched respectively. As a result of the first search, 100 and 170 studies were found in the WoS and Scopus, respectively. In both databases, no language restrictions were applied during the search process, allowing the inclusion of publications in languages other than English."

3.2. Screening

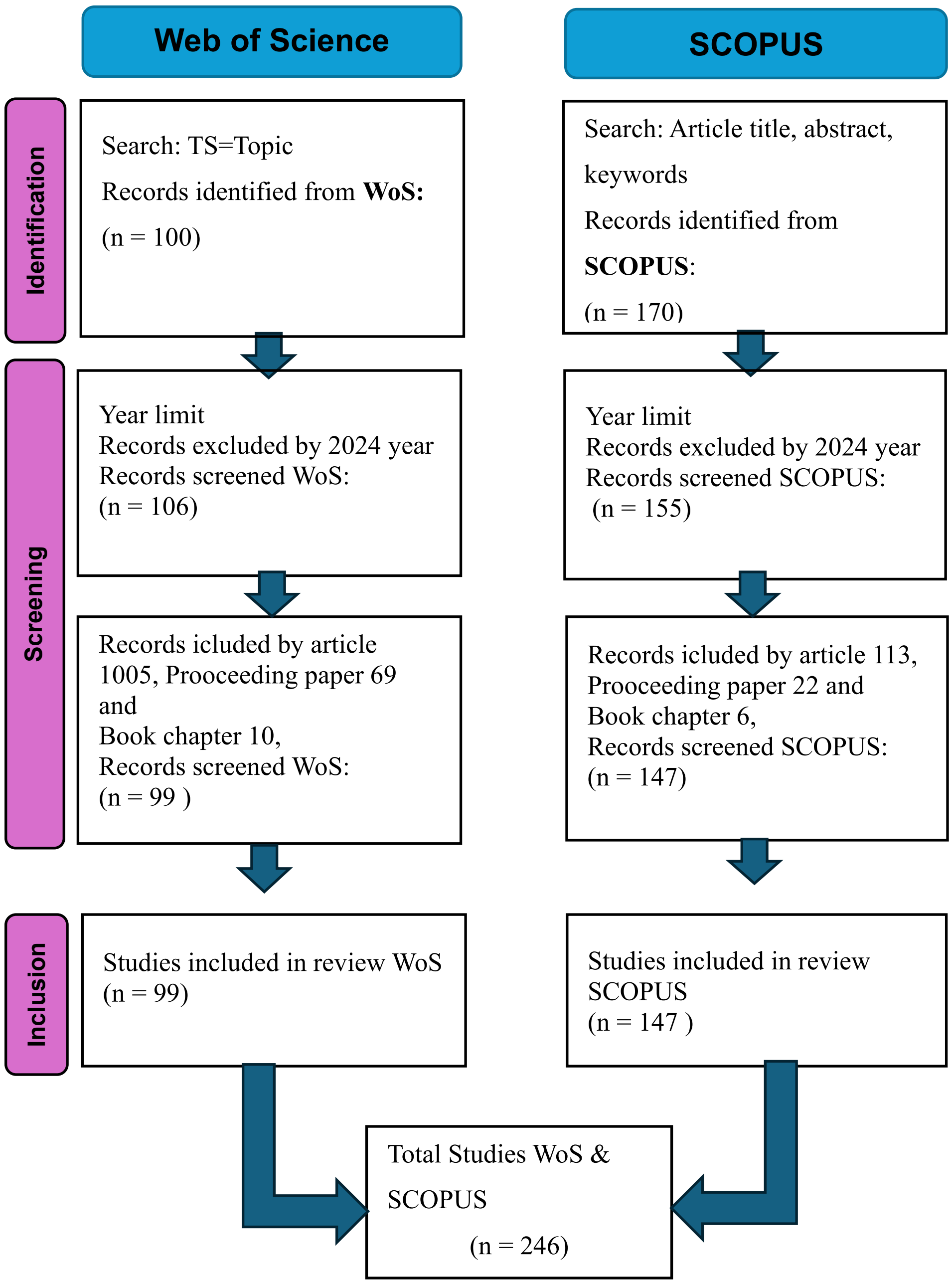
Since the last year of the search period, 2024, has not yet ended, it was excluded. Then, article, proceeding papers and book chapters were selected as document types. As a result, the total number of publications decreased to 99 for WoS and 147 for Scopus.

3.3. Inclusion

Among these documents, article, proceeding papers, and book chapters were selected for review. In total, 246 documents were retrieved (99 from the WoS database and 147 from the Scopus database). R-Studio software was used to identify and eliminate duplicate articles. In R-Studio software, 246 documents obtained from both databases were merged. As a result of the merger, 86 of the publications were removed because they were repeated. Furthermore, the majority of the documents examined were published in English, with only three written in Portuguese, one in Slovak, and one in German. However, in order to ensure the linguistic integrity of the research and increase comparability in the analysis process, studies written in languages other than English were excluded from the analysis. In this context, 160 data were obtained as a result of the data merging process.

The steps of the current investigation are depicted in Figure 2, which uses a PRISMA diagram to better show the stages of the research and increase its applicability for qualitative study. The information flow across the phases of a research project is shown by the PRISMA flow diagram (Bellucci et al., 2022). In this study, the PRISMA diagram was utilized to show the stages of both databases together.

Figure 1. PRISMA flow diagram



4. BIBLIOMETRIC ANALYSIS

In this part of the study, a comprehensive bibliometric analysis was performed using BiblioShiny R package software with a bibliometric dataset consisting of 160 puplications taken from WoS and Scopus databases. Within the scope of the study, machine learning in the field of auditing through bibliometric analysis includes By Year, Most Relevant Authors, Most Relevant Sources, Most Relevant Authors' Country, Most Frequently Repeated Words, Thematic Evolution analysis. Thus, the necessary answers to the research questions were sought and the findings were evaluated and presented with the help of tables, graphs and figures.

4.1. Main Informations

An overview of the bibliometric data used in this investigation is given in Table 1. There are 160 references altogether in the collection. The collection, which spans the years 1982 to 2023, includes the most recent research on the subject and has an average citation rate of 8.9 citations per document. The analysis of keywords includes many terms and concepts. The dataset can distinguish between single-author and multi-author studies.

Document types include article, proceeding papers, and book chapters. This dataset provides an overview of the knowledge in the field.

Table 1. Main Information

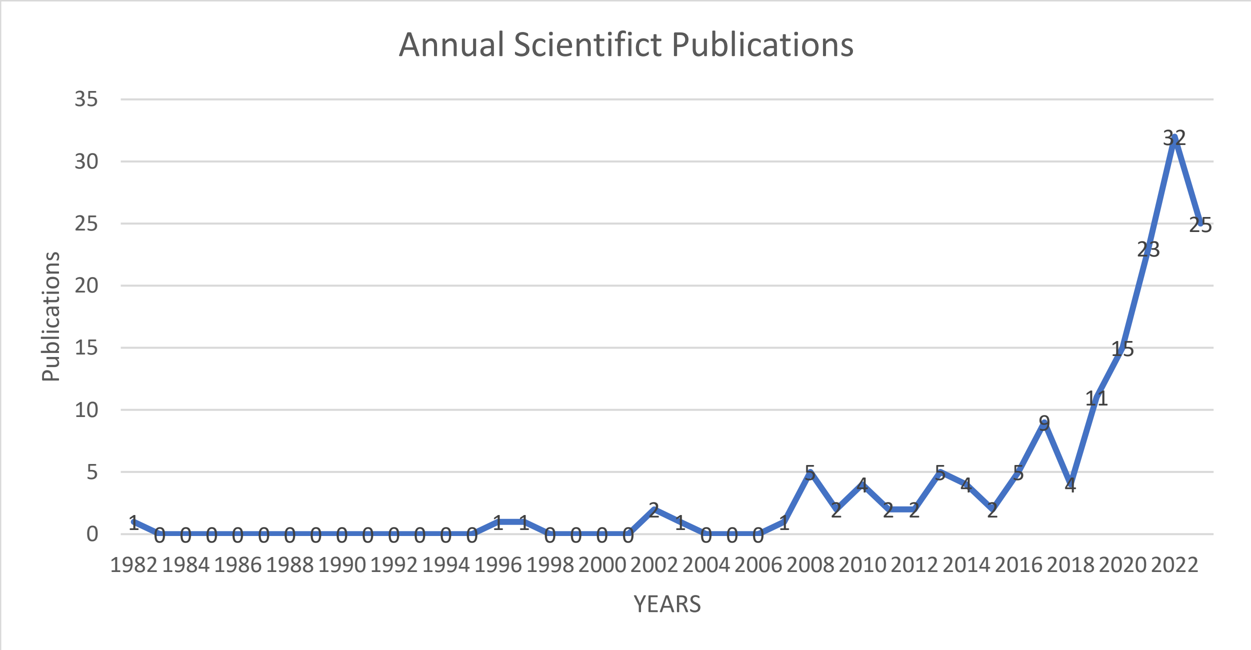
MAIN INFORMATION ABOUT DATA	
Description	**Results**
Timespan	1982:2023
Sources (Journals, Books, etc)	125
Documents	160
Annual Growth Rate %	8.37
Document Average Age	5.7
Average citations per document	8.9
DOCUMENT CONTENTS	
Keywords Plus (ID)	498
Author's Keywords (DE)	584
AUTHORS	
Authors	391
Single-authored docs	33
Co-Authors per Documents	2.73
International co-authorships %	20
DOCUMENT TYPES	
Article	125
Book chapter	6
Proceedings paper	29

Source: Biblioshiny R-Studio

4.2. Analysis of Publications By Year

When the literature on the use of machine learning algorithms in auditing is examined, there is a significant increase in the studies conducted in this field from 1982 to 2023. This increasing trend is given graphically in Figure 2. When this graph is analyzed, while the first publication related to the field in question was made in 1982; 25 publications were made in 2023, 32 in 2022, 23 in 2021, 15 in 2020, 11 in 2019, and 4 in 2018. While it followed a stagnant course from the 1980s to the end of the 2000s, there is a significant increase in the number of publications in the 2000s. The reason for this increase can be explained by the rapid advancement of technology. The findings show that both researchers and practitioners in the field are increasingly recognizing the possibilities offered by artificial intelligence technologies and reveal the transformation in the field of auditing.

