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How Can We Use Artificial Intelligence and Machine Learning in Accounting and Auditing: An Engineering Overview with the Mapping Method in the Field of Business

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Abstract

Today, the industry faces data-related challenges stemming from the use of artificial intelligence. Similarly, sustainability challenges in real world applications also arise. One of these is the accounting and auditing fields. Because of how to use artificial intelligence in this field and what technical approaches are not known enough. This study presents a machine learning approach with engineering and technical view. Because of the technical complexity, the papers on artificial intelligence and machine learning in accounting and auditing are often hard to evaluate and need a clear understanding of critical methodological parts. This paper aims to guide the key methodological aspects of artificial intelligence and machine learning for non-expert researchers of accounting and auditing. The proposed paper draws up the general framework for the use of machine learning, a sub-branch of artificial intelligence, in sustainable accounting studies. The most frequently used classification methods for accounting data and the metrics used in the evaluation of the results have been explained. In addition, the framework of recent studies such as bankruptcy prediction, financial distress, corporate failure, accounting fraud prediction, tax compliance problems, and financial difficulties conducted with accounting and auditing data has been examined. One of the findings obtained from

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this study is that although many studies in literature mention artificial intelligence with a few words, they decorate the title or keywords of the study with artificial intelligence. Keyword analyses are also among the findings of the study. All findings of the analysis emphasize the increasing importance of artificial intelligence in the field of accounting and auditing and the diversity of research in this field. If the notion of artificial intelligence is one of the essential components of future research, this study advises researchers to use it carefully in the study's title and keywords.

Key Words: Accounting, Artificial Intelligence, Auditing, Bibliometric Analysis, Machine Learning.

JEL Code: M40, M41

1. Introduction

Accounting is defined as "an information system that produces information explaining the formation of an organization's resources, the formation of these resources, the increases and decreases in these resources as a result of the organization's transactions, and the organization's financial status, and transmits these to the relevant persons and organizations." (Sevilengül, 2005). The functions of accounting are defined as "collecting information regarding company transactions that alter the company's resources and assets, which are completely or partially financial and can be expressed in money, determining their accuracy, recording, classifying, presenting the results obtained to the relevant persons in the form of a report, and analyzing and interpreting this information." (Küçüksavaş, 2001). In systems also called "Paperless Accounting;" Data regarding the transactions carried out in businesses are obtained, transferred, and stored electronically. (Gullkvıst, 2024). The use of information technologies in the performance of accounting transactions and the auditing of the accuracy and reliability of the financial statements obtained because of these transactions require the application of some new techniques. These techniques, called "Artificial Intelligence" and "Machine Learning", can be shaped according to need and can affect accounting processes. It is necessary to use these techniques in the audit of financial statements and reports obtained because of the process. This study aims to present a bibliometric analysis of academic publications in this field by addressing the use of artificial intelligence in accounting and auditing. As a result of a detailed query conducted in the Web of Science database (Web of Science, 2023). 402 academic studies published between 2010 and 2023 were reached. The query criteria cover studies focusing on accounting or auditing topics and artificial intelligence subfields such as deep learning and machine learning. It is possible to formulate the query criteria in detail as follows:

Refine results for "accounting" (Topic) OR "auditing" (Topic) AND deep learning (Topic) AND machine learning (Topic) and 4.61 Artificial Intelligence & Machine Learning (Citation Topics Meso) and Business Economics (Research Areas) and 2023 or 2022 or 2021 or 2020 or 2019 or 2018 or 2017 or 2016 or 2015 or 2014 or 2013 or 2012 or 2011 or 2010 (Publication Years)

The findings of the study are presented under the following headings: This study helps non-expert accounting and auditing researchers through essential methodological components of AI and machine learning. In addition, this study examines current work on this topic, including the use of artificial intelligence and machine learning in accounting and auditing. The suggested paper presents a broad framework for the application of machine learning, a subfield of artificial intelligence, in sustainable accounting research. The growth and citation trends of publications, types of publications, research orientations, publication languages, publishing houses, Web of Science indexes, funding organizations, and sustainable development goals. In addition, within the scope of productivity and effectiveness analyses, the most productive authors, institutions, and countries and the most effective authors, articles, institutions, and countries/regions were determined. Keyword analyses are also among the findings of the study. Also, in this paper, it is analyzed recent literature in this field by addressing the use of artificial intelligence and machine learning in accounting and auditing.

The goal of this comprehensive bibliometric analysis is to provide insight into the present state and emerging trends of artificial intelligence in the accounting and auditing field, thus supporting future research and applications.

The article first discusses the theoretical foundations of AI and machine learning and explains the general machine learning flow. It also covers the use of machine learning algorithms (Decision Trees, Naïve Bayes, Logistic Regression, Support Vector Machines (SVM), Neural Networks (NN), Random Forest (RF), AdaBoost, Extreme Gradient Boosting (XGBoost), CatBoost, K-Nearest Neighbor (KNN)). In the material and method section of the study, the process of obtaining data sets with bibliometric analysis is discussed. In addition, the concept of bibliometric analysis is emphasized, and the mapping method is briefly explained. For mapping applications, an overview of the VOSviewer-Visualizing scientific landscapes application is also provided.

2. Theorical Background of Machine Learning

Machine learning is the study of algorithms that are learn based on data and prior experience. It is used in a wide range of fields, including advertising, medical, military, and pedestrian applications. Within the field of artificial intelligence, machine learning comprises a collection of statistical instruments and algorithms that enable computers to learn from their data, provide valuable insights, and enhance their capabilities over time. Large data sets are used to train computers to identify functions and factors that allow the creation of models with predictive capabilities. Classification issues, which involve identifying the characteristics that set one class apart from another, are among the most popular applications of machine learning technology. The computer classifies observations during the learning process according to specific attributes. The regression problem is another machine learning technique that makes use of models trained on historical data to forecast future events (Liashenko, Kravets & Kostovetskyi, 2023; Daumé, 2017).

There are three types of machine learning algorithms: reinforcement, unsupervised, and supervised. As the model changes during a learning process, reinforcement approaches use data to define the model and help it respond to the changing environment. Still, most approaches that have been proposed in the literature have concentrated on supervised and unsupervised machine learning techniques. The existence of labels in the training data subset distinguishes these two primary classes from one another. Both predefined output features and input attributes are used in supervised machine learning. Depending on the number of counts in which the predefined attribute is accurately predicted, classified, or otherwise classified, algorithms try to forecast and classify the predetermined attribute. They also attempt to classify the predetermined features and measure their accuracy and misclassification, as well as other performance metrics. It is also critical to remember that learning ends when the algorithm performs at a level that meets acceptance. Using the training data, supervised algorithms initially carry out analytical tasks before building conditional functions to map the new instance of the feature. Algorithms necessitate predetermining maximum parameters for desirable outcomes and performance levels, as was previously indicated. Regression and classification algorithms are additional categories for supervised learning techniques (Alloghani, Al-Jumeily, Mustafina, Hussain & Aljaaf, 2020).

Unsupervised machine learning is the process of identifying patterns without the use of a target characteristic. Stated differently, every variable included in the analysis serves as an input, and because of the methodology, the methods are appropriate for association mining and clustering procedures. To implement supervised learning tasks, unsupervised learning algorithms can be utilized to generate labels in data. In other words, unsupervised clustering algorithms find naturally occurring groups in unlabeled data and then give each data value a label (Alloghani, Al-Jumeily, Mustafina, Hussain & Aljaaf, 2020).

There are various techniques for machine learning and many of them are used for auditing and accounting in literature. Here, we will briefly present some of them.

2.1. General Machine Learning Flow

The general scheme of machine learning is given in Figure 1 (Chakraborty & Ranjan, 2024). The machine learning process starts with data collection from several resources. The data are gathered from stock exchanges, firms, and companies. Sometimes the dataset is unbalanced, has wrong, missing, or the same values. So, an expert must preprocess the dataset. After the preprocessing such as cleaning, resizing, and balancing, the data labeling process is started. The label defines the class information. For example, if we have a bankrupt dataset then we can label the samples as bankrupt/not bankrupt or positive class/negative class. The next step is featuring extraction, and the features are specific information of the samples. The information is gathered from statistical, accounting, and other details of the samples.

Another important part of machine learning is data splitting. In the literature, there are two main approaches for splitting. The holdout method is defined as the splitting data set into two subsets the training set and the test set. The training set contains the samples between %60-%80 of the dataset, and the remaining part (i.e., %40-%20) is used for testing. Training and testing sets have already been developed by specialists in the field who are experts in data quality and the fitness of models using classifiers. The training procedure must utilize the same procedures for evaluating the actions of the learning model while learning or forecasting new, unknown data samples. A second validation set, which can be constructed from a training data set, is extremely useful for further assessing the model's correctness. The test set is used to evaluate the performance of the trained machine learning model (Al-Areqi & Konyar, 2022; Berghout & Benbouzid, 2022).

The other dataset-splitting method is the k-fold cross-validation test. This method is used to evaluate classification models to prevent wrong learning. Model performance is tested using test data that the model has never seen before. The data set to be handled by the model is separated into training and test data. This data set is randomly divided into k groups, with a different group selected each time for validation and the remaining k-1 groups used to train the model. Typically, the mean or standard deviation of model accuracy rates is used to calculate the results of k-fold cross-validation tests (Saleh et al,2022; Öngir et.al. 2025).

The hyperparameter tuning processes are another significant case that needs to be examined. The most crucial factors influencing the approximation-related convergence conditions of the loss function are the hyperparameters. While grid search methods can be employed in the current situation to offer more optimization and move nearer to the loss function's global minima, the previously outlined data-choosing methods can be utilized to choose suitable parameters within a randomly created grid. The learning process is carried out, and the learning model is constructed based on validation criteria after deciding on the best strategy for hyperparameter optimizations (Berghout & Benbouzid, 2022).

