Knowledge Processing Studies. 2025, 14, 5(1): 45-64.

International Journal of Knowledge Processing Studies
(KPS)

Homepage: http://kps.artahub.ir/

ORIGINAL RESEARCH ARTICLE

A Machine Learning Approach to Assessing Audit Quality in Company with Non-Switching Auditors: Random Forest Classifier Model

Mostafa Abdi[1], Azar Moslemi[2,*] , Mohsen Rashidi

[1]Ph.D. Candidate, Department of Accounting, Khomein Branch, Islamic Azad University, Khomein, Iran. abdi.mostafa@hotmail.com, 0000-0002-4617-8379
[2] Assistant Professor, Department of Accounting, Khomein Branch, Islamic Azad University, Khomein, Iran. (Corresponding Author). moslemi.azar@hotmail.com, 0000-0001-5025-2984
[3] Assistant Professor, Department of Economic and Administration Science Faculty, Lorestan University, Lorestan, Iran. m.rashidi.acc@gmail.com, 0000-0001-8198-0415

ARTICLE INFO

Article History:
Received: 2024-09-24
Revised: 2025-01-17
Accepted: 2025-02-04
Published Online: 2025-03-25

Keywords:
Audit Quality,
Machine Learning,
Auditor switch,
Non-Switching Firms,
Random Forest Classifier Model
Ensemble methods

*Number of Reference:*103
Number of Figures: 2
Number of Tables: 6

DOI: 10.22034/kps.2025.481292.1204

ABSTRACT

For many years, legislators have been concerned that a change in the auditor, along with the incentive to buy the audit opinion, can hurt the quality of the audit. Therefore, in all the studies conducted in this field, audit quality after the change in auditor has been investigated. However, this study examines the effect of auditor change probability on audit quality using a Random Forest Classifier model. In this study, using the machine learning technique and Random Forest Classifier model, the probability of auditor change and the effect of this probability on audit quality in companies without a change in auditors have been reviewed. The results show that companies with a high probability of auditor changes have lower audit quality. In the following, according to the hypotheses related to reducing audit costs in large companies based on the familiarity discount framework, the above result has been analyzed separately for large and small companies. The results show that larger companies, where there is the possibility of changing auditors, experience a greater decrease in audit quality. In addition to filling knowledge gaps regarding the challenges associated with the reliability of auditor opinions, it can provide insights into possible solutions and strategies to improve it. Researchers interested in classification-related topics can use this model to obtain the probability of a binary variable. **©authors**.

►**Citation:** Abdi, M., Moslemi, A., & Rashidi, M. (2025). A Machine Learning Approach to Assessing Audit Quality in Company with Non-Switching Auditors: Random Forest Classifier Model *International Journal of Knowledge Processing Studies (KPS)*, 5(1): 45-64. Doi: 10.22034/kps.2025.481292.1204

1. Introduction

According to agency theory, managers have many incentives to have their audit reports presented with a favorable opinion; they are looking for auditors who will behave according to their wishes and have less professional skepticism about financial statements. This kind of expectation can lead to the phenomenon of “opinion shopping” and increase the possibility of fraud in financial statements (Fakhari & Amiri, 2020; Yuejun, 2011). An auditor's opinion plays a crucial role in investors' decision-making processes, and disregarding it can have harmful effects. (Chen et al., 2012). A process known as “opinion shopping” in auditing literature causes impairment of the auditor's independence as one of the fundamental concepts of auditing (DeFond & Zhang, 2014). Decreasing audit quality undermines the reliability of financial statements, leading to reduced confidence in their accuracy and an increased likelihood of management bias and material errors (Budisantoso & Kurniawan, 2022; DeFond & Zhang, 2014).

Regulators have been concerned for many years that auditor switching to be motivated by opinion shopping, which can negatively impact the auditing market (Commission, 2010; Cowle et al., 2023; Securities & Commission, 1988; Senate, 1976). The concept of "opinion shopping" poses a threat to the independence of auditors, which in turn affects the quality of audits. Regulators implemented various policies to address this issue. The US Securities and Exchange Commission (SEC) requires companies to disclose any differences in opinions between auditors and companies when they switch auditors. The Sarbanes-Oxley Act of 2002 (SOX) gave the audit committee the responsibility of appointing an auditor previously held by management. These measures were designed to strengthen auditor independence and protect the integrity of the auditing process (Dhaliwal et al., 2015; Hunt et al., 2021; Newton et al., 2015). However, recent studies indicate that despite these efforts, there is still evidence that managers are involved in the selection of auditors and may engage in opinion shopping (Chung et al., 2019). This study can assist regulators in identifying audits that may lead to a decrease in audit quality, allowing them to take appropriate measures to address the issue and safeguard the integrity of financial reporting.