Figure 2. Annual Scientific Production

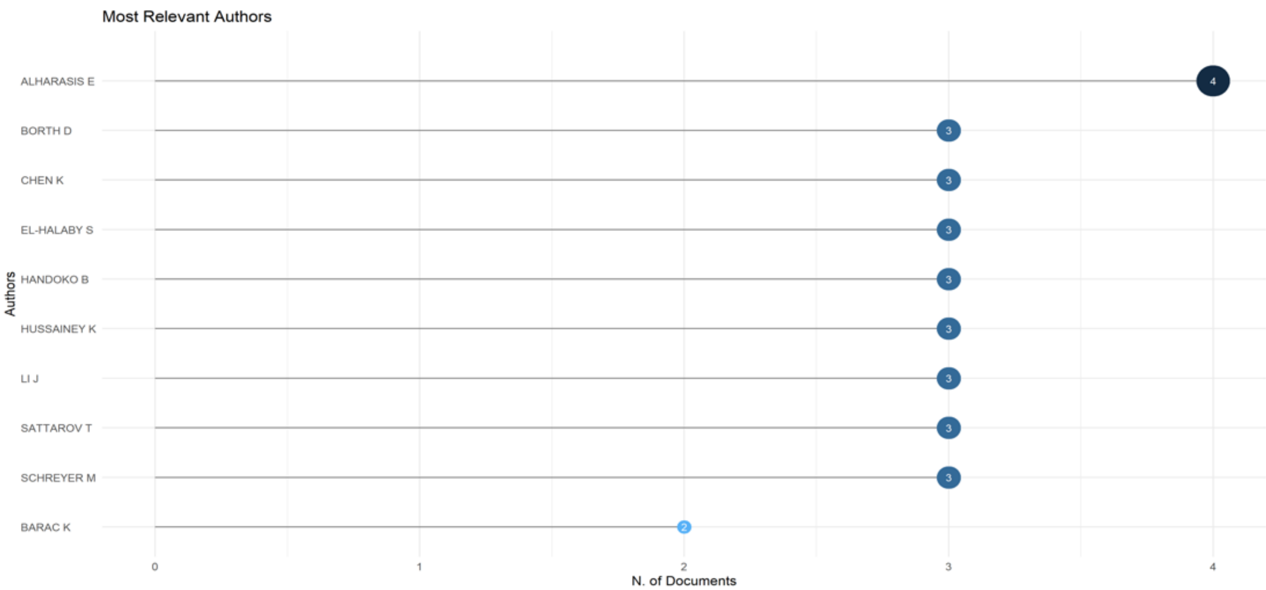


Source: Biblioshiny R-Studio

4.3. Most Relevant Authors

When the studies on the use of machine learning algorithms within the scope of auditing are analyzed, Alharasıs, E., takes the first place as the most influential authors in this field with 4 publications. This is followed by Borth, D., Chen, K., El-Halaby, S., Handoko, B., Hussaıney, K., Li, J., Sattarov, T., Schreyer, M., and Barac, K., respectively. The most influential authors are shown in Figure 3 with the number of studies they have conducted.

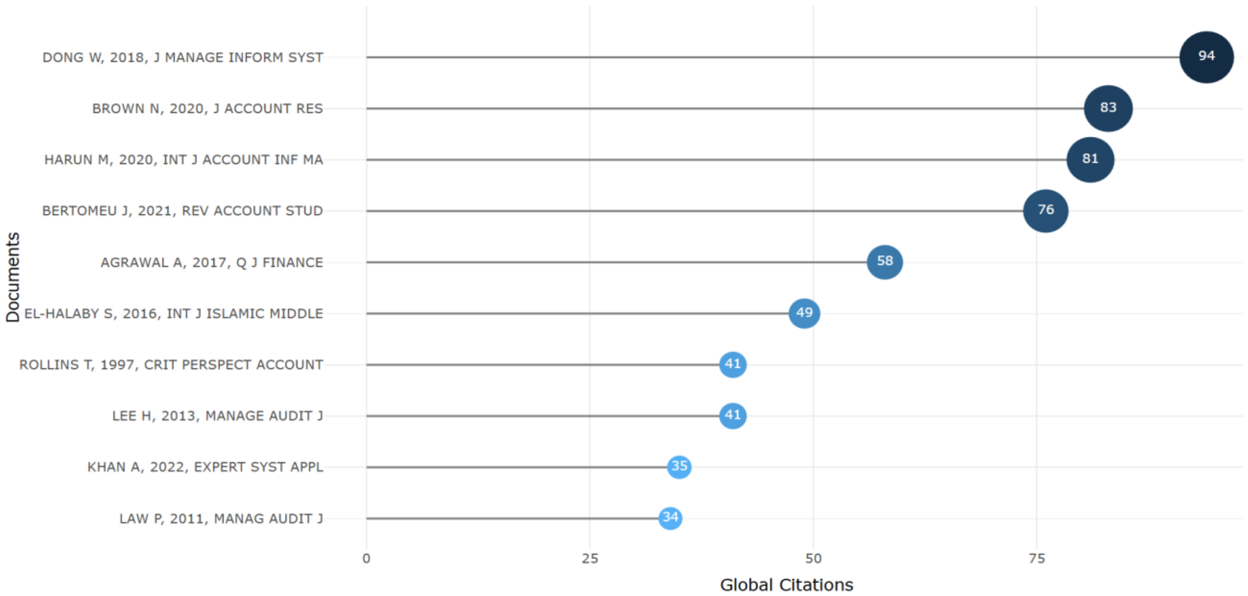
Figure 3. Most Relevant Authors



Source: Biblioshiny R-Studio

Figure 4 shows the 10 most cited publications related to machine learning in the field of auditing. The study with the highest number of global citations is by Dong W (2018), published in the Journal of Management Information Systems, with 94 citations. This is followed by Brown et al. (2020) (83 citations) and Harun et al. (2020) (81 citations). These three studies are highly influential publications that have made significant contributions to the theoretical and methodological framework of the field. Additionally, it is evident that the number of citations has intensified, particularly in studies published after 2020, indicating that the topic remains current and maintains its academic impact. This list serves as an important reference for identifying pioneering studies in the field.

Figure 4. Most Cited Publications

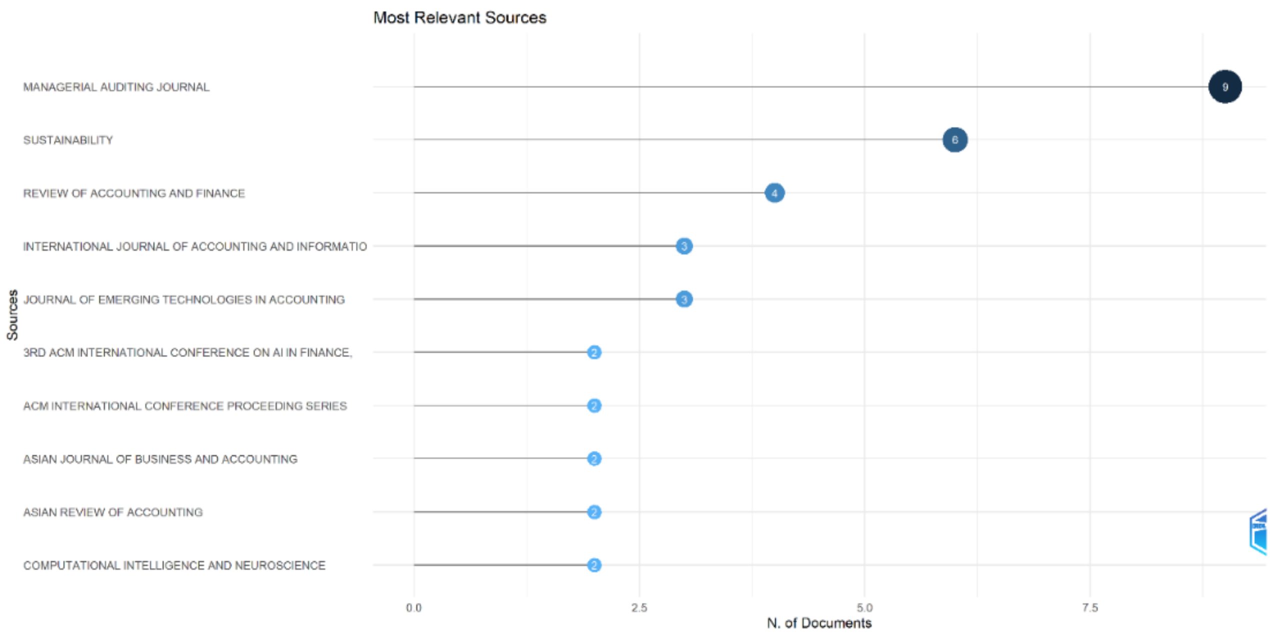


Source: Biblioshiny R-Studio

4.4. Most Relevant Sources

When examining the sources of studies on machine learning in auditing, the Managerial Auditing Journal (SSCI, Q2) emerges as the most prominent, with 62 publications. As shown in Figure 5, the top 10 journals in this field are predominantly indexed in high-impact SSCI categories (Q1 or Q2).

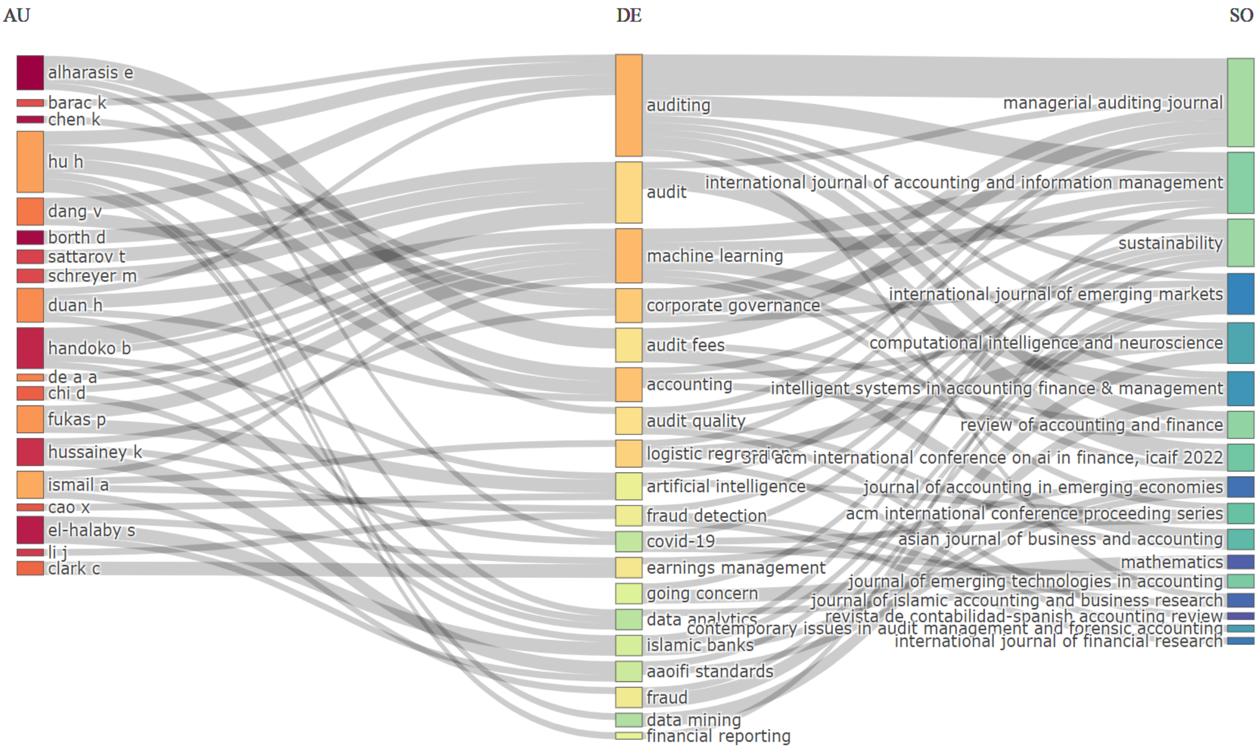
Figure 5. Most Relevant Source



Source: Biblioshiny R-Studio

Figure 6 is a Three-Fields Plot graph that visually represents the relationships between authors (20), keyword Plus (20), and source (20) in the relevant field. It shows that the resources, keywords, and authors are interconnected. The most frequently addressed themes and topics in each journal, along with their relationship to authors and sources, are illustrated in a three-dimensional graph. These connections reveal a common link aimed at exploring the effects of auditing and machine learning algorithms. As seen, the most frequently used source is the "Managerial Auditing Journal" In these sources, topics such as auditing, machine learning, corporate governance, audit fees, audit quality, and logistic regression are among those most frequently covered in this journal. At the same time, it is shown which themes are most commonly addressed by the most effective writers.