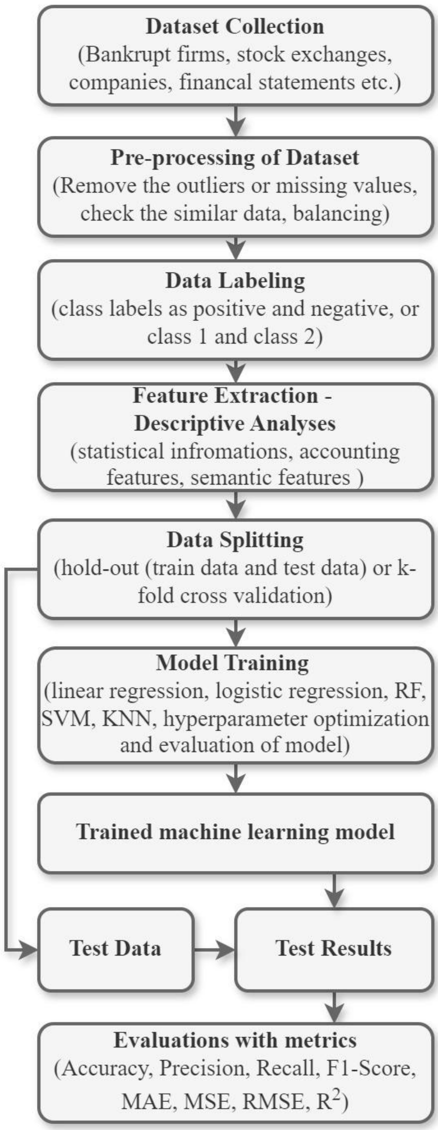

Figure 1. General Flowchart of Machine Learning

2.2. Machine Learning Algorithms

2.2.1. Decision Tree

Though decision tree algorithms are mostly employed for classification, it is crucial to remember that supervised learning can be based on either regression or classification algorithms. The method groups the attributes according to data values

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and sorts them using a tree-like interface. The algorithm functions, like a traditional tree, with branches and nodes that assume the values that an attribute may accept as a member of the class and nodes that indicate variable groups for categorization (Alloghani, Al-Jumeily, Mustafina, Hussain & Aljaaf, 2020).

Three separate phases are involved in decision tree classification. First, the algorithm produces the functionalities of both tree growth and tree pruning. Subsequently, the tree is expanded by designating every data value to a class according to the target variable's most often occurring value at each iteration. Reducing the older tree is the last step to maximize the performance of the resulting model (Alloghani, Al-Jumeily, Mustafina, Hussain & Aljaaf, 2020).

2.2.2. The Naïve Bayes

The Naïve Bayes algorithm's popularity stems from its basis in the Bayesian probability theorem. It is regarded as a semi-supervised method in most literature since it may be applied to tasks involving either classification or clustering. Naïve Bayes is an unsupervised learning technique that assigns data values to classes based on conditional probability, eliminating the need for result specification when used to create clusters. Naïve Bayes, however, is a supervised learning technique because it needs both input and target variables to categorize data. As a classifier, the algorithm builds Bayesian networks, which are trees that are constructed according to the condition probability of a result based on the probabilities that the input variables impose on it. Based on probability, the Naïve Bayes method assigns independent variables to classes using the Bayes theorem, which is mathematically expressed below in Eq (1) and Eq (2).

$$P(A) = \frac{P(B)P(B)}{P(A)} \qquad 1$$

$$P(A) = P(B) = \prod_{i=1}^{n} P(B) \qquad 2$$

Here, P(B|A) is the probability of event B will occur given that event A has occurred. The prior probability that event B will occur without regard to event A is represented by P(B). The prior probability that event A will occur without regard to occurrence B is represented by P(A). The conditional probability that event A will occur given that event B has already occurred is denoted by P(A|B). The input features, fi, are represented in the equation. Conditional probabilities are calculated for this feature using the training dataset's known probabilities of the target variables.

Bayes' theorem allows us to update the expectation about the probability of B will occur, considering new evidence A. In other words, Bayes' theorem helps us to predict the probability of the target class with the information of known features (Alloghani, Al-Jumeily, Mustafina, Hussain & Aljaaf, 2020). Bayesian networks, a type of statistical model that produces meaningful results when dealing with extremely uncertain occurrences, are one of the most common supervised machine learning methods. They employ Bayes' Theorem to detect behaviors associated with conditional probabilistic dependence. This model employs a set of random variables represented in statistical graph arcs and nodes that are defined based on conditional interaction; that is, they represent the probability that a desired event occurs as a result of another event that is also considered conditional, resulting in the conditional probability table. Bayesian networks, a type of statistical model that produces meaningful results when dealing with extremely uncertain occurrences, are one of the most common supervised machine learning methods. They employ Bayes' Theorem to detect behaviors associated with conditional probabilistic dependence. This model uses a set of random variables represented in a statistical graph by arcs and nodes that are defined based on conditional interaction; that is, they represent the probability that an event desired happens as a result of another event that is also thought to be conditional, resulting in the conditional probability table (De Jesus & Da Nóbrega Besarria, 2023).

2.2.3. Logistic Regression

Logistic regression is a prominent method for predicting dataset failures. Logistic regression models connect a set of explanatory variables and a qualitative dependent variable. The membership of the data in a certain category is determined by the qualitative dependent variable. Logistic regression is one of the most widely utilized risk analysis tools. It appears as a feature that distinguishes it from discriminant linear regression: it can detect nonlinear growth by default using a sigmoid function format, resulting in faster growth and higher prediction accuracy in many circumstances. When the dependent variable takes on binary values, as it does in classification issues, this approach is frequently employed. Its implementation entails calculating the likelihood that an event will occur given a set of factors. The logistic regression can be represented in its functional form as follows where the formula is used to get the failure probability function. The function in Eq. (3) is known as the logistic or sigmoid function commonly used in the logistic regression.

$$P = \frac{1}{1 + e^{-(\sum_{i=1}^{N} \beta_i X_i + \beta_0)}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}} \quad 3$$

where xn are the explanatory input variables to predict the probability of the P. β0, β1, ..., βn are representing the coefficients of the variables estimated by the logistic regression model. P is the probability of the binary outcome that an item would take on a certain value where represented in terms of a categorical variable (De Jesus & Da Nóbrega Besarria, 2023; Ben Jabeur, Stef & Carmona, 2023).

2.2.4. Support Vector Machines (SVMs)

Support vector machines (SVMs) are a collection of similar supervised learning methods that are commonly employed to solve classification problems. SVMs are powerful learning algorithms for classification and regression where the original algorithm was proposed by Cortes and Vapnik (1995). By increasing the margin between failed and non-failed enterprises, support vector machines aim to find the best-separating hyperplanes between them. Input variables can be drawn into a high-dimensional feature space using various SVM methods. In addition, the maximum likelihood method can be used to express and estimate coefficients. However, SVMs have many drawbacks, including noisy classes, trouble determining the right parameter values, and trouble processing big datasets (Ben Jabeur, Stef & Carmona, 2023).

The kernel function of SVM, which converts the original data into high-dimensional data to enable group separation, is the most key component of the system. SVM is a practical and effective method for classification because of this idea. Finding a hyperplane with the widest distance to categorize is what we need to accomplish when the kernel function converts the original sample data into high-dimensional data. Furthermore, the performance of categorization is significantly impacted by the choice of kernel. A linear or non-linear function can serve as the "kernel". When the data is linearly split, the former is primarily used. Because empirical data analysis is complex, the linear kernel function does not yield good prediction and classification accuracy because data—especially economic data—rarely are separable. The error section and non-linear kernel functions are thus permitted to be used by the support vector machine The RBF kernel and other non-linear kernels are challenging to analyze or even discuss since the linear kernel doesn’t offer very good predictability in non-separable datasets; nevertheless, in non-separable circumstances, its prediction could be improved (Liashenko, Kravets & Kostovetskyi, 2023; Qu, Quan, Lei & Shi, 2019).

2.2.5. Neural Networks (NN)

One of the most widely used machine learning techniques is neural networks (NN) or artificial neural networks (ANN), which are also likely the source of inspiration for other computational techniques. It draws a comparison to human neural processing, which is multilayered and depends on input variables to define the first layer and output variables to form the final layer. Most of the output variables are each sample's label or tag. A single classifier may not perform as well as an ensemble model, which is created by combining multiple single NNs (Qu, Quan, Lei & Shi, 2019).

The amount of link weights and the information flow inside the network are determined by NN model architecture. In distinct types of feed-forward NNs, the trendiest design is Multilayer Perceptron (MLP), which has only three layers. General Regression neural networks, Radial Basis Function neural networks, and Extreme Learning Machines are three common feedforward ANNs. The Long Short-Term Memory (LSTM) neural network is an improvement on recurrent neural networks (RNNs) that are intended to tackle the well-known vanishing gradient problem. Three categories of hybrid models are covered in this review: data-intensive, technique-intensive, and model-intensive. Convolutional neural networks, or CNNs, are the most widely utilized neural networks in the deep learning field (Berghout & Benbouzid, 2022; Chen, Song, Liu, Yang & Li, 2020).

2.2.6. Random Forest (RF)

Random forests work by training multiple decision trees on random selections of features and then averaging their predictions. Known as ensembles, these models are made up of numerous other models and can improve the performance of the underlying model, in this case, decision trees. When building trees, the random forest algorithm adds another degree of unpredictability by looking for the best feature from a random group of features when splitting a node, as opposed to looking for the absolute best feature. When n is the total number of features, by default, it samples n features. More tree diversity is produced by the method, which trades higher bias for lower variance and typically produces a better model overall (Géron, 2022).

2.2.7. AdaBoost

The statistical classification meta-algorithm AdaBoost (Adaptive Boosting) can be applied to a variety of unique learning techniques to get better overall performance. The boosted classifier's result is determined by the weighted average of the outputs from the additional training algorithms (also known as "weak learners"). While AdaBoost is most frequently demonstrated for binary classification, it may be applied to many other classes and intervals on the real line. Since AdaBoost adjusts subsequent weak learners to give samples that were misclassified by earlier classifiers priority, it is an adaptive algorithm. Because it requires less tweaking of the parameters and is easier to use than other machine learning algorithms, AdaBoost has several advantages over others. AdaBoost implementations do not exhibit overfitting, because the parameters are not adjusted simultaneously and stage-wise estimations hinder the learning process. AdaBoost employs gradual training and boosting methodology. AdaBoost demonstrations therefore need to employ data with high quality. Furthermore, it is susceptible to anomalies and noise of the dataset, which means that these components must be eliminated before using the data (Sharma & Bora, 2022).

2.2.8. Extreme Gradient Boosting (XGBoost)

The gradient boosting algorithm is another popular boosting method. Like AdaBoost, gradient boosting involves adding predictors to an ensemble one after the other, with each addition correcting the one before it. Unlike AdaBoost, which modifies the weight of the instance with every iteration, this approach attempts to fit the latest forecast to the previous predictor's residual errors (Géron, 2022). Extreme Gradient Boosting (XGBoost) is a recently developed machine learning technique for selecting features and regression. Because of its capacity to function in every setting, it has emerged as a preferred machine learning method. The most well-known is XGBoost, an adaptive machine-learning method for boosting trees. The inclusion of a regularization feature to the loss function is XGBoost's most significant contribution to machine learning. This part considers both the complexity of the producing ensemble and the prognostics at each split. Furthermore, by adjusting several hyperparameters like dropouts, column subspaces, learning rate, forest complexity, terms of regularization, tree single complexity, and so on, users of XGBoost can lessen the probability that their models will become overfit (Sharma & Bora, 2022).