Figure 6. Three-fields plot (Authors 20, Keyword Plus 20, And Source 20)

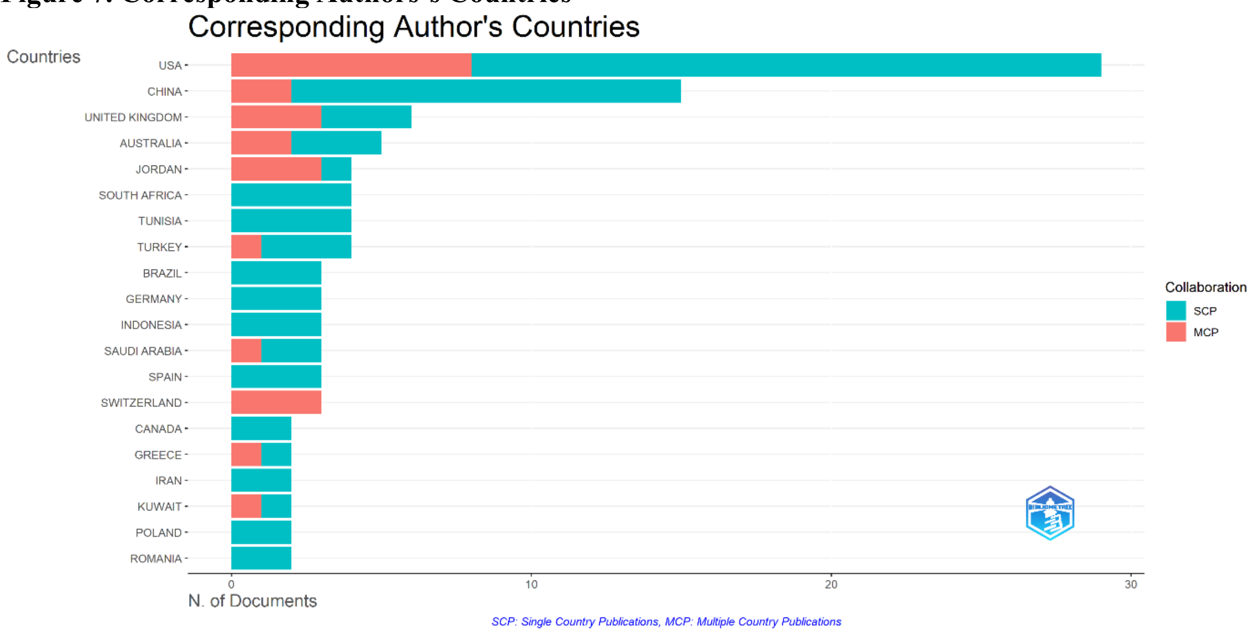


Source: Biblioshiny R-Studio

4.5. Most Relevant Authors's Country

When we look at the countries of the authors in studies involving the use of machine learning algorithms in auditing, the USA ranks first with a total of 29 studies. Figure 7 presents the top 20 countries. China 15, UK 6, Australia 5, Jordan 4, South Africa 4, Tunisia 4, Turkey 4, Brazil 3, Germany 3, Indonesia 3, Saudi Arabia 3, Spain 3, Switzerland 3, Canada 2, Greece 2, Iran 2, Kuwait 2, Poland 2, Romania 2 is being monitored with work.

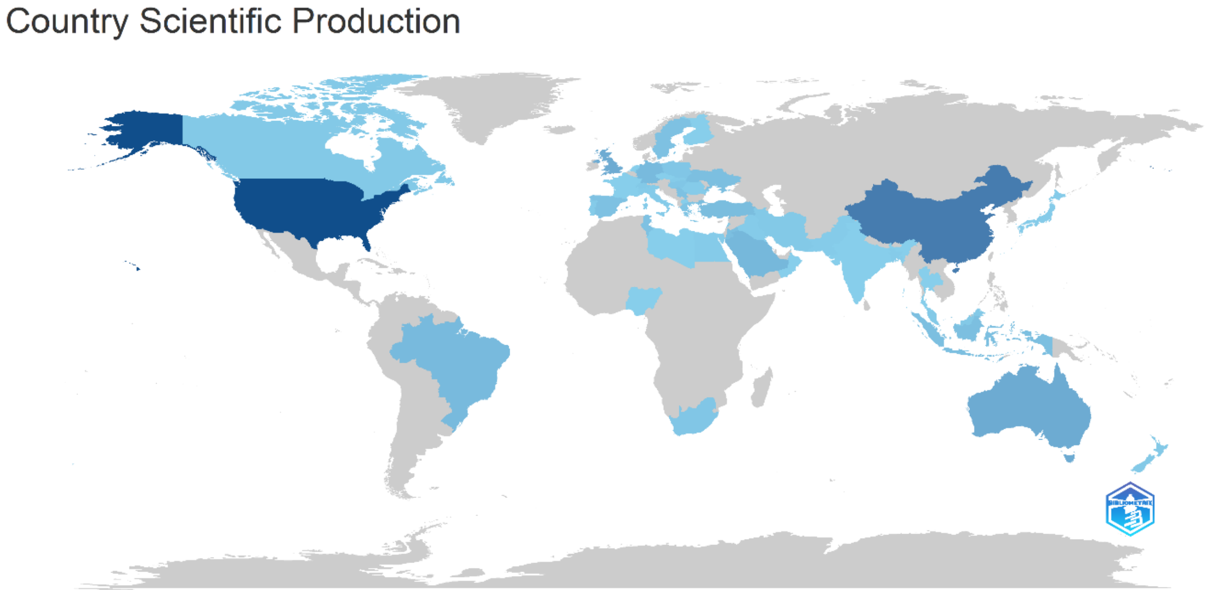
Figure 7. Corresponding Authors's Countries



Source: Biblioshiny R-Studio

Figure 8 shows that the studies conducted in this field span a wide geography. While 56 of the studies are from the USA, they are followed by China with 35, Australia with 15, the UK with 15, Saudi Arabia with 10, Brazil with 9, Germany with 9, Turkey with 8, Indonesia with 7, Jordan with 7, Ukraine with 7, Serbia with 6, Spain with 6, Sweden with 6, Tunisia with 6, Greece with 5, Hungary with 4, Poland with 4, South Africa with 4, and Canada with 3.

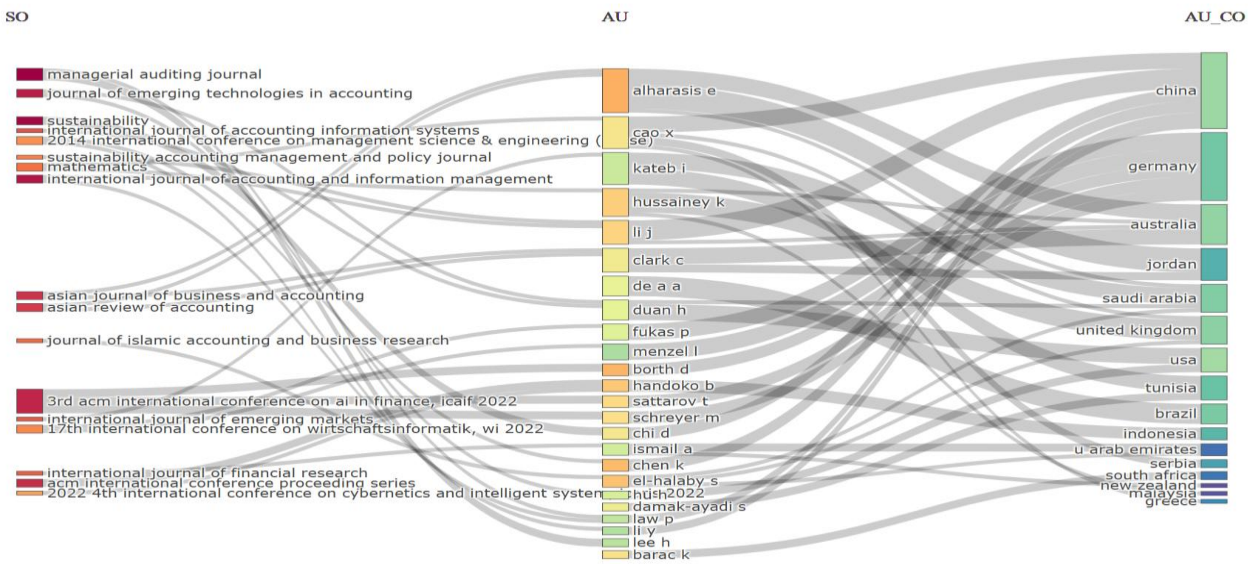
Figure 8. Country Scientific Production



Source: Biblioshiny R-Studio

Figure 9 is a three-fields plot analysis showing the relationships between source (SO), author (AU), and author country (AU_CO) in studies on machine learning in auditing. In the visual, *Managerial Auditing Journal* and *Journal of Emerging Technologies* in Accounting stand out as the most productive journals, while authors such as *Alharasis E., Cao X., and Kateb I.* are among the most contributing names. At the country level, *China, USA, Germany,* and *Australia* stand out as the countries contributing the most to the field. This situation shows that machine learning technologies are becoming widespread in the field of auditing on a global scale but are particularly concentrated in certain countries. In addition, productivity in the literature is seen to occur through both academic journals and international conferences, reflecting the importance of interdisciplinary interaction.

Figure 9. Three-fields plot (Source 25, Authors 25, And Authors's Countries 25)



Source: Biblioshiny R-Studio

4.6. Most Frequently Repeated Words

Word analyses have been examined separately as binary word analyses and ternary word analyses in the biblioshiny software. In Figures 10 and 11, the most frequently discussed topics in the field of auditing are revealed through binary and triple word analyses, and the most commonly used machine learning algorithms in the field of auditing are determined. These visual mapping methods reveal the most prominent themes of attention in the field.

As shown in Figure 10, the keywords were extracted from the abstracts, resulting in a total of 1000 keywords used to create the visual. The size of the words in this visual represents the most frequently repeated pairs of words within the abstracts. So much so that the most frequently repeated word in the field of auditing is "machine learning," which has been repeated a total of 68 times. When we list the most frequently mentioned machine learning algorithms in the field of auditing, the following stand out: *Logistic Regression (*LogR*), Artificial İntelligence, Linear Regression (LR), Regression Analysis, Regression Model, Deep Learning (DL), Multiple Linear, Regression (MLR), Neural Network, Ordinary Least Squares (OLS), And Squares Regression*. Thus, it can be stated that within the scope of the study, the logistic regression method is one of the most frequently used machine learning algorithms by researchers in the field of auditing. When looking at the topics in the field of auditing, they include, in order, financial statements, audit quality, corporate governance, financial reporting, audit committee, audit fees, fraud detection, accounting information, earnings management, audit firms, financial statements, Islamic banks, audit committees, audit reports, information systems, auditing enforcement, and so on.