2.2.9. CatBoost

CatBoost is a method for converting category input into numerical data. It replaces any categorical feature in the training set with the mean value of the target, as well as the target probability throughout the dataset. A gradient-boosting decision tree is the foundation of the contemporary machine learning method CatBoost. Because CatBoost is good at managing categorical features, it is better than other modern gradient-boosting decision tree-based machine learning algorithms. The gradient approach's bias can be overcome with CatBoost. CatBoost is an organized boosting strategy that substitutes for the usual algorithm's gradient estimation approach. This technique can improve the model's capacity for generalization while reducing the effects of gradient bias on prediction changes (Sharma & Bora, 2022).

2.2.10. K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a robust supervised learning method that may be used for classification and regression. KNN maintains all the available data points together with the labels or values that correlate to them during training. KNN computes the distances between each new data point and every stored point to forecast the class or value of a new data point. The K nearest neighbors is then chosen based on these distances. The majority class among these neighbors is assigned to the new point by KNN for classification. The average (or weighted average) of the values of its closest neighbors is predicted by the regression. The choice of the number of neighbors, K, and the distance metric (Euclidean, Manhattan, Minkowski, etc.) used to evaluate data point similarity, and the decision algorithm used to give labels based on neighbor classes are all important components of KNN. Although KNN is simple to comprehend and apply, its effectiveness can be affected by the choice of K and the properties of the data collection, such as dimensionality and distribution. Nevertheless, KNN is helpful for preliminary data exploration and baseline modeling (Al-Areqi & Konyar, 2022).

2.3. Evaluation Methods

Evaluations of the machine learning models are a crucial part of the process to give fair information about the model. During the test stage, some samples are predicted as a class and some of them are predicted as another class. The results of the prediction can be the same as the actual/real class or predicted as the wrong class. As seen in Table 1 the confusion matrix defines the number of the predicted samples for true or false predictions of classification problems. True positive (TP) and true negative (TN) define the numbers of the true prediction of the positive and negative samples, respectively. False positive (FP) defines the number of negative samples predicted wrongly as positive samples. False negative (FN) defines the number of positive samples predicted wrongly as negative samples (Al-Areqi & Konyar, 2022).

Table 1. Confusion Matrix

Classes		**Actual/Real Class**	
		Positive (1)	Negative
Predicted Class	Positive (1)	True Positive	False Positive
	Negative (0)	False Negative	True Negative

Once the confusion matrix is found, the evaluation criteria/metrics can be found with the help of this matrix:

Accuracy: It is the most important criterion among model evaluation criteria. It is calculated by dividing the number of valid predictions from the model by the total number of samples. Equation (4) contains an equation for calculating the accuracy value.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad 4$$

Precision: It can be found by dividing the number of positive classes that the model predicts correctly by the number of all positive classes. The sensitivity value can be calculated with the equation in (5).

$$Precision = \frac{TP}{TP + FP} \quad 5$$

Recall/Sensitivity: It is calculated by dividing the number of true positive classes predicted by the model by the total number of positively predicted classes. The precision value can be computed using the equation in (6).

$$Recall/Sensitivity = \frac{TP}{TP + FN} \quad 6$$

F-Score: To make precision and sensitivity numbers more useful, the f-score is generated as a weighted average of these values. It is the most utilized evaluation criterion after accuracy value. The f-score can be determined using the equation in (7).

$$F - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad 7$$

The ROC (Receiver Operator Characteristics) curve: The ROC curve is another evaluation criterion commonly employed in classification problems. The ROC curve is used to display and assess performance in classification issues. The X axis of the ROC curve represents the FP ratio, while the Y axis represents the TP ratio. TP ratio is equal to the Recall/Sensitivity value. The FP ratio is calculated with Eq. (8). The ROC curve shows that as the curve approaches the upper left corner, a worse classification is made than when reaching the center areas, where the data for that class is better classified.

$$FP\ Ratio = \frac{FP}{FP + TN} \quad 8$$

AUC (Area Under the Curve) value: The AUC value indicates the area between the ROC curve and the x-axis. The AUC value is an evaluation criterion for ROC curves.

The above metrics are used for assessment of classification problems. When there are continuous numerical values and it has been compared the actual values and predicted values, the regression is used. In the regression algorithms the same methods which are given above (RF, DT, SVM etc.) are executed. The performance of machine learning is calculated with the similarity or dissimilarity of real samples and predicted samples. Mean Absolute Error (MAE), Mean Squared Error (MSE), R-squared (R^2) Score and Root Mean Squared Error (RMSE) are the most popular metrics (Kocaoğlu, Turgut & Konyar, 2022) [15]. Assume we have a dataset with "n" samples and the i.th actual sample is y_i and i.th predicted sample is $\hat{y}_i$ for the following metrics.

Mean Absolute Error (MAE): In statistics and machine learning, Mean Absolute Error (MAE) is a popular metric. This is a measurement of the typical absolute disparities between actual and anticipated values in a dataset. MAE is calculated as equation in (9)

$$MAE = \frac{1}{n}(\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (9)$$

Mean Squared Error (MSE): MSE is calculated as the mean square of the difference between estimated and real values. The MSE is determined as in equation (10).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (10)$$

Root Mean Squared Error (RMSE): RMSE is the cost function of the square root of the MSE. The RMSE prevents the output from errors of the input.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (11)$$

R-squared (R^2) Score: R-squared is a statistical measure used to assess the degree of confidence of fit of a regression model. The value of R-squared ranges from 0 to 1. R-squared is at its highest when the model fits the data perfectly and there is no discrepancy between the predicted and actual values. It is calculated as equation in (12) where y_{avg} denotes the average of all actual samples.

$$R^2\ Score = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i - y_{avg}\right)^2} \quad (12)$$

3. Methodology

The objective of this study is to use bibliometric analysis to present academic research that examines the use of artificial intelligence in accounting and auditing. For this purpose, the relevant data set was obtained because of a detailed query conducted on the Web of Science database on 31.12.2023. The Web of Science databases were selected for this study because they include recent high-quality publications that are valid worldwide and can be reported systematically. The query link can be specified as follows:

https://www.webofscience.com/wos/woscc/summary/385d6d20-0eca-439d-bb91-f9217d251e7a-c15c730c/date-descending/1

The query was conducted considering certain restrictions. The keywords used in the topic section were "accounting", "auditing", "deep learning", and "machine learning", while for Citation Topics Meso it was "Artificial Intelligence

& Machine Learning". The research area was limited to "Business Economics". The publication year was limited to 2010-2023 to analyze current publications. As a result of the query, 402 studies were reached. It is possible to formulate the comprehensive query criteria as follows:

Refine results for "accounting" (Topic) OR "auditing" (Topic) AND deep learning (Topic) AND machine learning (Topic) and 4.61 Artificial Intelligence & Machine Learning (Citation Topics Meso) and Business Economics (Research Areas) and 2023 or 2022 or 2021 or 2020 or 2019 or 2018 or 2017 or 2016 or 2015 or 2014 or 2013 or 2012 or 2011 or 2010 (Publication Years)

The query result was exported in BibTeX and .cvs format. The obtained data set was analyzed with the bibliometric analysis method; frequency tables were created with the Excel program and mapped with the VOSviewer program. Bibliometric analysis is defined as the numerical analysis of publications produced by individuals or institutions in a certain field, in a certain period, and in a certain region and the examination of the relationships between these publications (CABIM, 2023). Bibliometric analysis aims to determine the volume and growth pattern of literature for a specific field. The analysis provides an opportunity to evaluate academic contributions in a field and provides a retrospective view of published literature (Guleria & Kaur, 2021). This analysis method statistically examines cross-country collaborations and authors, citations, institutions, and publication years of selected publications. It then aims to reveal the general structure of a specific disciplinary field with the statistical findings obtained (Özbağ, Esen & Esen, 2019).

Bibliometric analyses combined with visualization-based software provide effective options for addressing clustering problems. For this reason, the VOSviewer program was used in the analysis processes of the study. VOSviewer is a computer program that creates bibliometric maps focusing on graphical representation and easy access to the internet (Eck & Waltman, 2009).

This software is used to analyze clustering solutions based on direct citation relationships of scientific publications and to visualize trends in research topics with research collaboration (Eck & Waltman, 2009; McAllister, Lennertz & Mojica, 2021). It is also widely used for concurrency analysis in platform research (Ding & Yang, 2020). Owing to these features, VOSviewer visualizes the impact and relationships of scientific research, contributing to the evaluation of academic performance and a better understanding of the dynamics in the field of research (Güney & Ala, 2024).

4. Findings

In this section, the part of the study focuses on the analysis findings.

4.1. Fundamental Information of Publication

This section consists of the following headings such as growth and citation trends of publications, types of publications, research orientations, publication languages, publishing houses, Web of Science indexes, funding organizations, and sustainable development goals. In addition, within the scope of productivity and effectiveness analyses, the most productive authors, institutions, and countries and the most effective authors, articles, institutions, and countries/regions were determined.

4.1.1. Annual Indicators of Publications

Figure 2 is based on statistical data representing publications made over a certain period (1957-2023). When publications made by year are examined, it is observed that the highest number of publications was reached in 2022 with a rate of 8.615%. Another remarkable year is 2016, which ranks second with a rate of 7.264%. In addition, 2011 and 2015 are also among the important publication years with rates of 5.068% and 4.899%, respectively. When the figures are examined in general, the small number of publications in the last five years, including 2023, is striking. In addition, it is also significant that the few publications there were from the period until the mid-1990s.