Figure 10. Most Frequently Repeated Double Words

Source: Biblioshiny R-Studio

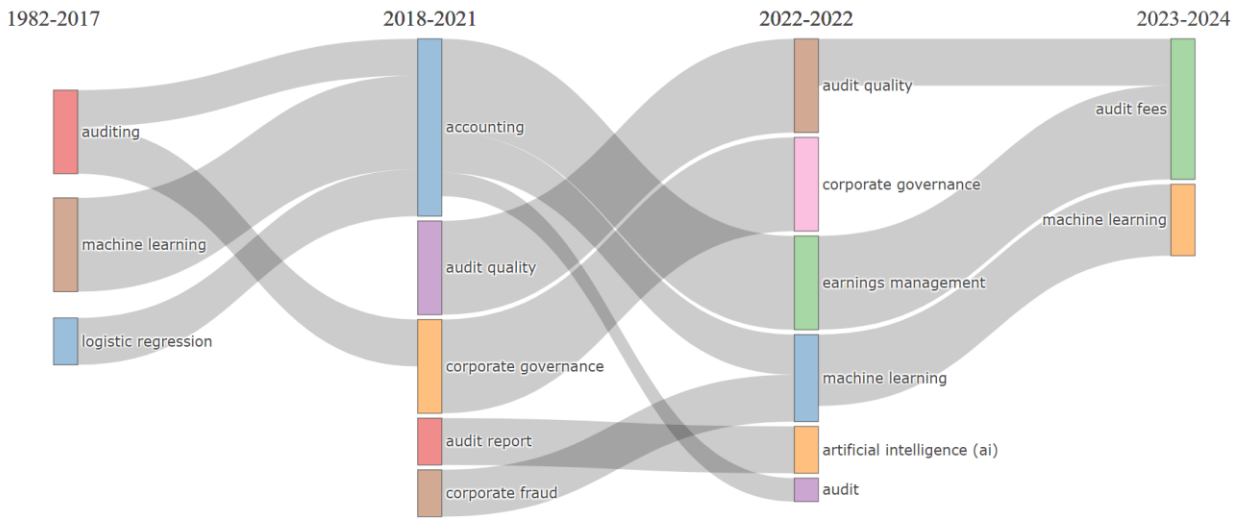
Thanks to Figure 11, the most frequently used machine learning algorithms in the field of auditing are once again brought to light. It highlights the frequency and importance of machine learning algorithms used in the field of auditing, characterized by very thick and large fonts. These words are extracted from abstracts, totaling 1000 words. When looking at the triple word analysis presented in Figure 9, terms such as *LogR Analysis, MRL, LogR Model And Models, LR Analysis, Multivariable Logistic Regression, OLS Regression, Artificial Neural Network (ANN), and SVM* are among the most frequently repeated words. Therefore, it is one of the machine learning algorithms used in the field of auditing. When looking at it within the scope of auditing, the terms that come to mind in order are: financial statement fraud, financial reporting quality, corporate governance mechanisms, corporate social responsibility, international financial reporting, financial reporting standards, internal audit function, audit committee characteristics, and audit committee independence. These words highlight the studies conducted in the field of auditing in recent years.

Figure 11. Most Frequently Repeated Triple Words

Source: Biblioshiny R-Studio

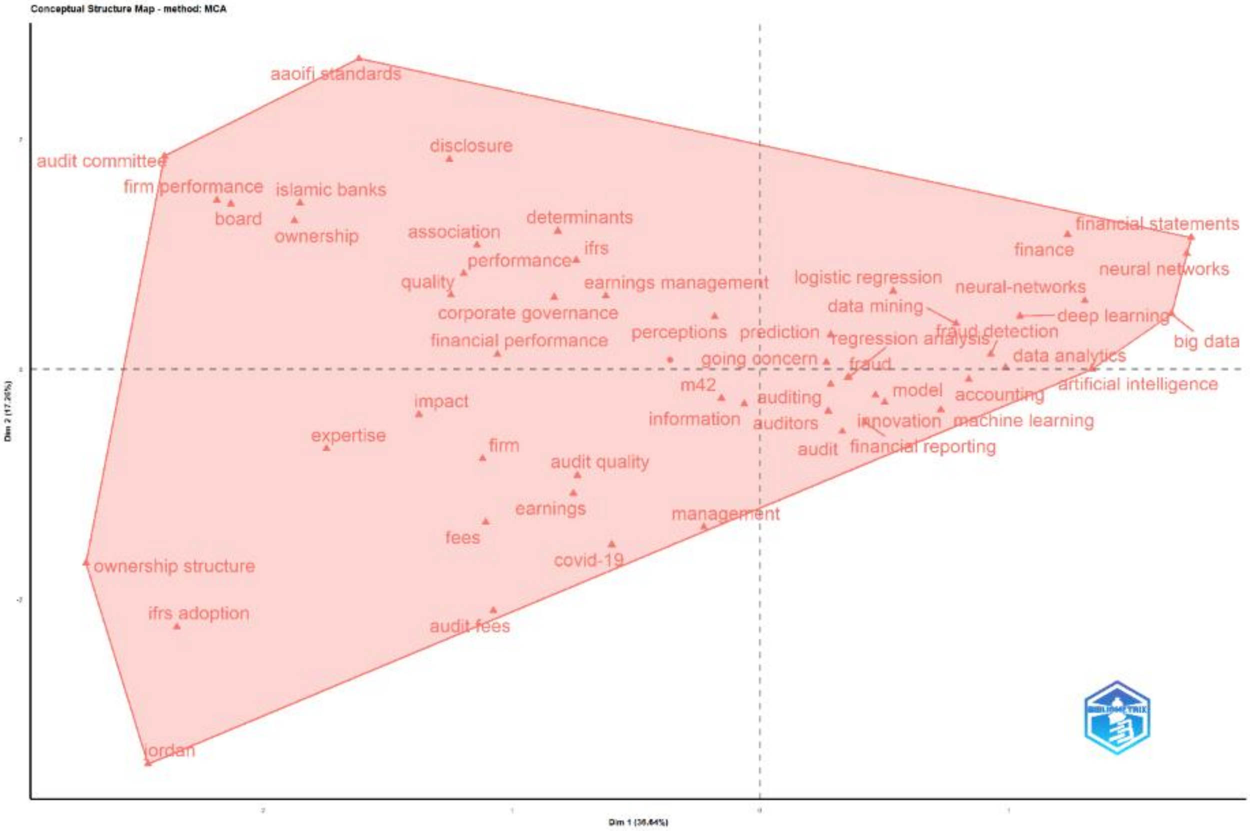
The thematic evolution of keywords has been examined in support of the most frequently repeated words and is visually presented in Figure 12. When examining the thematic evolution map, it can be observed that studies related to logistic regression analyses of the most frequently recurring words date back to the 1980s. As we approach the present day, it can be observed that research in the field of machine learning has increased, and new machine learning algorithms have emerged.

Figure 12. Thematic Evolution



Source: Biblioshiny R-Studio

Figure 13. Multiple Correspondence Analysis



Source: Biblioshiny R-Studio

The conceptual structure map in Figure 13 was created using the Multiple Correspondence Analysis (MCA) method applied to bibliometric data. The two main dimensions (Dim 1: 36.64% and Dim 2: 17.25%) on the map explain 53.89% of the variance in the literature, representing a significant conceptual density. In the graph, concepts such as ‘artificial intelligence,’ ‘machine learning,’ ‘deep learning,’ ‘LogR,’ ‘neural networks,’ and ‘fraud detection’ are clustered in the upper right region. This indicates that artificial intelligence-based models are coming to the fore in the field of auditing and accounting. On the other hand, the presence of classic corporate governance themes such as ‘audit committee,’ ‘corporate governance,’ ‘earning management,’ ‘firm performance,’ and ‘financial performance’ in the middle and upper left regions indicates that these areas retain their place in traditional audit literature. In addition, concepts such as ‘IFRS adoption,’ ‘ownership structure,’ ‘audit fees,” and ‘Jordan’ in the lower left corner reveal that the study has strong links to specific regional/regulation-focused literature. These results confirm that, as stated in the study's findings, with technological transformation, the audit and accounting literature is both shifting towards new digital applications and becoming linked to corporate structures in regional contexts.

5. MACHINE LEARNING ALGORITHMS FOR DIFFERENT AUDIT TOPICS

Many academics and practitioners have used ML algorithms in auditing. In this part of the study, 160 academic studies using ML algorithms in auditing were analyzed. Theoretical and review studies were excluded from these studies, and studies focusing directly on applications were identified. According to the findings obtained, various studies on ML in the subfields of auditing have been classified. In this way, it has been tried to identify the most effective algorithms within the scope of auditing and to evaluate their contributions to the field of auditing on the basis of performance by considering different data sets from different countries.

5.1. Audit Quality

While traditional audit methods are based on manual analyses and take a lot of time, anomalies in big data generated by ML can be detected, and error probabilities can be minimized. Table 2 shows the studies conducted in the field of audit quality and the ML algorithms used in these studies together with the countries where the data sets are located (see Appendix, Table 2). When the studies in the field of audit quality are analyzed in Table 2, it is seen that OLS and LogR algorithms are widely used. In addition, Long Short-Term

Memory (LSTM) and Deep Belief Network (DBN) algorithms, which are deep learning techniques, are also used. Therefore, it can be said that LR and LogR are widely used in the field of audit quality.

5.2. Financial Reporting and Reporting Standards

As seen in Table 3, LogR is frequently used to analyze financial reporting standards, but the model power varies according to the studies. It is also seen that the linear regression model is also frequently used. When this field is evaluated in general, it is seen that artificial intelligence, ML, and statistical analyses are used. The Beneish Model and LogR gave a very successful result (accuracy: 98.3%) in the detection of financial statement manipulations (Erdoğan & Erdoğan, 2020). In the Accounting and Auditing Enforcement Releases, SVM is quite successful (Davalos & Feroz, 2022). As the use of neural networks (ANN) and deep learning models (LSTM) increases (Schreyer et al., 2022), it is thought that it may be possible to achieve higher accuracy rates.

5.3. Fraud, Fraud Detection ve Detecting Anomalies

Table 4 shows the performance measures of a large number of ML methods on fraud detection data from different countries with different data sources (see Appendix, Table 4). Here, Random Forest (RF) (99,25%) and Gated Recurrent Unit (GRU) (99%) accuracy is seen as the most powerful algorithms. However, the data sets, variables, objectives, and methods used in the studies are different from each other. For example, XGBoost achieved 76% accuracy in one study, while RF achieved 99.25% accuracy, and SVM achieved 80% accuracy in another study. However, this difference may be due not only to the algorithms but also to the variables, data sets, and model optimization processes used. Therefore, it cannot be said that a single algorithm has the best performance in all cases. In addition, it is seen that ML algorithms are widely used in fraud detection.

5.4. Corporate Governance and Audit Committee

Table 5 presents the algorithms used in studies on corporate governance and audit committees in different countries using different data sets (see Appendix, Table 5). The studies have analyzed firms in Zimbabwe, UAE, Hong Kong, Tehran, Egypt, Taiwan, USA, Bangladesh, GCC countries, and developing countries. The most commonly used model is OLS, but algorithms such as LogR, Multinomial Logistic Regression (MlogR), and Binary Logistic Regression (BlogR) are also used. Different components of corporate governance (audit committees, board structure, social responsibility, auditor selection, and fraud detection) were analyzed. The highest accuracy rate was achieved by Law (2011) where LogR achieved 92.1%.

5.5. Islamic Finance Audit

The number of studies conducted within the scope of Islamic finance (İslamic Banks, Accounting and Auditing Organization for Islamic Financial Institution’s (AAOIFI) Governance Standards, AAOIFI Governance Standards) in auditing is gradually increasing. Table 5 presents the studies in the field of Islamic Finance Auditing. While the OLS method is used in most of the studies on Islamic finance (El-Halaby & Hussainey, 2016; Rehman et al., 2020; Elgattani & Hussainey, 2021; Ullah et al., 2018), El-Halaby et al., (2020) used LR and Probit analysis and concluded that Probit analysis is better than LR.

5.6. Earning Management, Audit Opinion Prediction and Going-Concern

In studies on earnings management, data sets obtained from different countries are analyzed not only with statistical methods but also with ML techniques. Dbouk & Zaarour (2017) used machine learning methods such as Naıve Bayes (NB), ANN, and Decision Trees (DT) in their study conducted in Lebanon. On the other hand, Gaio et al., (2021) preferred the OLS regression method in their study on listed companies in Europe.