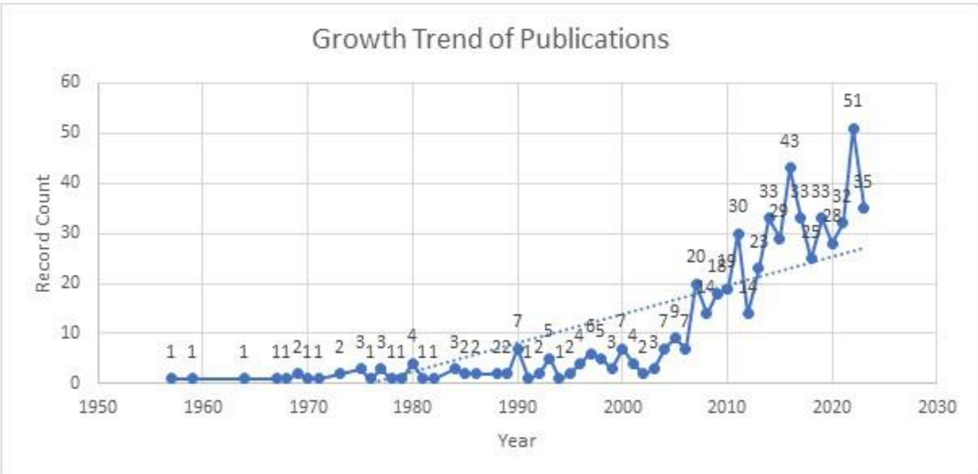

Figure 2. Growth Trend of Publications (1957-2023)

Figure 3 is based on statistical data representing the number of citations made over a certain period (1957-2023). Citation numbers are an important metric that reflects how influential a publication is in academic circles and how widely it is referenced. In the figure, the year 2023 stands out with the highest number of citations, representing a rate of 0.13%. On the other hand, the year 2016 also has a

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remarkable citation number, with a rate of 0.07%. In the general figure, an increasing trend in citation numbers is observed in the period up to 2020. However, a significant decrease in citation numbers was observed in 2020 and after.

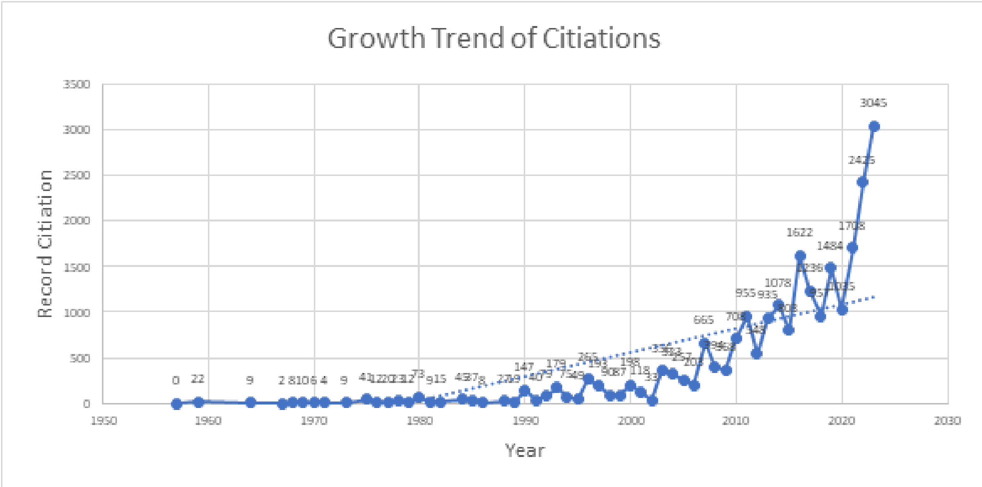

Figure 3. Growth Trend of Citations (1957 – 2023)

Figure 4 shows the number of publications in the field. The most publications were made in 2022 and constitute a sizable proportion of 11.9% of all publications. When the whole figure is examined, it is seen that there has been an increase in the number of publications in this field since 2010.

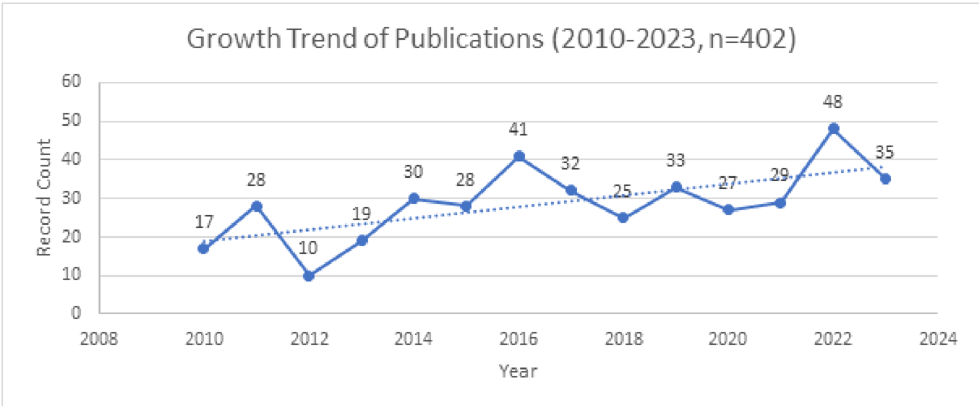

Figure 4. Growth Trend of Publications (2010-2023, n=402)

4.1.2. Publication Types and Research Directions

Figure 5 is based on data representing document types published in the field. According to the figure, the document type "Article" accounts for most of the resource collection with a large share of 75.871%. The document type "Proceeding Paper" comes in second place with a share of 22.388%. Document types such as "Book Chapters", "Early Access", and "Review Article" account for a smaller percentage of the total records.

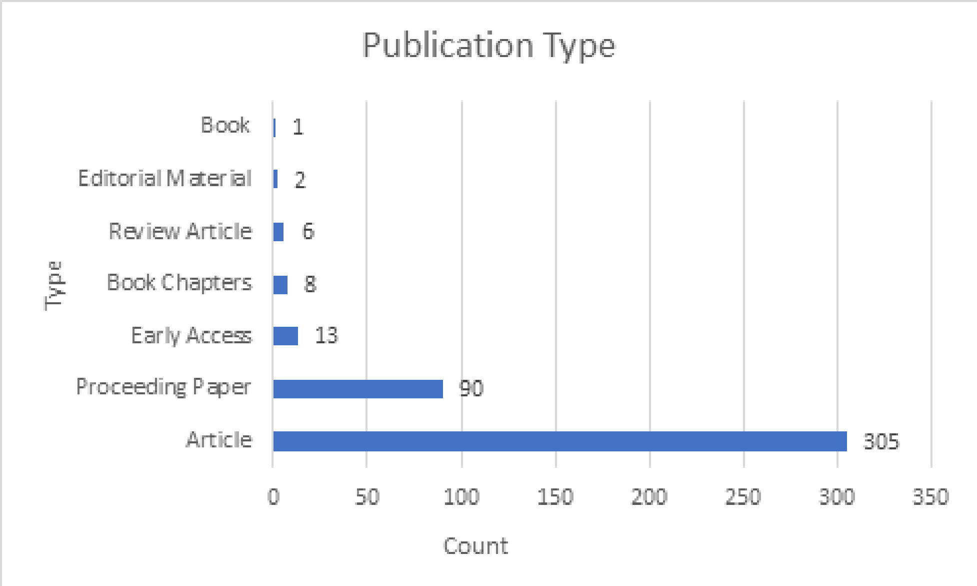

Figure 5. Distribution of Publication Types

4.1.3. Publication Languages

Table 2 shows the distribution of languages preferred in the publications and presents the proportion of each language in the total records. According to the review, a sizable proportion of the records in the source collection—93.532% of the total—are in English, indicating the language's dominance. Although other languages comprise a smaller percentage of the total records, this diversity reflects the interest in different language groups. Languages such as Spanish, Portuguese, Slovak, Russian, Czech, German, and Chinese are represented in academic sources, and research and publications on a variety of topics are being conducted across these languages.

Table 2. Distribution of Publication Languages

Rank	Languages	Record Count	% of 402
1	English	376	93.532
2	Spanish	9	2.239
3	Portuguese	7	1.741
4	Slovak	4	0.995
5	Russian	3	0.746
6	Chinese	1	0.249
7	Czech	1	0.249
8	German	1	0.249

4.1.4. Distribution Publication Publishers

Table 3 shows the publishing houses where academic studies are published and the distribution of their shares in the total records. According to the table, the publishing house "Elsevier" has the largest share in the resource collection with a rate of 16.169%. The second and third "Wiley" and "Springer Nature" contributed 9.453% and 7.463%, respectively. Other publishing houses represent a smaller percentage of the total records.

Table 3. Distribution of Publishers (Top 20)

Rank	Publishers	Record Count	% of 402
1	Elsevier	65	16.169
2	Wiley	38	9.453
3	Springer Nature	30	7.463
4	Emerald Group Publishing	28	6.965
5	Taylor & Francis	23	5.721
6	Mdpi	12	2.985
7	Amer Accounting Assoc	9	2.239
8	Vilnius Gediminas Tech Univ	9	2.239
9	Incisive Media	8	1.990
10	Melandrium	6	1.493
11	Kaunas Univ Technol	5	1.244
12	Anglo-Amer Univ	4	0.995
13	IEEE	4	0.995
14	Int Business Information Management Assoc-Ibima	4	0.995
15	Masarykova Univ	4	0.995
16	Sage	4	0.995
17	Sciendo	4	0.995
18	Tomas Bata Univ Zlin	4	0.995
19	Univ Federal Parana	4	0.995
20	Vsb-Tu Ostrava, Fac Econ	4	0.995

4.1.5. Publication’s Web of Science Index

Table 4 shows the classification of publications under Web of Science indexes and shows the share of each index in the total records. According to the analysis, "Social Sciences Citation Index (SSCI)" stands out as the index with the highest number of records (40.796%). Thus, it constitutes almost half of the total records, indicating a great focus on research in the field of social sciences. The second place "Emerging Sources Citation Index (ESCI)" and the third place

"Conference Proceedings Citation Index – Social Science & Humanities (CPCI-SSH)" are ranked 34.328% and 22.139%, respectively. Other indexes, although representing a smaller percentage of the total records, provide a specific focus on certain disciplines by including different academic resources.

Table 4. Web of Science Index

Rank	Web of Science Index	Record Count	% of 402
1	Social Sciences Citation Index (SSCI)	164	40.796
2	Emerging Sources Citation Index (ESCI)	138	34.328
3	Conference Proceedings Citation Index – Social Science & Humanities (CPCI-SSH)	89	22.139
4	Science Citation Index Expanded (SCI-EXPANDED)	32	7.960
5	Book Citation Index – Social Sciences & Humanities (BKCI-SSH)	9	2.239
6	Conference Proceedings Citation Index – Science (CPCI-S)	5	1.244
7	Book Citation Index – Science (BKCI-S)	1	0.249

4.1.6. Funding Agencies of Publication

Table 5 shows the funding sources of published research. The Spanish Government stands out as the funding agency with the highest number of records, accounting for 2.736% of the total records. The National Natural Science Foundation of China Nsfc, which ranks second, makes a significant contribution to publications with a rate of 2.488%. China stands out as an actor allocating significant funding sources to scientific research. Although other funding agencies represent smaller percentages of the total records, they have various funding sources from different economic regions, such as the European Union, the Fundacao Para A Ciencia E A Tecnologia Fct from Portugal, and the Ministry of Science and Technology from Taiwan. The field under analysis has no data in 303 record(s) (75.373%).

Table 5. Distribution of Funding Agencies (Top 20)

Rank	Funding Agencies	Record Count	% of 402
1	Spanish Government	11	2.736
2	National Natural Science Foundation of China Nsfc	10	2.488

3	Vedecka Grantova Agentura Msvvas Sr A Sav Vega	7	1.741
4	European Union Eu	4	0.995
5	Fundacao Para A Ciencia E a Tecnologia Fct	4	0.995
6	Australian Research Council	3	0.746
7	Grant Agency Of the Czech Republic	3	0.746
8	Slovak Research and Development Agency	3	0.746
9	Fundamental Research Funds for The Central Universities	2	0.498
10	Gobierno De Aragon	2	0.498
11	Ministry Of Science and Higher Education Poland	2	0.498
12	Social Sciences and Humanities Research Council Of Canada Sshrc	2	0.498
13	University Of Kwazulu Natal	2	0.498
14	Actuaries Institute Australia	1	0.249
15	Alperia Energy S P A	1	0.249
16	Andalusian Regional Ministry of Economy Knowledge Business And University Pai Group	1	0.249
17	Babes Bolyai University	1	0.249
18	Bank Of Dalian	1	0.249
19	Beijing Universities Advanced Disciplines Initiative China	1	0.249
20	Belgian Federal Science Policy Office	1	0.249

4.1.7. Publication's Sustainable Development Goals

Table 6 shows the classification of publications in terms of Sustainable Development Goals. The goal of "Decent Work and Economic Growth" stands out as the most emphasized goal, accounting for 81.095% of the total records. On the other hand, the goal of "Good Health and Well Being" is represented by 2.985%. This shows that research on health and quality of life has a smaller share of the resource collection. The field under analysis has no data in 64 record(s) (15.920%).

Table 6. Distribution of Sustainable Development Goals

Sustainable Development Goals	**Record Count**	**% of 592**
Decent Work and Economic Growth	326	81.095
Good Health and Well Being	12	2.985

4.2. Productivity Analysis

4.2.1. The Most Productive Authors

Table 7 provides a ranking of the 20 most productive authors. The 7 authors with the most publications share the first place with 4 publications. It was also seen that the second place is shared by 11 authors with 3 publications.

Table 7. Distribution of The Most Productive Authors (Top 20)

Rank	Author	Documents	Citations	Total Link Strength
1	Abinzano, Isabel	4	13	10
2	Camska, Dagmar	4	9	2
3	Juhaszova, Zuzana	4	5	6
4	Kadzinski, Milosz	4	210	9
5	Laitinen, Erkki K.	4	49	10
6	Parajka, Branislav	4	7	1
7	Tumpach, Milos	4	22	5
8	Altman, Edward I.	3	257	6
9	Delgado-Vaquero, David	3	3	5
10	Girdzijauskas, Stasys	3	14	5
11	Gulamhussen, Mohamed Azzim	3	42	5
12	Jones, Stewart	3	114	2
13	Kaspar, Ralf	3	22	4
14	Kubascikova, Zuzana	3	8	5
15	Micudova, Katerina	3	3	0
16	Morales-Diaz, Jose	3	3	5
17	Muga, Luis	3	12	8
18	Paksiova, Renata	3	7	4
19	Acosta-Gonzalez, Eduardo	2	44	3
20	Amiram, Dan	2	3	3

4.2.2. The Most Productive Organizations

Table 8 lists the publishing houses by their document numbers. "Univ Econ Bratislava" has the greatest number of documents among all organizations. After seven documents, "Vilnius Univ" comes in second. Six documents from four institutions share third place. By document counts, additional organizations are also included in the table.

Table 8. Distribution of The Most Productive Organizations (Top 20)

Rank	Organization	Documents	Citations	Total Link Strength
1	Univ Econ Bratislava	11	33	0
2	Vilnius Univ	7	21	3
3	Univ Complutense Madrid	6	41	13
4	Univ Econ	6	19	3
5	Univ Edinburgh	6	66	8
6	Univ Zilina	6	49	2
7	Nyu	5	265	7
8	Univ Sydney	5	128	5
9	Univ W Bohemia	5	25	0
10	Vilnius Gediminas Tech Univ	5	115	2
11	Czech Tech Univ	4	3	2
12	Ho Chi Minh City Open Univ	4	49	9
13	Kaunas Univ Technol	4	9	3
14	Poznan Univ Tech	4	210	8
15	Univ Econ Prague	4	5	3
16	Univ Publ Navarra	4	13	1
17	Univ Vaasa	4	49	5
18	Univ Valencia	4	33	2
19	Brno Univ Technol	3	15	0
20	Bucharest Univ Econ Studies	3	2	2

4.2.3. The Most Productive Countries

Table 9 contains statistical data based on the number of documents that evaluate the scientific activities of various countries in the field. The United States has the largest number of documents with 49 documents, followed by the Czech Republic with 43 documents. Spain is in third place with 38 documents. The other countries are also listed in the table according to their number of documents.

Table 9. Distribution of The Most Productive Countries (Top 20)

Rank	**Country**	**Documents**	**Citations**	**Total Link Strength**
1	USA	49	773	24
2	Czech Republic	43	160	6
3	Spain	38	399	15
4	Peoples R China	27	268	17
5	England	26	987	26
6	Slovakia	26	97	3
7	Germany	16	210	6
8	Australia	15	205	12
9	Lithuania	15	143	2
10	Poland	13	239	7
11	Brazil	12	18	3
12	Romania	10	19	1
13	Greece	9	87	3
14	Portugal	9	30	3
15	Italy	9	131	5
16	Finland	8	63	8
17	Taiwan	8	116	7
18	Türkiye	8	133	1
19	Canada	7	93	6
20	France	7	111	6

4.3. Influentiality Analysis

4.3.1. The Most Influential Authors

Table 10 presents statistical data by ranking the most influential authors in the field according to the number of documents. Abinzano, Isabel and Laitinen, Erkki K. stand out with a total link strength of 10. Kadzinski, and Milosz are in second place, Muga, and Luis are in third place. When the table is evaluated in general, it is possible to say that there are significant differences between the authors in terms of the number of documents, total link strength, and number of citations. Figure 6 shows the map of the most influential authors.

Table 10. Distribution of The Most Influential Authors (Top 20)

Rank	Author	Total Link Strength	Citations	Documents
1	Abinzano, Isabel	10	13	4
2	Laitinen, Erkki K.	10	49	4
3	Kadzinski, Milosz	9	210	4
4	Muga, Luis	8	12	3
5	Vo, Duc Hong	7	2	2
6	Vu, Nam Thanh	7	2	2
7	Altman, Edward I.	6	257	3
8	Camacho-Minano, Maria-Del-Mar	6	43	2
9	Castano, Francisco J.	6	8	2
10	Castro, Paula	6	8	2
11	Chikodza, Eriyoti	6	4	2
12	Durana, Pavol	6	7	2
13	Gonzalez-Urteaga, Ana	6	12	2
14	Gumbo, Victor	6	4	2
15	Jiang, Cuiqing	6	12	2
16	Juhaszova, Zuzana	6	5	4
17	Li, Zhiyong	6	4	2
18	Matenda, Frank Ranganai	6	4	2
19	Munoz-Izquierdo, Nora	6	43	2
20	Pascual-Ezama, David	6	43	2

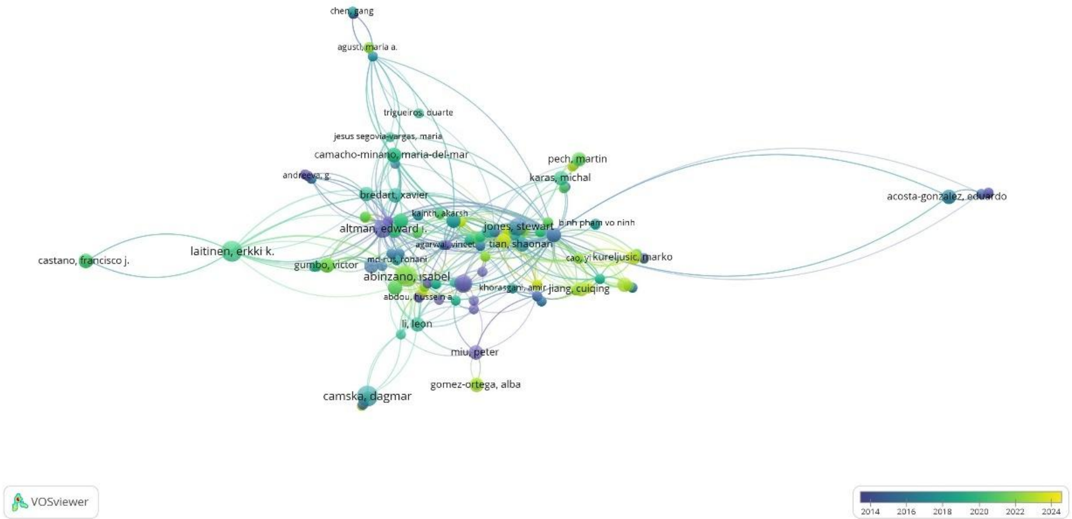

Figure 6. The Map of The Most Influential Authors

4.3.2. The Most Influential Papers

When Table 11 is examined, it is seen that the first five articles that stand out have made significant contributions to the topics of financial distress and bankruptcy prediction. In addition, those articles represent studies that have received wide academic attention. The first ranked article in the table (Altman, Sabato & Wilson, 2010), examines the value of non-financial information in risk management in small and medium-sized enterprises. The second- ranked article, (Beaver, McNichols & Rhie, 2005), investigates the evidence on the informative nature of financial statements and evaluates the effectiveness of financial ratios in bankruptcy prediction. The third-ranked article, (Jones & Hensher, 2004), considers a mixed logit model to predict firm financial distress. Among other studies, (Agarwal & Taffler, 2007) questions the 25- year performance of the Taffler z-score model, and (Amani & Fadlalla, 2017) reviews the literature on data mining applications in accounting and provides a framework. The article by (Tian, Yu & Guo, 2015) also examines firm bankruptcy predictions by focusing on variable selection. This ranking represents a range of important research covering a variety of approaches to financial risk and bankruptcy prediction. Each article presents different methodologies and perspectives in the field of financial failure prediction, thus providing a broad perspective for financial analysts, researchers, and practitioners.