Studies hatve focused on predicting audit opinions using financial data from different countries. These studies also employed various machine learning applications. Audit opinions are critical to determining the accuracy of financial reports and whether a company's financial position is reliable. By estimating audit opinions, auditors can use them to plan audit procedures, control their performance, and analyze variables that affect the likelihood of obtaining a qualified opinion (Sánchez-Serrano et al., 2020). Sánchez-Serrano et al. (2020), in their study conducted in Spain, achieved an accuracy rate of 86% by using the ANN algorithm. On the other hand, Gaganis & Pasiouras (2007) applied the LogR algorithm on Asian banks. Saeedi (2023) used the Gradient Boosting algorithm in his analysis on the stock exchanges in the USA (NYSE, AMEX, NASDAQ) and achieved a high accuracy rate of 97.5%.

Going-concern prediction is an important analysis to determine whether a business will continue its operations in the coming period (Chi & Shen, 2022). Chi & Shen (2022) achieved an accuracy of 95.65% by using XGBoost, ANN, SVM, and C5.0 (DT) algorithms in their study conducted in Taiwan. In particular, the C5.0 (DT) model showed the highest performance. Chi & Chu (2021), also in Taiwan, achieved a 96.15% accuracy rate by using LSTM and GRU. In this study, the LSTM model provided the highest accuracy rate.

5.7. Other Studies

The following studies are classified as ‘Audit Reputation and Auditor's Choice and Auditor Specialization, Fair Value Accounting and Audit Fees, Internal Audit and Internal Control, Auditing Education and Audit Professional, Accounting Misstatements, Auditing Decisions Prediction, Digital Accounting, Cloud Accounting, Intelligent Auditing, Environmental Responsibility Audit, Financial Distress, Climate Change Performance and Financial Distress, Risk Committee, and Big 4 Auditing Firms.’. It was observed that OLS and LOgR were used in the majority of these studies. Bertomeu et al., (2021) conducted an analysis on the detection of ongoing accounting misstatements using the Audit Analytics Non-Reliance Restatement Database. Machine learning algorithms such as Gradient Boosted Regression Trees, Random Forest, RUSBoost, and Backward Logit were applied in the study; the results showed that RUSBoost and GBRT models performed the best. In another study, Duan et al., (2023) conducted an analysis on government accounting information systems and audit processes in the USA. Machine learning algorithms such as Sentiment Analysis (SA), Random Forest, Naive Bayes, and XGBoost were used in the study; the results showed that the XGBoost model showed the most successful performance with an accuracy rate of 98%.

6. CONCLUSION

This study presents a comprehensive bibliometric analysis of machine learning applications in auditing, revealing the most frequently used methods and their contributions to the field. Within the scope of the study, 160 studies obtained from the Web of Science and Scopus databases were analyzed. In the bibliometric analysis, elements such as Main Information, Analysis of Publications By Year, Most Relevant Authors, Most Relevant Sources, Most Relevant Authors' Country, Most Frequently Repeated Words, and Thematic Evolution were evaluated.

The findings show that academic studies on the use of machine learning in auditing have increased significantly from 1982 to 2023. While Alharasis stands out among the most influential authors in the field, “the Journal of Managerial Auditing” is identified as one of the most productive publication sources in this field. When the geographical distribution of the studies is analyzed, it is seen that the majority of the studies are conducted in the USA, but the interest in this field is also increasing in other countries.

The analyses show that in recent years, advanced algorithms such as deep learning, Beetle Antennae Search (BAS), LSTM, Random Forest, and XGBoost are more preferred. In particular, logistic regression (LogR) and linear regression (OLS) are widely used in audit quality and financial reporting analyses, while advanced machine learning algorithms such as Random Forest, GRU, and XGBoost have been found to provide higher accuracy in more complex problems such as fraud detection. However, logistic regression and linear regression have been the most widely used machine learning techniques in auditing since the 1980s and remain valid today. Although more advanced methods such as deep learning have emerged, regulatory requirements and the need for interpretability of the models still cause traditional statistical techniques to be used as the main methods in auditing research. Therefore, the widespread use of logistic regression and linear regression can be explained by their statistical robustness, their ability to model the relationships between financial variables, and their interpretability.

Since the data sets, variables, objectives, and methods used in the studies are different from each other, the accuracy rates of the algorithms vary. For example, in a study on fraud detection, XGBoost achieved 76% accuracy, while Random Forest achieved 99.25% accuracy and SVM achieved 80% accuracy in another study. However, it is considered that these differences are not only due to the algorithms themselves, but also due to the variables used, the structure of the data sets, and the model optimization processes. Therefore, it cannot be said that a single algorithm has the best performance in all scenarios; instead, the appropriate model selection should be made by considering the context in which each algorithm is strong.

The research findings can contribute to the development of more sophisticated, data-driven approaches that enhance audit processes. This study provides a guide for accountants and auditors to identify the most appropriate machine learning algorithms. Furthermore, the study emphasizes the necessity of addressing auditing from an interdisciplinary perspective and brings new perspectives to the literature in this context. This study is limited to sources obtained from the Web of Science and Scopus databases and is restricted to machine learning applications in the fields of auditing. It is suggested that future research should focus on increasing the effectiveness of machine learning in auditing processes by examining different data sets and new machine learning algorithms. In particular, developing new approaches to improve the performance of deep learning techniques in audit processes is considered an important research opportunity in this field. In conclusion, this study provides a comprehensive roadmap for research on machine learning in auditing, which is a subfield of accounting, and is expected to contribute significantly to both academic and practical developments in this area.

ABBREVIATONS

AAER: Auditing Enforcement Releases

KNN: K-Nearest Neighbors,

LDA: Linear Discriminant Analysis

LIME: Local Interpretable Model-Agnostic Explanations

NABAS: Non-linear Activated Beetle Antennae Search

RNN: Recurrent Neural Network,

SEC: Security And Exchange Commission

SHAP: Shapley Additive Explanations

SLogR: Sequential Logistic Regression

SVM-FK: Support Vector Machine with Financial Kernel

TSC: Time Series Classification

XAI: Explainable Artificial Intelligence

REFERENCES

Abou-El-Sood, H. (2008). The Usefulness of Accounting Information, Economic Variables, and Corporate Governance Measures to Predict Corporate Failure [SSRN Scholarly Paper]. Rochester, NY: Social Science Research Network. Retrieved from https://papers.ssrn.com/abstract=2967010

Agus, A., & Aziza, N. (2020). The Effects of Ethical Factors in Financial Statement Examination: Ethical Framework of the Input Process Output (IPO) Model in Auditing System Basis. *International Journal of Financial Research*, *11*(2), 136. https://doi.org/10.5430/ijfr.v11n2p136

Agustí, M. A., & Orta-Pérez, M. (2023). Big data and artificial intelligence in the fields of accounting and auditing: a bibliometric analysis. *Spanish Journal of Finance and Accounting/Revista Española de Financiación y Contabilidad*, *52*(3),412-438. https://doi.org/10.1080/02102412.2022.2099675

Ahsan, M. M., Luna, S. A., & Siddique, Z. (2022). Machine-Learning-Based Disease Diagnosis: A Comprehensive Review. *Healthcare*, *10*(3), 541. https://doi.org/10.3390/healthcare10030541

Alharasis, E. E. (2023). Evaluation Of Ownership Structure And Audit-Quality In The Wake Of The Covid-19 Crisis: Empirical Evidence From Jordan. *International Journal of Law and Management*, *65*(6), 635–662. (world). https://doi.org/10.1108/IJLMA-03-2023-0035

Alsmady, A. A. (2023). The Moderating Role Of Audit Quality Between Earning Management And Sustainable Investment Opportunities: Evidences From Gulf Cooperation Council Countries. *International Journal of Applied Economics, Finance and Accounting*, *16*(1), 18–32. https://doi.org/10.33094/ijaefa.v16i1.874

Aria, M., & Cuccurullo, C. (2017). Bibliometrix: An R-Tool For Comprehensive Science Mapping Analysis. *Journal of Informetrics*, *11*(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

Ashtiani, M. N., & Raahemi, B. (2023). An Efficient Resampling Technique for Financial Statements Fraud Detection: A Comparative Study. *2023 3rd International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, 1–7. Tenerife, Canary Islands, Spain: IEEE. https://doi.org/10.1109/ICECCME57830.2023.10253185

Baatour, K., & Saada, M. B. (2022). Regulatory Accounting Environment, Cultural Values And Board Efficacy In Developing Countries. *PSU Research Review*, *8*(2), 428–442. (world). https://doi.org/10.1108/PRR-07-2021-0036

Bakumenko, A., & Elragal, A. (2022). Detecting Anomalies in Financial Data Using Machine Learning Algorithms. *Systems*, *10*(5), 130. https://doi.org/10.3390/systems10050130

Barta, G. (2018). The Increasing Role Of IT Auditors In Financial Audit: Risks And Intelligent Answers. *Business, Management and Economics Engineering*, *16*, 81–93. https://doi.org/10.3846/bme.2018.2142

Bellucci, M., Bianchi, D. C., & Manetti, G. (2022). Blockchain In Accounting Practice And Research: Systematic Literature Review. *Meditari Accountancy Research*, *30*(7), 121–146. (world). https://doi.org/10.1108/MEDAR-10-2021-1477

Bertomeu, J., Cheynel, E., Floyd, E., & Pan, W. (2021). Using Machine Learning To Detect Misstatements. *Review of Accounting Studies*, *26*(2), 468–519. https://doi.org/10.1007/s11142-020-09563-8

Biczyk, P., & Wawrowski, Ł. (2023). Detecting and Isolating Adversarial Attacks Using Characteristics of the Surrogate Model Framework. *Applied Sciences*, *13*(17), 9698. https://doi.org/10.3390/app13179698

Bineid, M., Beloff, N., Khanina, A., & White, M. (2023). CADM: Big Data to Limit Creative Accounting in Saudi-Listed Companies. *2023 18th Conference on Computer Science and Intelligence Systems (FedCSIS)*, 103–110. https://doi.org/10.15439/2023F3888

Brown, N. C., Crowley, R. M., & Elliott, W. B. (2020). What Are You Saying? Using *topic* to Detect Financial Misreporting. *Journal of Accounting Research*, *58*(1), 237–291. https://doi.org/10.1111/1475-679X.12294

Cardona, L. F., Guzmán-Luna, J. A., & Restrepo-Carmona, J. A. (2024). Bibliometric Analysis of The Machine Learning Applications in Fraud Detection on Crowdfunding Platforms. *Journal of Risk and Financial Management*, 17(8), 352. https://doi.org/10.3390/jrfm17080352

Chen, H., Tan, X., & Cao, Q. (2021). Air Pollution, Auditors' Pessimistic Bias And Audit Quality: Evidence From China. *Sustainability Accounting, Management and Policy Journal*, *12*(1), 74–104. https://doi.org/10.1108/SAMPJ-07-2019-0277

Chen, Y., & Wu, Z. (2022). Financial Fraud Detection of Listed Companies in China: A Machine Learning Approach. *Sustainability*, *15*(1), 105. https://doi.org/10.3390/su15010105

Chen, Y., Wu, Z., & Yan, H. (2022). A Full Population Auditing Method Based on Machine Learning. *Sustainability*, *14*(24), 17008. https://doi.org/10.3390/su142417008

Chi, D. J., & Shen, Z. D. (2022). Using Hybrid Artificial Intelligence and Machine Learning Technologies for Sustainability in Going-Concern Prediction. *Sustainability*, 14(3), 1810. https://doi.org/10.3390/su14031810

Chi, D.-J., & Chu, C.-C. (2021). Artificial Intelligence in Corporate Sustainability: Using LSTM and GRU for Going Concern Prediction. *Sustainability*, *13*(21), 11631. https://doi.org/10.3390/su132111631

Chien, C.-C., Chen, K. Y., & Wu, S.-Y. (2008). Corporate Governance And Auditor Selection: Evidence From Taiwan. *Corporate Ownership & Control*, *492*, 66.

Cho, S., Vasarhelyi, M. A., Sun, T. (Sophia), & Zhang, C. (Abigail). (2020). Learning from Machine Learning in Accounting and Assurance. *Journal of Emerging Technologies in Accounting*, *17*(1), 1–10. https://doi.org/10.2308/jeta-10718

Dai, X., & Zhu, W. (2022). Intelligent Financial Auditing Model Based on Deep Learning. *Computational Intelligence and Neuroscience*, *2022*, 1–5. https://doi.org/10.1155/2022/8282854

Davalos, S., & Feroz, E. H. (2022). A Textual Analysis of The US Securities And Exchange Commission's Accounting And Auditing Enforcement Releases Relating to The Sarbanes–Oxley Act. *Intelligent Systems in Accounting, Finance and Management*, *29*(1), 19–40. https://doi.org/10.1002/isaf.1506

Dbouk, B., & Zaarour, I. (2017). Towards A Machine Learning Approach For Earnings Manipulation Detection. *Asian Journal of Business and Accounting*, *10*(2), 215–251.

Dewayanto, T. (2021). A Bibliometric Analysis and Visualization Of Accounting Fraud Detection Using Machine Learning Research. *Fokus Ekonomi : Jurnal Ilmiah Ekonomi*, *16*(2), 455–471. https://doi.org/10.34152/fe.16.2.455

Do, D. T., Dang, V. S., Pham, V. D., Le, V. L., & Dang, V. T. (2023). Influence Of Local Independent Audit Firms' Service Quality on Customer Satisfaction. *Corporate Governance and Organizational Behavior Review*, *7*(3, special issue), 307.

Dong, W., Liao, S., & Zhang, Z. (2018). Leveraging Financial Social Media Data for Corporate Fraud Detection. *Journal of Management Information Systems*, *35*(2), 461–487. https://doi.org/10.1080/07421222.2018.1451954

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How To Conduct A Bibliometric Analysis: An Overview and Guidelines. *Journal of Business Research*, *133*, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

Duan, H. K., Vasarhelyi, M. A., Codesso, M., & Alzamil, Z. (2023). Enhancing The Government Accounting Information Systems Using Social Media Information: An Application of Text Mining and Machine Learning. *International Journal of Accounting Information Systems*, *48*, 100600. https://doi.org/10.1016/j.accinf.2022.100600

Eldyasty, M. M., & Elamer, A. A. (2023). Audit (Or) Type and Audit Quality In Emerging Markets: Evidence from Explicit Vs. Implicit Restatements. *Review of Accounting and Finance*, *22*(4), 489–507. https://doi.org/10.1108/RAF-02-2023-0046

Elgattani, T., & Hussainey, K. (2021). The Impact of AAOIFI Governance Disclosure on Islamic Banks Performance. *Journal of Financial Reporting and Accounting*, *19*(3), 434–454. https://doi.org/10.1108/JFRA-03-2020-0053

El-Halaby, S., & Hussainey, K. (2016). Determinants Of Compliance with AAOIFI Standards By Islamic Banks. *International Journal of Islamic and Middle Eastern Finance and Management*, *9*(1), 143–168. https://doi.org/10.1108/IMEFM-06-2015-0074

El-Halaby, S., Albarrak, H., & Grassa, R. (2020). Influence Of Adoption AAOIFI Accounting Standards on Earning Management: Evidence from Islamic Banks. *Journal of Islamic Accounting and Business Research*, *11*(10), 1847–1870. https://doi.org/10.1108/JIABR-10-2019-0201

Elmghaamez, I. K., Gerged, A. M., & Ntim, C. G. (2020). Financial Market Consequences of Early Adoption of International Standards on Auditing: International Evidence. *Managerial Auditing Journal*, *35*(6), 819–858. https://doi.org/10.1108/MAJ-04-2019-2233

Erdoğan, M., & Erdoğan, E. O. (2020). Financial Statement Manipulation: A Beneish Model Application. In S. Grima, E. Boztepe, & P. J. Baldacchino (Eds.), *Contemporary Studies in Economic and Financial Analysis* (pp. 173–188). Emerald Publishing Limited. https://doi.org/10.1108/S1569-375920200000102014

Ever, D., & Demircioğlu, E. N. (2022). Yapay Zekâ Teknolojilerinin Kalite Maliyetleri Üzerine Etkisi. *Çukurova Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, *31*(1), 59–72. https://doi.org/10.35379/cusosbil.1023004

Ferris, K. R. (1982). A Note on The Use of Regression Analysis In Accounting: Coping With Multicollinearity. *Accounting & Finance*, *22*(1), 41–53. https://doi.org/10.1111/j.1467-629X.1982.tb00129.x

Fukas, P., Menzel, L., & Thomas, O. (2022). Augmenting Data with Generative Adversarial Networks to Improve Machine Learning-Based Fraud Detection. *Wirtschaftsinformatik 2022 Proceedings*. Retrieved from https://aisel.aisnet.org/wi2022/analytics_talks/analytics_talks/4

Gaganis, C., & Pasiouras, F. (2007). A Multivariate Analysis of The Determinants Of Auditors' Opinions On Asian Banks. *Managerial Auditing Journal*, *22*(3), 268–287. https://doi.org/10.1108/02686900710733143

Gaio, C., Gonçalves, T., & Pereira, A. (2021). Financial Crisis and Impairment Recognition in Non-Financial Assets. *Review of Business Management*, *23*(2), 370–387. https://doi.org/10.7819/rbgn.v23i2.4108

Harun, M. S., Hussainey, K., Mohd Kharuddin, K. A., & Farooque, O. A. (2020). CSR Disclosure, Corporate Governance and Firm Value: A study on GCC Islamic Banks. *International Journal of Accounting & Information Management*, *28*(4), 607–638. https://doi.org/10.1108/IJAIM-08-2019-0103

Hezam, Y. A., Anthonysamy, L., & Suppiah, S. D. K. (2023). Big data analytics and auditing: A review and synthesis of literature. *Emerging Science Journal*, *7*(2), 629-642. http://dx.doi.org/10.28991/ESJ-2023-07-02-023

https://doi.org/10.3390/su132111631

Iyer, V. M., Bamber, E. M., & Griffin, J. (2012). Characteristics Of Audit Committee Financial Experts: An Empirical Study. Managerial Auditing Journal, 28(1), 65–78. https://doi.org/10.1108/02686901311282506

Kang, H. (2024). Optimization of Enterprise Accounting Audit Risk Identification and Prevention Strategy Based on Machine Learning. *Journal of Electrical Systems*, *20*(9s), 79–84.

Kateb, I., & Belgacem, I. (2024). Navigating Governance and Accounting Reforms In Saudi Arabia's Emerging Market: Impact of Audit Quality, Board Characteristics, And IFRS Adoption On Financial Performance. *International Journal of Disclosure and Governance*, *21*(2), 290–312. https://doi.org/10.1057/s41310-023-00193-5

Kateb, I., Nafti, O., & Zeddini, A. (2023). How To Improve the Financial Performance Of Islamic Banks In The MENA Region? A Shariah Governance Perspective. *International Journal of Emerging Markets*, *ahead-of-print*(ahead-of-print). (world). https://doi.org/10.1108/IJOEM-03-2023-0434

Khan, A. T., Cao, X., Li, S., Katsikis, V. N., Brajevic, I., & Stanimirovic, P. S. (2022). Fraud Detection in Publicly Traded U.S Firms Using Beetle Antennae Search: A Machine Learning Approach. *Expert Systems with Applications*, *191*, 116148. https://doi.org/10.1016/j.eswa.2021.116148

Khorsheed, H. S., Ismael, N. B., & Mahmod, S. H. O. (2024). The Impact Of Artificial Intelligence and Machine Learning On Financial Reporting And Auditing Practices. *International Journal of Advanced Engineering, Management and Science*, *10*(6), 30–37. https://doi.org/10.22161/ijaems.106.4

Khuzaae, M. H. A., Almihna, Z. A. K., & Al-bdairi, A. A. K. (2019). The Impact Of Corporate Governance And Supply Chain Management On The Accounting and Auditing Environment. *International Journal of Supply Chain Management*, 8(1), 367-373. https://www.researchgate.net/publication/351985165

Kiliç, M., Uyar, A., & Ataman, B. (2016). Preparedness Of the Entities for The IFRS For Smes: An Emerging Country Case. *Journal of Accounting in Emerging Economies*, *6*(2), 156–178. https://doi.org/10.1108/JAEE-01-2014-0003

Krieger F, Drews P, &Velte P. (2021). Explaining The (Non-) Adoption of Advanced Data Analytics in Auditing: A Process Theory. Int J Account Inf Syst 2021;41: 100511. https://doi.org/10.1016/j.accinf.2021.100511

Krieger, F., Drews, P., & Velte, P. (2021). Explaining The (Non-) Adoption Of Advanced Data Analytics in Auditing: A Process Theory. *International Journal of Accounting Information Systems*, *41*, 100511. https://doi.org/10.1016/j.accinf.2021.100511

Kulk, G. P., Peters, R. J., & Verhoef, C. (2009). Quantifying IT estimation risks. *Science of Computer Programming*, *74*(11), 900–933. https://doi.org/10.1016/j.scico.2009.09.001

Lamboglia, R., Lavorato, D., Scornavacca, E., & Za, S. (2021). Exploring the relationship between audit and technology. A bibliometric analysis. *Meditari Accountancy Research*, *29*(5), 1233-1260. https://doi.org/10.1108/MEDAR-03-2020-0836

Land, J. K. (2010). CEO Turnover Around Earnings Restatements And Fraud. *Pacific Accounting Review*, *22*(3), 180–198. https://doi.org/10.1108/01140581011091666

Law, P. (2011). Corporate Governance and No Fraud Occurrence In Organizations: Hong Kong Evidence. *Managerial Auditing Journal*, *26*(6), 501–518. https://doi.org/10.1108/02686901111142558

Lee, H.-L., & Lee, H. (2013). Do Big 4 Audit Firms Improve the Value Relevance Of Earnings And Equity? *Managerial Auditing Journal*, *28*(7), 628–646. (world). https://doi.org/10.1108/MAJ-07-2012-0728

Liao, B., Huang, Z., Cao, X., & Li, J. (2022). Adopting Nonlinear Activated Beetle Antennae Search Algorithm for Fraud Detection of Public Trading Companies: A Computational Finance Approach. *Mathematics*, *10*(13), 2160. https://doi.org/10.3390/math10132160

Liaras, E., Nerantzidis, M., & Alexandridis, A. (2024). Machine Learning In Accounting And Finance Research: A Literature Review. *Review of Quantitative Finance and Accounting*, *63*(4), 1431–1471. https://doi.org/10.1007/s11156-024-01306-z

Lin Lindawati, A. S., & Handoko, B. L. (2022). How Information Technology Literacy Moderated Factors Affecting Quality of Computer-Based Audit. *2022 4th International Conference on Cybernetics and Intelligent System (ICORIS)*, 1–6. https://doi.org/10.1109/ICORIS56080.2022.10031571

Máté, D., Sadaf, R., Oláh, J., Popp, J., & Szűcs, E. (2019). The Effects of Accountability, Governance Capital, And Legal Origin on Reported Frauds. *Technological and Economic Development of Economy*, *25*(6), 1213–1231. https://doi.org/10.3846/tede.2019.10717

Nielsen, S. (2022). Management Accounting and The Concepts of Exploratory Data Analysis and Unsupervised Machine Learning: A Literature Study And Future Directions. *Journal of Accounting & Organizational Change*, *18*(5), 811–853. https://doi.org/10.1108/JAOC-08-2020-0107