Table 11. Distribution of The Most Influential Papers (Top 15)

Rank	Document	Publication Name	Links	Citations (Wos)
1	(Altman, Sabato & Wilson, 2010)	The value of non-financial information in small and medium-sized enterprise risk management	22	217
2	(Beaver, McNichols & Rhie, 2005)	Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy	20	194
3	(Jones & Hensher, 2004)	Predicting firm financial distress: A mixed logit model	18	185
4	(Agarwal & Taffler, 2007)	Twenty-five years of the Taffler z-score model: does it really have predictive ability?	16	81
5	(Amani & Fadlalla, 2017)	Data mining applications in accounting: A review of the literature and organizing framework	15	60
6	(Tian, Yu & Guo, 2015)	Variable selection and corporate bankruptcy forecasts	15	124
7	(Libby, 1975)	Accounting Ratios and Prediction of Failure- Some Behavioral Evidence	12	85
8	(Tascón & Castaño, 2012)	Variables And Models for the Identification and Prediction of Business Failure: Revision of Recent Empirical Research Advances	12	34
9	(Kureljusic & Karger, 2024)	Forecasting in financial accounting with artificial intelligence - A systematic literature review and future research agenda	11	1
10	(Serrano-Cinca, Gutiérrez-Nieto & Bernate-Valbuena, 2019)	The use of accounting anomalies indicators to predict business failure	11	17

11	(Jones & Wang, 2019)	Predicting private company failure: A multi-class analysis	11	24
12	(Bauer & Agarwal, 2014)	Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test	11	97
13	(Jones, 2017)	Corporate bankruptcy prediction: a high dimensional analysis	10	78
14	(Lacher, Coats, Sharma & Fant, 1995)	A Neural-Network for Classifying the Financial Health of a Firm	10	110
15	(Carling, Jacobson, Lindé & Roszbach, 2007)	Corporate credit risk modeling and the macroeconomy	10	106

Figure 7 is a map showing the interconnections of the most influential publications in terms of citations yearly. The size of the dots indicates that the impact size of that publication is significant. There is a coordinated structure with the years from dark blue to yellow. The lines between the publications emphasize the relationships between the publications in terms of impact and citations.

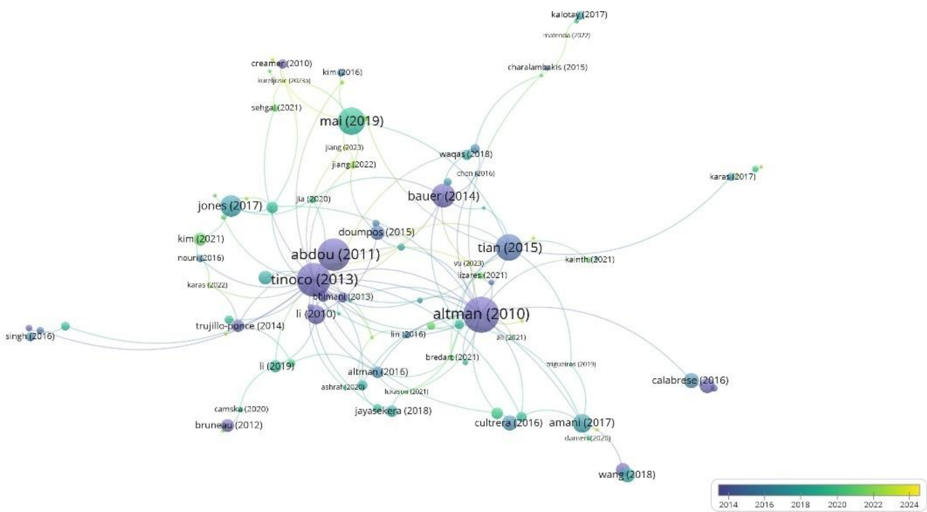

Figure 7. Map of The Most Influential Papers

4.3.3. The Most Influential Organizations

Table 12 was created to determine the most effective organizations in the field. Organizations led by "Univ Leeds" have left a significant mark in the literature with their high total link power and citation counts. Institutions such as "Nyu" and "San Jose State Univ" attract attention with their high citations and

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intensive referencing despite their limited number of documents. In addition, prestigious institutions such as "Royal Bank Scotland" and "Univ Sydney" are among the other effective organizations that stand out with their citations and document counts. Other organizations that are effective in the field are included in the table.

Table 12. Distribution of The Most Influential Organizations (Top 20)

Rank	Organization	Total Link Strength	Documents	Citations
1	Univ Leeds	110	3	437
2	Nyu	52	5	265
3	San Jose State Univ	42	2	254
4	Royal Bank Scotland	41	1	219
5	Univ Sydney	39	5	128
6	Univ Cincinnati	28	1	125
7	Wuhan Univ	28	2	127
8	Univ Edinburgh	27	6	66
9	Mcmaster Univ	21	3	89
10	Univ Publ Navarra	19	4	13
11	Bw Partner	18	1	98
12	Cranfield Sch Management	18	1	98
13	Univ Waikato	18	2	31
14	Stevens Inst Technol	17	3	145
15	Univ Vaasa	16	4	49
16	Natl Grad Inst Policy Studies	15	1	1
17	Univ Bradford	15	1	1
18	Univ Duisburg Essen	15	3	15
19	Univ Monterrey	15	1	17
20	Univ Zaragoza	15	2	57

Figure 8 is a map showing the relationships between universities and similar organizations where publications are made, in terms of impact, on a yearly basis. The size of the dots indicates that the impact size of that organization is significant. While the organizations indicated in dark blue were prominent in 2014 and before, the organizations indicated in yellow came to the forefront towards 2024. The lines between the organizations represent the impact and relationships of these organizations with each other.

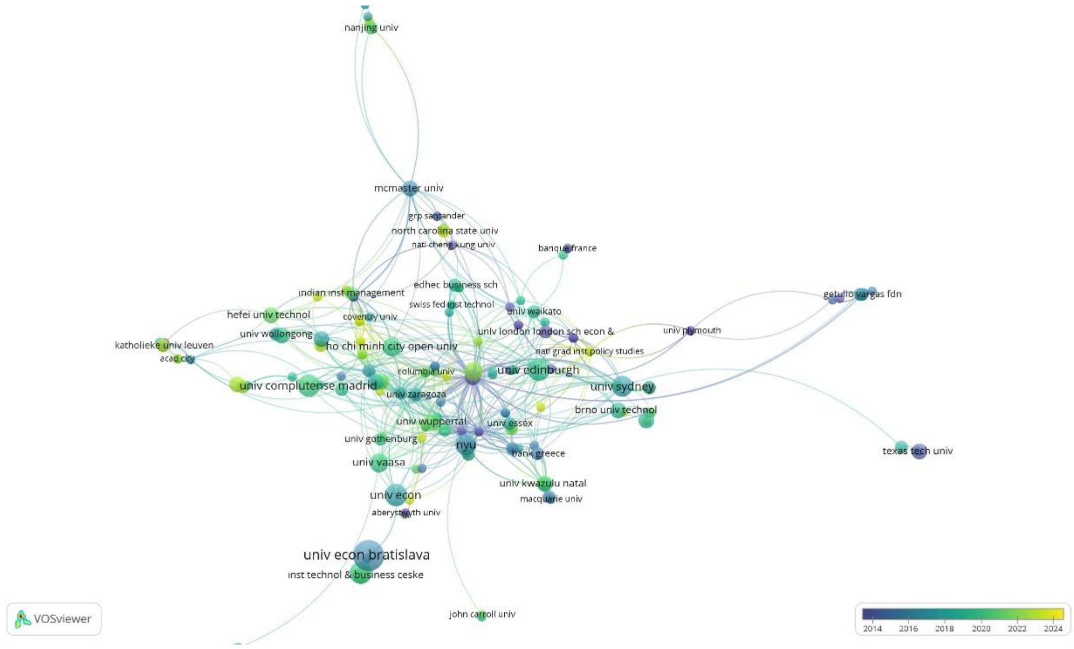

Figure 8. The Map of The Most Influential Organizations

4.3.4. The Most Influential Countries / Regions

Table 13 was created to determine the most effective countries publishing in this field. According to the table, "England" stands out as the most influential country in this field, attracting attention with 163 total link strengths and 987 citations. "USA", which is in second place, has created a significant scientific impact with 101 total link strength and 773 citations. Countries such as "Peoples R China", "Australia", and "Spain" also attract attention in terms of total link strength.

Table 13. Distribution of The Most Influential Countries / Regions (Top 20)

Rank	Country	Total Link Strength	Documents	Citations
1	England	163	987	26
2	USA	101	773	49
3	Peoples R China	60	268	27
4	Australia	57	205	15
5	Spain	54	399	38
6	Netherlands	38	232	5
7	Germany	37	210	16
8	France	35	111	7
9	Canada	30	93	7
10	Greece	26	87	9
11	Scotland	26	75	7
12	Portugal	21	30	9
13	New Zealand	19	43	5
14	Vietnam	19	51	6
15	Japan	18	54	5

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16	Taiwan	17	116	8
17	Belgium	16	46	5
18	Czech Republic	16	160	43
19	Finland	15	63	8
20	Italy	15	131	9

Figure 9 is a map showing the relationship and impact of the countries/regions where the publications were made over the years. The size of the dots indicates that the impact size of that country/region is significant. While the countries/regions indicated in dark blue were prominent in 2014 and before, the countries/regions indicated in yellow came to the fore towards 2024. The lines between the countries/regions emphasize the relationships of the countries/regions with each other in terms of impact and citations, yearly.