Nyakurukwa, K. (2022). The Zimbabwe Code on Corporate Governance (Zimcode) and Financial Performance. *Journal of African Business*, *23*(3), 549–567. https://doi.org/10.1080/15228916.2021.1889871

Oala, L., Murchison, A. G., Balachandran, P., Choudhary, S., Fehr, J., Leite, A. W., … Wiegand, T. (2021). Machine Learning for Health: Algorithm Auditing & Quality Control. *Journal of Medical Systems*, *45*(12), 105. https://doi.org/10.1007/s10916-021-01783-y

Ocak, M., Ozkan, S., & Can, G. (2022). Continuing Professional Education and Audit Quality: Evidence from an Emerging Market. *Asian Review of Accounting*, *30*(4), 432–464. https://doi.org/10.1108/ARA-12-2021-0235

Oyerogba, E. O. (2021). Forensic Auditing Mechanism and Fraud Detection: The Case of Nigerian Public Sector. *Journal of Accounting in Emerging Economies*, *11*(5), 752–775. https://doi.org/10.1108/JAEE-04-2020-0072

Papík, M., & Papíková, L. (2019). Detection Models for Unintentional Financial Restatements. *Journal of Business Economics and Management*, *21*(1), 64–86. https://doi.org/10.3846/jbem.2019.10179

Pérez Pérez, Y., Camacho Miñano, M. D. M., & Segovia-Vargas, M. J. (2021). Risk On Financial Reporting in The Context of The New Audit Report In Spain. *Revista de Contabilidad*, *24*(1), 48–61. https://doi.org/10.6018/rcsar.363001

Ramzan, S., & Lokanan, M. (2024). The Application of Machine Learning To Study Fraud in The Accounting Literature. *Journal of Accounting Literature*, *ahead-of-print*(ahead-of-print). (world). https://doi.org/10.1108/JAL-11-2022-0112

Ranta, M., Ylinen, M., & Järvenpää, M. (2023). Machine Learning in Management Accounting Research: Literature Review and Pathways for the Future. *European Accounting Review*, *32*(3), 607–636. https://doi.org/10.1080/09638180.2022.2137221

Sadique, R. B. M., Ismail, A. M., Roudaki, J., Alias, N., & Clark, M. B. (2019). Corporate Governance Attributes in Fraud Detterence. *International Journal of Financial Research*, *10*(3), 51. https://doi.org/10.5430/ijfr.v10n3p51

Saeedi, A. (2023). A High-Dimensional Approach to Predicting Audit Opinions. *Applied Economics*, *55*(33), 3807–3832. https://doi.org/10.1080/00036846.2022.2118224

Salem, R. B., Damak-Ayadi, S., & Saïhi, M. (2017). Determinants of full IFRS adoption. *International Journal of Managerial and Financial Accounting*. (world). Retrieved from https://www.inderscienceonline.com/doi/10.1504/IJMFA.2017.084776

Sánchez-Serrano, J. R., Alaminos, D., García-Lagos, F., & Callejón-Gil, A. M. (2020). Predicting Audit Opinion in Consolidated Financial Statements with Artificial Neural Networks. *Mathematics*, *8*(8), 1288. https://doi.org/10.3390/math8081288

Schreyer, M., Sattarov, T., & Borth, D. (2022). Federated and Privacy-Preserving Learning of Accounting Data in Financial Statement Audits. *Proceedings of the Third ACM International Conference on AI in Finance*, 105–113. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3533271.3561674

Shahroor, H. G., & Ismail, A. I. (2022). Corporate Governance Mechanisms and Earnings Management Activities: Evidence from the UAE Banking Sector. *FIIB Business Review*, 23197145221099099. https://doi.org/10.1177/23197145221099099

Shapovalova, A., Kuzmenko, O., Polishchuk, O., Larikova, T., & Myronchuk, Z. (2023). Modernization Of the National Accounting And Auditing System Using Digital Transformation Tools. *Financial & Credit Activity: Problems of Theory & Practice*, 4(51). https://doi.org/10.55643/fcaptp.4.51.2023.4102

Sheela, S., Alsmady, A. A., Tanaraj, K., & Izani, I. (2023). Navigating the Future: Blockchain's Impact on Accounting and Auditing Practices. *Sustainability*, *15*(24), 16887. https://doi.org/10.3390/su152416887

Shepherd, B. E., & Yu, C. (2011). Accounting for Data Errors Discovered from an Audit in Multiple Linear Regression. *Biometrics*, *67*(3), 1083–1091. https://doi.org/10.1111/j.1541-0420.2010.01543.x

Soltani, M., Kythreotis, A., & Roshanpoor, A. (2023). Two Decades Of Financial Statement Fraud Detection Literature Review; Combination Of Bibliometric Analysis And Topic Modeling Approach. *Journal of Financial Crime*, *30*(5), 1367–1388. https://doi.org/10.1108/JFC-09-2022-0227

Souza, F. Ê. A. de, Botinha, R. A., Silva, P. R., & Lemes, S. (2015). Comparability of Accounting Choices in Future Valuation of Investment Properties: An Analysis of Brazilian and Portuguese Listed Companies. *Revista Contabilidade & Finanças*, *26*, 154–166. https://doi.org/10.1590/1808-057x201500580

Staszkiewicz, P., & Werner, A. (2021). Reporting and Disclosure of Investments in Sustainable Development. *Sustainability*, *13*(2), 908. https://doi.org/10.3390/su13020908

Tran, T. C. T., Ha, X. T., Le, T. H. P., & Nguyen, N. T. (2019). Factors affecting IFRS adoption in listed companies: Evidence from Vietnam. *Management Science Letters*, 2169–2180. https://doi.org/10.5267/j.msl.2019.7.035

Ucoglu, D. (2020). Current Machine Learning Applications in Accounting And Auditing. *Pressacademia*, *12*(1), 1–7. https://doi.org/10.17261/Pressacademia.2020.1337

Ullah, Md. H., Khanam, R., & Tasnim, T. (2018). Comparative Compliance Status Of AAOIFI And IFSB Standards: An Empirical Evidence From Islami Bank Bangladesh Limited. *Journal of Islamic Accounting and Business Research*, *9*(4), 607–628. https://doi.org/10.1108/JIABR-11-2014-0040

Ur Rehman, Z., Zahid, M., Rahman, H. U., Asif, M., Alharthi, M., Irfan, M., & Glowacz, A. (2020). Do Corporate Social Responsibility Disclosures Improve Financial Performance? A Perspective of the Islamic Banking Industry in Pakistan. *Sustainability*, *12*(8), 3302. https://doi.org/10.3390/su12083302

Waresul Karim, A. K. M., van Zijl, T., & Mollah, S. (2013). Impact Of Board Ownership, CEO-Chair Duality And Foreign Equity Participation On Auditor Quality Choice of IPO Companies. *International Journal of Accounting & Information Management*, *21*(2), 148–169. https://doi.org/10.1108/18347641311312285

Wasito, I., Simon, F. E. B. R. Y. A. N. T. I., & Diandra, K. (2023). Time Series Classification for Financial Statement Fraud Detection Using Recurrent Neural Networks Based Approaches. *Journal of Theoretical and Applied Information Technology*, 15, 23.

Westland, C., J. (2017). An Empirical Investigation of Analytical Procedures Using Mixture Distributions. *Intelligent Systems in Accounting, Finance and Management*, 24(4), 111-124. https://doi.org/10.1002/isaf.1405

Yang, M. (2024). Topic Modeling of Financial Accounting Research Over 70 Years. *International Studies of Economics*, *19*(4), 617–643. https://doi.org/10.1002/ise3.88

Yang, Y., & Simnett, R. (2023). Determinants And Quality of Audits and Reviews of Small Charities Financial Statements. *International Journal of Auditing*, *27*(4), 220–240. https://doi.org/10.1111/ijau.12310

Zahra, S. A., & Rusfian, E. Z. (2022). Effects Of Company Structure On The Relationship Between Environmental Auditing and Financial Reporting Quality. *Procedia Environmental Science, Engineering and Management*, *8*(4), 995-1002.

Zhang, C. (Abigail), Cho, S., & Vasarhelyi, M. (2022). Explainable Artificial Intelligence (XAI) in auditing. *International Journal of Accounting Information Systems*, *46*, 100572. https://doi.org/10.1016/j.accinf.2022.100572

Zhou, Y., Liu, J., & Lei, D. (2024). The Effect of Financial Reporting Regimes On Audit Report Lags and Audit Fees: Evidence from Firms Cross-Listed In The USA. *Journal of Financial Reporting and Accounting*, 22(4), 917-941. https://doi.org/10.1108/JFRA-09-2021-0261

APPENDIX

Table 2. *Audit Quality*

Algorithms	Dataset (Country)	Author
LogR	Egypt	(Eldyasty & Elamer, 2023)
OLS	China	(Chen, Tan, & Cao, 2021)
OLS	Kingdom of Saudi Arabia	(Kateb & Belgacem, 2024)
OLS, LogR	Turkey	(Ocak, Ozkan, & Can, 2022)
LSTM,DBN	Beijing	(Dai & Zhu, 2022)
LR	Indonesia	(Agus & Aziza, 2020)
OLS	Gulf Cooperation Council Countries	(Alsmady, 2023)
LR	Vietnam	(Do, Dang, Pham, Le, & Dang, 2023)
OLS	Jakarta: public accounting firms	(Lin Lindawati & Handoko, 2022)
OLS	Taiwan capital market	(Lee & Lee, 2013)
OLS	Jordan	(Alharasis, 2023)
SLogR	Australian	(Yang & Simnett, 2023)
LR	Indonesia	(Zahra & Rusfian, 2021)
MLR	Latin America	(Shepherd & Yu, 2011)
LogR	Hong Kong, Finland, US	(Kulk, Peters, & Verhoef, 2009)

Table 3. Financial Reporting and Reporting Standards

Algorithms	Dataset (Country)	Author	Performance Evaluation
XAI: SHAP, LIME	USA	(Zhang, Cho, & Vasarhelyi, 2022)	-
OLS	110 Countries	(Elmghaamez, Gerged, & Ntim, 2020)	-
OLS	ACFE	(Máté, Sadaf, Oláh, Popp, & Szűcs, 2019)	-
MLogR	101 Countries	(Salem, Damak-Ayadi, & Saïhi, 2017)	-
LogR	Turkey	(Kiliç, Uyar, & Ataman, 2016)	
LogR	Vietnam	(Tran, Ha, Le, & Nguyen, 2019)	-
LogR	Brazilian and Portuguese	(Souza, Botinha, Silva, & Lemes, 2015)	-
MLR	Spain	(Pérez Pérez, Camacho Miñano, & Segovia-Vargas, 2021)	-
ANN, LSTM	Saudi-listed companies	(Bineid, Beloff, Khanina, & White, 2023)	-
LogR	European-based companies	(Staszkiewicz & Werner, 2021)	-

LDA, LOGR	USA SEC	(Papík & Papíková, 2019)	Accuracy: 70.96% (LDA) Accuracy 62.22% (LogR)
DL	USA (Philadelphia, Chicago, York)	(Schreyer et al., 2022)	Average Precision: 61.9%, 86,9%,74.9%
SVM, SA, KNN, NB	US STOCK	(Davalos & Feroz, 2022)	Accuracy: 97% (SVM)
LogR	In Borsa İstanbul, Turkey	(Erdoğan & Erdoğan, 2020)	Accuracy: 98.3%
LDA (Bayesian)	USA SEC	(Brown, Crowley, & Elliott, 2020)	Accuracy: 59%

Table 4. Fraud, Fraud Detection ve Detecting Anomalies

Algorithms	**Dataset (Country)**	**Author**	**Performance Evaluation**
NABAS, AdaBoost, RUSBoost, LogR, SVM-FK	USA	(Liao, Huang, Cao, & Li, 2022)	Accuracy: 85,4% (NABAS)
DT (ID3, CART, C4.5)	China	(Chen et al., 2022)	Macro-average: 83% (CART)
BLogR, OLS	Nigerian public sector	(Oyerogba, 2021)	Nagelkerke R^2=32% (BLogR)
BAS, SVM, RUSBoost	US: SEC's Accounting and AAERs	(Khan et al., 2022)	Accuracy: 84,9% (BAS)
SVM, LR, ANN, DT	UGC	(Dong, Liao, & Zhang, 2018)	Accuracy: 80% (SVM)
Logit, SVM, XGBoost	US: SEC	(Fukas, Menzel, & Thomas, 2022)	Accuracy: 0.761 (XGBoost)
MFFNN, SVM, Naıve Bayes	US: SEC	(Ashtiani & Raahemi, 2023)	Accuracy: 0.863 (MLFFNN)
LogR	USA	(Land, 2010)	-
LogR	Malaysia	(Sadique, Ismail, Roudaki, Alias, & Clark, 2019)	-
TSC, RNN, Simple RNN, LSTM, GRU	US: AAERs, US: SEC	(Wasito et al., 2023)	Accuracy: 99% (GRU)
DNN,R, DT, SVM, RF, KNN, NB, ANN Models	Sweden	(Bakumenko & Elragal, 2022)	Recall Avg Macro :99,25%(RF)

Table 5. Corporate Governance and Audit Committee

Algorithms	Dataset (Country)	Author	Performance Evaluation
OLS	Zimbabwe Stock Exchange	(Nyakurukwa, 2022)	-
OLS	The Listed National Banks İn The UAE.	(Shahroor & Ismail, 2022)	-
OLS	GCC countries	(Harun, Hussainey, Mohd Kharuddin, & Farooque, 2020)	-
LogR	Hong Kong	(Law, 2011)	Accuracy:92.1%
OLS	Developing Countries	(Baatour & Saada, 2022)	-
LR	Tehran Stock Exchange.	(Khuzaae, Adnan, Almihna, Awad, & Al-Bdairi, 2019)	-
LogR	Egypt	(Abou-El-Sood, 2008)	Accuracy: 78.2%
MLogR, BLogR	Taiwan	(Chien, Chen, & Wu, 2008)	-
LogR	USA	(Iyer, Bamber, & Griffin, 2012)	Accuracy: 82.1%,
LogR	Bangladesh	(Waresul Karim, van Zijl, & Mollah, 2013)	-

Table 6. Islamic Finance Audit

Algorithms	Dataset (Country)	Author
OLS	40 countries	(El-Halaby & Hussainey, 2016)
OLS	8 countries	(Elgattani & Hussainey, 2021)
OLS	Pakistan	(Ur Rehman et al., 2020)
LR, Probit	26 different countries	(El-Halaby et al., 2020)
OLS	Shariah	(Kateb, Nafti, & Zeddini, 2023)
OLS	Bangladesh	(Ullah et al., 2018)

Araştırma Makalesi

A Bibliometric Analysis On The Use Of Machine Learning İn Auditing

Denetimde Makine Öğreniminin Kullanımına Yönelik Bibliyometrik Bir Analiz

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GENİŞLETİLMİŞ ÖZET

Günümüzde finansal denetim alanında makine öğrenimi teknolojilerinin uygulanmasına yönelik talep artmaktadır (Bakumenko ve Elragal, 2022, s.1). Makine öğrenimi uygulamalarının muhasebe ve denetimde yaygın olarak kullanılması, bu konudaki bilimsel araştırmalarda önemli bir eğilime yol açmıştır (Cho ve ark., 2020, s.1). Muhasebenin finansal muhasebe (Yang, 2024; Liaras ve ark., 2024), yönetim muhasebesi (Nielsen, 2022; Ranta ve ark., 2023) ve hile denetimi (Ramzan ve Lokanan, 2024; Cardona ve ark., 2024; Dewayanto, 2021) gibi çeşitli alt alanlarında bibliyometrik çalışmalar yapılmış olmasına rağmen denetim alanında makine öğrenmesinin kullanımına ilişkin kapsamlı bir bibliyometrik analiz henüz yapılmamıştır. Bunun yanında literatürde denetim alanında makine öğrenmesinin kullanımına ilişkin çeşitli çalışmalar bulunmaktadır. Örneğin, finansal rapor hile tespiti (Soltani ve ark., 2023), finansal raporlama ve denetim süreçlerinde makine öğrenmesinin rolü (Khorsheed ve ark., 2024) ve büyük denetim firmalarının makine öğrenmesi stratejileri (Ucoglu, 2020) gibi konularda akademik araştırmalar yapılmıştır. Ancak, mevcut çalışmalar genellikle belirli alt alanlara odaklanmaktadır ve finansal denetimde en yaygın kullanılan makine öğrenimi yöntemlerini kapsamlı bir şekilde ele alan bütünsel bir analiz bulunmamaktadır.

Bu çalışmanın amacı denetim alanında kullanılan en uygun makine öğrenmesi yöntemlerini belirlemek ve bu yöntemlerin denetim alanına katkılarını ortaya koymaktır. Bu amaç doğrultusunda bibliyometrik analiz yöntemi kullanılarak, Scopus veri tabanından 147, Web of Science veri tabanından ise 99 olmak üzere toplam 246 çalışma incelenmek amacıyla veriler birleştirilmiştir. Verilerin birleştirilmesinin ardından kapsamlı analiz için 160 çalışma seçilmiştir. Bibliyometrik verilerin analizi, Biblioshiny yardımıyla R-Studio programında Bibliometrix paketi kullanılarak yapılmıştır. Özetle çalışma kapsamında Scopus ve Web of Science veri tabanlarından elde edilen 160 çalışma analiz edilmiştir. Bibliyometrik analizde *Ana Bilgi, Yayınların Yıla Göre Analizi, En İlgili Yazarlar, En İlgili Kaynaklar, En İlgili Yazarların Ülkesi, En Sık Tekrarlanan Kelimeler* ve *Tematik Evrim* gibi unsurlar değerlendirilmiştir. Ardından, denetimde makine öğreniminin kullanımına ilişkin çalışmalar denetimin farklı alt alanlarına ayrılarak sınıflandırılmıştır. Bulgular, denetim alanında makine öğreniminin kullanımıyla ilgili akademik çalışmaların 1982'den 2023'e kadar önemli ölçüde arttığını göstermektedir. Alharasis, alandaki en etkili yazarlar arasında öne çıkarken, "The Journal of Managemential Auditing" bu alandaki en üretken yayın kaynaklarından biri olarak tanımlanmaktadır. Çalışmaların coğrafi dağılımı incelendiğinde, çalışmaların çoğunluğunun ABD'de yapıldığı, ancak bu alana olan ilginin diğer ülkelerde de arttığı görülmektedir.

Ayrıca, denetimde makine öğreniminin kullanımına ilişkin çalışmalar denetimimin farklı alt alanlarına ayrılarak sınıflandırılmıştır. "*Denetim Kalitesi, Finansal Raporlama ve Raporlama Standartları, Sahtecilik, Sahtecilik Tespiti ve Anomalilerin Tespiti, Kurumsal Yönetim ve Denetim Komitesi, İslami Finans Denetimi, Kazanç Yönetimi, Denetim Görüşü Tahmini ve Devamlılık, Denetim İtibarı ve Denetçinin Seçimi ve Denetçi Uzmanlığı, Adil Değer Muhasebesi ve Denetim Ücretleri, İç Denetim ve İç Kontrol, Denetim Eğitimi ve Denetim Uzmanı, Muhasebe Yanlış Beyanları, Denetim Kararları Tahmini, Dijital Muhasebe, Bulut*

Muhasebesi, Akıllı Denetim, Çevresel Sorumluluk Denetimi, Finansal Sıkıntı, İklim Değişikliği Performansı, Risk Komitesi ve Büyük 4 Denetim Şirketi" denetimde makine öğreniminin uygulandığı başlıca alanlar olarak belirlenmiştir.

Bulgular, son yıllarda denetim alanında derin öğrenme, BAS, LSTM, Random Forest ve XGBoost gibi gelişmiş algoritmaların daha çok tercih edildiğini göstermektedir. Özellikle lojistik regresyon (LogR) ve doğrusal regresyon (OLS) denetim kalitesi ve finansal raporlama analizlerinde yaygın olarak kullanılırken, Random Forest, GRU ve XGBoost gibi gelişmiş makine öğrenimi algoritmalarının hile tespiti gibi daha karmaşık problemlerde daha yüksek doğruluk sağladığı bulunmuştur. Ancak, lojistik regresyon ve doğrusal regresyon, 1980'lerden beri denetimde en yaygın kullanılan makine öğrenimi teknikleri olmuştur ve bugün de geçerliliğini korumaktadır. Derin öğrenme gibi daha gelişmiş yöntemler ortaya çıkmış olsa da, düzenleyici gereklilikler ve modellerin yorumlanabilirliğine duyulan ihtiyaç, denetim araştırmalarında hala ana yöntem olarak geleneksel istatistiksel tekniklerin kullanılmasına neden olmaktadır. Bu durumda, lojistik regresyon ve doğrusal regresyonun yaygın kullanımı, istatistiksel sağlamlıkları, finansal değişkenler arasındaki ilişkileri modelleme yetenekleri ve yorumlanabilirlikleri ile açıklanabilir. Çalışmalarda kullanılan veri setleri, değişkenler, amaçlar ve yöntemler birbirinden farklı olduğundan algoritmaların doğruluk oranları da değişmektedir. Örneğin, dolandırıcılık tespiti üzerine yapılan bir çalışmada XGBoost %76 doğruluk elde ederken, Random Forest başka bir çalışmada %99,25 doğruluk, SVM ise %80 doğruluk elde etmiştir. Ancak bu farklılıkların yalnızca algoritmaların kendisinden değil, kullanılan değişkenlerden, veri setlerinin yapısından ve model optimizasyon süreçlerinden de kaynaklandığı düşünülmektedir. Dolayısıyla tek bir algoritmanın tüm senaryolarda en iyi performansa sahip olduğu söylenemez; bunun yerine her algoritmanın güçlü olduğu bağlam göz önünde bulundurularak uygun model seçimi yapılmalıdır.

Araştırma bulguları, denetim süreçlerini geliştiren daha sofistike, veri odaklı yaklaşımların geliştirilmesine katkıda bulunabilmektedir. Bu çalışma, muhasebecilere ve denetçilere en uygun makine öğrenimi algoritmalarını belirlemeleri için bir rehber sunmaktadır. Ayrıca, çalışma denetimin disiplinler arası bir bakış açısıyla ele alınmasının gerekliliğini vurgulamakta ve bu bağlamda literatüre yeni bakış açıları getirmektedir. Gelecekteki araştırmaların, farklı veri setlerini ve yeni makine öğrenimi algoritmalarını inceleyerek denetim süreçlerinde makine öğreniminin etkinliğini artırmaya odaklanması önerilmektedir. Özellikle, denetim süreçlerinde derin öğrenme tekniklerinin performansını iyileştirmek için yeni yaklaşımlar geliştirmek, bu alanda önemli bir araştırma fırsatı olarak kabul edilmektedir. Sonuç olarak, bu çalışma, muhasebenin denetim alanında makine öğrenimi üzerine yapılacak araştırmalar için kapsamlı bir yol haritası sunmakta; bu yönüyle hem akademik hem de pratik gelişmelere önemli katkılar sağlamayı hedeflemektedir.