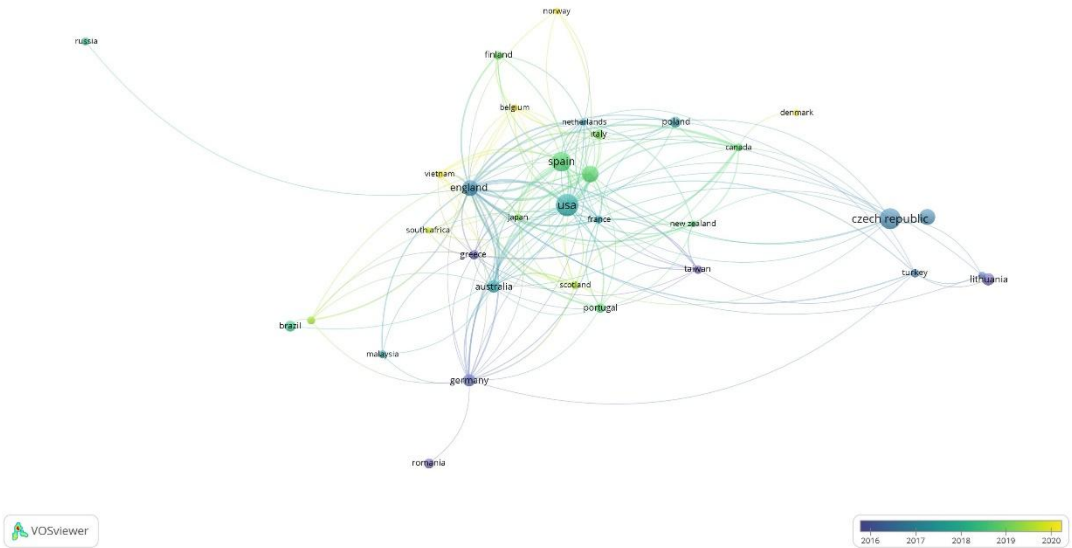

Figure 9. The Map of The Most Influential Countries / Regions

4.4. Keyword Analysis

Table 14 shows the keywords that are frequently used in publications. According to the table:

Bankruptcy: The word "Bankruptcy", with a frequency of occurrence in 33 documents in total and a link strength of 136, shows that this word is intensively discussed in the literature and that there is a wide research effort. The statistics emphasize the significant role of bankruptcy in financial literature, revealing that there are extensive studies on this subject and an important level of knowledge in this field.

Financial Distress: The word "Financial Distress", with a frequency of occurrence in 24 documents and a link strength of 97 in total, represents the literature focusing on the management of financial distress and the early detection of these situations.

Accounting: The word "Accounting", with a frequency of occurrence in 21 documents and a total link strength of 95, reflects the fundamental role of accounting in financial analysis.

Bankruptcy Prediction: The word "Bankruptcy Prediction", with a frequency of occurrence in 21 documents and a total link strength of 77, emphasizes the importance of studies aimed at pre-evaluating the future bankruptcy risks of financial institutions.

Financial Ratios: The word "Financial Ratios", with a frequency of occurrence in 18 documents and a total link strength of 70, shows that financial ratios play a significant role in financial failure prediction models.

Credit Risk: The word "Credit Risk", with a frequency of occurrence in 16 documents and a total link strength of 75, shows that credit risk is a critical factor in financial failure prediction.

Machine Learning: The word "Machine Learning", with a frequency of occurrence in 16 documents and a total link strength of 78, shows that machine learning methods are gaining increasing popularity in financial forecasting models.

Financial Reporting: The word "Financial Reporting", with a frequency of occurrence in 12 documents and a total link strength of 33, shows that accurate and transparent financial reporting plays a critical role in financial failure prediction processes.

Accounting Information: The word "Accounting Information", with a frequency of occurrence in 9 documents and a total link strength of 39, shows that accounting information is a critical factor in financial analysis and prediction processes.

Financial Analysis: The word "Financial Analysis", with a frequency of occurrence in 11 documents and a total link strength of 33, shows that analyses conducted to evaluate the financial situations of companies play a significant role in financial failure prediction processes.

Prediction: The word "Forecasting", with a frequency of occurrence in 9 documents and a total link strength of 40, emphasizes the importance of studies conducted to predict future developments in financial distress prediction.

Neural Networks: The word "Neural Networks", with a frequency of occurrence in 8 documents and a total link strength of 30, shows that neural networks are effectively applied in financial distress prediction models.

Data Mining: The word "Data Mining", with a frequency of occurrence in 9 documents and a total link strength of 31, shows that data mining plays a significant role in creating financial distress prediction models.

Financial Distress Prediction: The word "Financial Distress Prediction", with a frequency of occurrence in 8 documents and a total link strength of 29, emphasizes the importance of the literature on financial distress prediction.

SMEs: The word "SMEs," with a frequency of occurrence in 8 documents and a total link strength of 36, shows that the financial health of SMEs and failure prediction is an important topic in the literature.

Table 14. Distribution of The Most Popular Keywords (Top 20)

Rank	Keyword	Occurrences	Total Link Strength
1	Bankruptcy	33	136
2	Financial Distress	24	97
3	Accounting	21	95
4	Bankruptcy Prediction	21	77
5	Financial Ratios	18	70
6	Credit Risk	16	75
7	Machine Learning	16	78
8	Financial Reporting	12	33
9	Financial Analysis	11	33
10	Accounting Information	9	39
11	Data Mining	9	31
12	Financial Statements	9	31
13	Prediction	9	40
14	Creative Accounting	8	27
15	Financial Distress Prediction	8	29
16	Logistic Regression	8	34
17	Neural Networks	8	30
18	Smes	8	36
19	Ifrs 9	8	33
20	Business Failure	7	25

Figure 10 is a map showing the relationship and impact of keywords mentioned in publications over the years. The size of the dots indicates that the impact size of that keyword is significant. While the keywords/concepts specified in dark blue were prominent in terms of research in 2014 and before, the concepts specified in yellow came to the forefront towards 2024. The lines between the keywords/concepts emphasize the relationships of these concepts in terms of impact yearly.

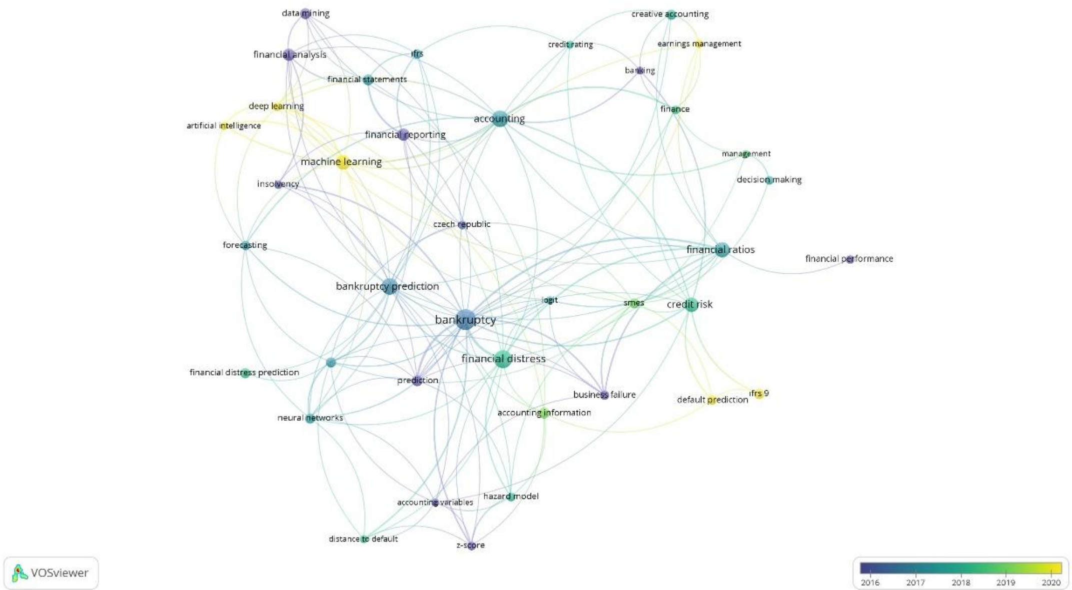

Figure 10. The Map of The Keywords

5. General Analysis of Recent Machine Learning Studies in Accounting and Auditing

In this section, some selected recent studies will be briefly presented to reveal the status and development trends of the use of artificial intelligence and machine learning in the field of accounting and auditing. Instead of presenting detailed analyses of the studies, basic frameworks such as the focused sector and datasets, machine learning methods used, the purpose of the study and the metrics used will be evaluated.

In the study of Aranha & Bolar (2023), based on their market share, 1149 large and medium-sized Indian enterprises from a variety of industries were examined, and a bankruptcy prediction was made. For a dataset that included both operational and bankrupt enterprises, the effectiveness of machine learning approaches such as neural networks, RF, AdaBoost, and logistic regression in forecasting a company's bankruptcy was assessed. Metrics like AUC, Accuracy, F1, Precision, and Recall are used to assess the outcomes. This study investigates whether neural networks are superior to other techniques.

In the study of Vu et al. (2023), machine learning techniques were utilized to evaluate financial distress due to Covid using annual data from 492 public non-financial Vietnamese enterprises registered on the Ho Chi Minh Stock Exchange

(HOSE) and the Hanoi Stock Exchange (HNX) from 2012 to 2021. They used 4,920 firm-year observations, which corresponded to 251 firms on the HOSE and 241 firms on the HNX. One of the regression approaches, LASSO (Least Absolute Shrinkage Selection Operator), is used to extract the elements that are producing distress from the data set. To assess the model's validity, a comparison was done using the Altman Z-score model and the AUC.

To extract the textual sentiment from the management discussion and analysis (MDA) sections, annual reports of publicly listed enterprises on the Shanghai and Shenzhen stock exchanges that were saved as "pdf" files were gathered by Yao et al. (2024). After a variety of preprocessing techniques were used to tokenize the reports in the dataset, a dataset with over half a million phrases was created. Using Naïve Bayes sentiment analysis on the texts, crash risk prediction was carried out. The Naïve Bayes results were compared to the output of other techniques, including RF, SVMs, Neural Networks, Linear Regression, and Gradient Boosting Decision Tree.

Nour et al. (2023) used the binary logistic regression method to comprehend the relationship between corporate governance practices and corporate failure. The annual reports of 35 businesses registered on the Palestinian Stock Exchange between 2010 and 2019 provided data for the model.

A comprehensive analysis of artificial intelligence forecasting in financial accounting is presented in the study of Kureljusic and Karger (2023). Forecasts of bankruptcy, financial analysis, fraud, and error detection are all included in this study. The study demonstrates that in all three application areas, SVMs, neural networks, and RFs offer reliable and accurate predictions.

The work of de Jesus et al. (2023) creates a new bank bankruptcy risk rating metric for banks trading on the Brazilian stock exchange using the unsupervised machine learning technique K-means clustering. Five Bayesian machine learning models were used to compare the outcomes: Naïve Bayes (NB), RF, AdaBoost, SVM, and Decision Trees (DT). The findings were compared with the outcome of the logistic regression.

The suitability of machine learning for managing accounts receivable is examined in Kureljusic and Metz (2023). Grid search is utilized in RF, XGBoost, and neural network prediction models to find the optimal set of hyperparameters that will produce more reliable and accurate predictions.

The purpose of the study of the Wang et al. (2023) is to elucidate the key components of raising one's credit score. The quarterly fundamental data from the US market businesses' Compustat Database was used to compile the 332 accounting variables (features) that make up the fundamental data. These features include balance sheets and income statement data. The target rating is derived from

Standard and Poor's credit ratings. The sparsity algorithm's performance was evaluated using Multi-Layer Perception (MLP) as the machine learning method. Next, using a Convolutional Neural Network (CNN) architecture—which performs far better than MLP—the studies were redone. They suggest a sparsity algorithm that solves the credit rating problem by generating a counterfactual explanation.

In the study of Rahman & Zhu (2023), Accounting fraud was predicted using logistics regression, AdaBoost, XGBoost, CUSBoost, and RUSBoost classifiers. The results are based on the 12 financial measures and 28 financial data used to detect accounting fraud for 33,544 firm-year cases (3456 fraud and 30,088 non-fraud) of China A-Share listed enterprises. The classifiers' performance was tested using the AUC and AUPR (area under the precision- recall curve) methods.

The purpose of Van Der Heijden (2022) is to demonstrate the efficacy of a machine learning approach for addressing prediction-based research challenges in accounting. The information was compiled from firm-year data from North American corporations spanning 2010 to 2019. The study uses machine learning approaches such as linear discriminant analysis and an RF classifier to estimate a firm's industry sector based on publicly available financial statement data.

The paper of Agusti et al. (2023) examines the current literature on auditing and accounting using AI and big data.

In the Koç et al. (2022), machine learning-based forecasting of deferred taxes in international accounting is tested using KNN, RF, SVM, Adaboost, and artificial neural networks. This study tries to estimate the following year's temporary differences of 31 enterprises in the wholesale trade, retail trade, and restaurants/hotels sectors based on the figures in their financial reports for the 2015-2019 period and twelve important economic indices.

Jiang et al. (2022) propose a system for predicting financial difficulty in unlisted public corporations by incorporating semantic information from current reports. The dataset includes all information technology service firms classified as normal or in financial hardship in 2018 or 2019. Missing values and outliers in accounting data are preprocessed. A set of accounting features was extracted, and predictions were made using logistic regression, decision trees, KNN, and RF models. The AUC, H-measure, and Kolmogorov- Smirnov tests are used to predict the performance of each model.

The research of Uddin et al. (2022) investigates the effect of hybridizations on the classification performance of complex machine learning classifiers such as gradient boosting and RF utilizing multi-stage hybrid models combined with the logistic regression model. The classifier performance for credit default prediction is evaluated using sensitivity, specificity, accuracy, and AUC performance indicators.

Jørgensen & Igel (2021) offer a mechanism to help accounting firms connect financial transactions to their associated accounts. The dataset was acquired from 473 companies, and the machine learning model was RF. The RF findings were compared to logistic regression, KNN, and a majority classifier.

The study of Kalinová (2021) combines ANN with Kohonen networks to process and cluster the accounting and other financial accounts of transport companies in the Czech Republic from 2015 to 2018.

To develop explanatory variables, the research of Li & Zhou (2021) simulated Chinese corporate bond default using semi-annual and annual accounting data on Chinese enterprises' debt issues from 2012 to 2017. They extracted the key characteristics and utilized AdaBoost, a gradient boosting classifier, RF, an extra tree (ET), and two classical bagging models in machine learning. The model performance was tested using AUC scores.

The purpose of the study of Kim & Upneja (2021) is to develop an accurate business failure prediction model for the restaurant industry during economic downturns utilizing an ensemble model and decision trees. The dataset contains 1432 company failure observations and 1315 nonbusiness failure observations from the Compustat database generated by Standard and Poor's Institutional Market Services between 1980 and 2017.

The article of Brédart et al. (2021) uses logistic regression, SVM, neural networks, decision trees, and extreme machine learning approaches to forecast business and human resource failures. The financial ratios and human resource variables data from Belgian enterprises were employed in the learning procedures. The findings were evaluated using model accuracy, FP ratio, and FN ratio (Type I and Type II errors).

In the study of Popa et al. (2021) a neural network financial performance prediction model for 456 financial data points from 57 Romanian enterprises was provided.

In Cao et al. (2022) a Bayesian network model was put forth by them to forecast the bankruptcy of 32,344 US companies between 1961 and 2018. The Bayesian network was built using the financial ratios chosen using the LASSO, and the model parameters were computed.

The research of Jones & Wang (2019) attempts to demonstrate the use of machine learning techniques in finance and accounting. They predicted a range of private firm failure states using the TreeNet method, an advanced machine learning technique based on gradient boosting, from failed vs. non-failed to more complicated multi class scenarios with up to five stages of failure.

The convolutional neural network-based deep learning models for textual disclosure-based business bankruptcy predictions are presented in the paper of Mai et al. (2019). In terms of AUS and model accuracy, the outcomes were contrasted with the machine learning models of logistic regression, SVM, and RF.

To identify value-added tax compliance problems in accounting data, the study of Lahann et al. (2019) applied machine learning. The dataset, which includes 11 distinct attributes and 541783 journal entries, was gathered in a single month in 2018. The effectiveness of SVM, RFs, naive Bayes, KNN, and decision trees were compared. The Accuracy, Precision, Recall, F score, AUC, and MCC metrics were used to assess the outcomes.

Behr & Weinblat (2017) employed a machine learning approach based on reinforcement learning to forecast defaults using accounting data for 1019312 enterprises in 2011 and 945062 firms in 2010 among seven European Union nations. Two datasets from 2010 and 2011 were used to estimate the firms' insolvency status. Features including age, industry, company size, debt ratio, return on assets, return on sales, fixed assets ratio, etc. were used to train the model. Model findings based on three-fold cross validation assessed using metrics for accuracy, precision, recall, F score, and AUC.

The paper of Davalos et al. (2019) suggests a machine learning model for an ensemble bankruptcy classifier of companies facing financial distress which cited "US Securities and Exchange Commission's Accounting and Auditing Enforcement Releases". A genetic algorithm was used to classify the dataset, and the outcomes were contrasted with those of three more ensemble classifiers: DT, the majority vote, and the aggregated compensatory technique.

To anticipate insolvency, data discrepancies are employed in the paper of Mendes et al. (2014) as a signal of financial difficulty. They are utilizing it in conjunction with conventional accounting factors to forecast insolvency. They made use of three datasets that were based on 2033 Brazilian Health Maintenance Organizations' financial statements from 2001 to 2007. Sixteen classification techniques, including SVM, Naïve Bayes, RF, and LR, were employed to evaluate the application of data discrepancies in the prediction of insolvency.

The study of Tinoco & Wilson (2013) creates risk models that forecast bankruptcy and financial difficulties for listed corporations. The dataset includes proxies for changes in the macroeconomic environment, stock market information, and accounting data. A neural network approach and Altman's original Z-score specification are used to assess the logistic regression model's performance in terms of AUC, TP ratio, and FP ratio.

To forecast company bankruptcy based on financial statements and equity markets, Peat & Jones (2012) employed a neural network model. Data from 523 firm years between 2000 and 2002 are used in the training and model building process.

The purpose of the study of Trustorff et al (2011) is to compare the effectiveness of logistic regression models and SVMs for credit risk prediction default classification. As default indicators, the dataset of 78,000 financial statements from 2000 to 2006 is utilized. Out of the 31049 German enterprises in the dataset, 1,112 had default or failed to fulfill their credit commitments.

In the study of Creamer & Freund (2010), machine learning is presented as a tool to support financial analysis tasks. The study contrasts the Adaboost findings with those from bagging, RFs, and logistic regression. For the training procedure of the experiments, one sample of SP 500 businesses, American Depository Receipts (ADRs) of Latin American companies, and Latin American banks were each subjected to tenfold cross validation.

6. Conclusions

In this study, which aims to present a comprehensive bibliometric analysis of the literature on the use of artificial intelligence in the accounting and auditing fields; a total of 402 academic studies published in the Web of Science database between 2010 and 2023 were examined. These studies were evaluated within the framework of various criteria such as publication types, languages, citation trends, publishing houses, financing sources and sustainable development goals.

The analysis results show that 2022 was the year with the highest number of publications and an increasing trend in the number of citations was observed until 2023. Most of the studies were in the "Article" genre, and it was determined that the English language was dominant among the publications. "Elsevier", "Wiley" and "Springer Nature" publishing houses stand out as the publishing houses with the largest share in literature. In addition, the “Social Sciences Citation Index (SSCI)" was the most used index. In terms of funding sources, the Spanish Government, and the National Natural Science Foundation of China (NSFC) made the largest contribution. It was determined that the most emphasized goal among the sustainable development goals was "Good Business and Economic Growth".

According to the results of the productivity analysis, among the most productive writers in the field of artificial intelligence and accounting/auditing, 7 writers stand out with 4 publications, while 11 writers follow them with 3 publications. Among the most productive institutions, "Univ Econ Bratislava" is the most productive institution, while "Vilnius Univ" is in second place. When the situation is considered in terms of the most productive countries; the United States reached the highest number, the Czech Republic was second and Spain was third.

According to the results of the effectiveness analysis, Abinzano, Isabel, and Laitinen, Erkki K. stand out among the most influential authors. Among the most influential publications, the article "Altman et al. (2010)" ranks first, followed by "Beaver et al. (2005)" and "Jones & Hensher (2004)". Among the institutions, "Univ Leeds" stands out as the most influential institution, while "Nyu" and "San Jose State Univ" stand out with their high citation numbers. At the country level, the United Kingdom stands out as the most influential country, while the United States ranks second. China, Australia, and Spain also create significant scientific impact.

According to keyword analysis, terms such as "Bankruptcy", "Financial Distress" and "Accounting" are widely used in literature. "Bankruptcy Prediction" and "Financial Ratios" are important in assessing bankruptcy risks. Methods such as "Machine Learning" and "Data Mining" have gained increasing popularity in financial distress prediction models. In addition, the term "SMEs" indicates that the financial health of small and medium-sized enterprises is an important topic in research.

All findings of the analysis emphasize the increasing importance of artificial intelligence in the field of accounting and auditing and the diversity of research in this field. This study recommends that if artificial intelligence is one of the essential components of future research, researchers should be cautious when using the concept in the study's title and keywords.

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