Audit quality is a concern for regulators, particularly when companies switch auditors. Therefore, previous research on opinion shopping has focused on auditor switching and its impact on audit quality. However, a more significant concern arises when auditors accept audit work to retain a client, even when they are aware of threats to their independence. In such cases, market participants are unaware of any auditor switch and not informed about potential weaknesses in financial reporting. Our research contributes to the literature by identifying companies that have not switched auditors, but still face impaired auditor independence. We recognize that in certain cases, despite a high probability of switching auditors, some companies opt to maintain their current auditors, suggesting a compromise in auditor independence to retain the client. This research aims to explain a scenario in which companies on the Tehran Stock Exchange (TSE) have not switched auditors, but where there are indications of compromised independence. By excluding companies with switch auditors, this study aims to isolate the potential impact of uninterrupted auditor-client relationships on audit quality. This focus enables researchers to explore the extent to which the absence of an auditor switch is linked to lower audit quality. Hence, in this study, machine learning techniques are utilized to identify companies that may have the potential to switch auditors but choose not to do so.

This study, conducted in Iran, is the first to examine the relationship between audit quality and companies that continue to use current auditors when they have the option to switch. This particular focus is of significant importance because, in such cases, where no visible signs of auditor switching are observed, the issue of audit quality becomes even more crucial. The findings of this study provide new insights into the factors that contribute to auditor opinion shopping, and help expand our understanding of this field.

2. Literature Review

2.1. Definition of opinion shopping

Considering that there is no single definition of opinion shopping, it is necessary to examine what researchers think of it. It seems that all the definitions of opinion shopping were taken from the US Securities and Exchange Commission. The commission believes that the opinion shopping refers to the situation that "the company is looking for an auditor who is willing to support the company's proposed accounting procedures and help the company achieve its reporting objectives" (Securities & Commission, 1988).

To this end, researchers have provided the following definitions to understand and deduce this concept. Chen et al. (2015) stated that opinion shopping refers to the employer's willingness to consult with auditors with the attitude of obtaining a favorable opinion when the current auditors issue an unfavorable opinion, or when there is a disagreement on certain accounting matters that could result in receiving an adverse opinion. In fact, in this case, the manager of the company can switch his current auditor and avoid the possibility of publishing an unfavorable opinion; in this way, he can choose the auditing firm according to his wishes (Chen et al., 2016b). In another argument of the Public Company Accounting Oversight Board (PCAOB) (2013), the purchase of the auditor's opinion is related to the incentives that encourage auditors to focus on the interests of the owners who pay their fees instead of paying attention to the interests of investors. In another definition, buying an auditor's opinion refers to the act of switching the auditor to receive a favorable opinion about an accounting procedure or financial statements (Board, 2013; Lennox, 2000; Lennox, 2002). Also, Xie et al. (2011) stated that opinion shopping includes the efforts made by the manager to influence or even manipulate the auditor's decisions to obtain a more favorable audit opinion (Xie et al., 2010).

2.2. Auditor switch and opinion shopping

Managers have a strong desire for their audit reports to be acceptable because negative opinions in these reports can have significant consequences. If audit reports are published with a negative opinion, they may adversely affect managers' remuneration, the company's ability to participate in the stock market, and, ultimately, the company's stock price. Economic conditions, efforts to eliminate errors, and bonus and benefit plans tied to reported earnings can all contribute to an increased incentive for managers to seek favorable opinions and potentially engage in opinion shopping (Bayo Flees & Mouselli, 2023) .

Audit literature suggests that if managers find auditors' services unacceptable, they may consider switching auditors as a viable strategy to achieve their desired objectives. This assumption is based on the condition that the new auditor has limited knowledge about the employer, leading to the belief that switching auditors positively impacts the likelihood of opinion shopping (Lennox, 2000; Lu, 2006). Switching auditors can be perceived as a means of influencing opinion shopping and achieving the desired goals. However, it is important to consider the specific circumstances and regulations surrounding auditor switching and its effects on independence, audit quality, and financial statement misstatements (Lu, 2006). In this regard, many studies have shown that the switch of auditor occurs by ‘‘opinion shopping” because the new auditors become economically dependent on the employers and act according to the employer's wishes (Chung et al., 2021; Chung et al., 2019). In addition, many studies show that the switch of auditor not only achieves the ‘‘opinion shopping,” but also makes the new auditor's opinion more robust (Krishnan, 1994). In addition, in cases where companies switch auditors for no reason and the type of opinion improves, this indicates that ‘‘opinion shopping” has probably occurred (Lennox, 2000).

Opinion shopping refers to the practice of seeking favorable audit opinions by switching auditors. This involves companies searching for auditors who may provide a more favorable assessment of their financial statements (CHEN et al., 2016a). Companies that switch auditors for reasons such as disagreement with the auditor or obtaining a less conservative opinion may be at increased risk of audit quality issues.

However, the effect of auditor switches on the quality of auditing and financial reporting is a complex issue with no clear consensus. Auditor switches have implications for both audit quality and financial reporting. It is important to assess the reasons for these switches and their potential consequences. Some studies have indicated that companies that switch auditors for reasons such as disagreement with the auditor or the pursuit of a less conservative opinion may be at risk of lower audit quality.

However, evidence on this issue is mixed, and it is unclear whether auditor switches always lead to lower audit quality. These switches could result in a loss of independence, reduced skepticism, or compromised objectivity, all of which are essential for high-quality audit processes (Hu et al., 2022). However, opinions on the impact of auditor switches vary. Different perspectives exist on the effects of such switches on audit quality and financial reporting. Some argue that switches in auditors may improve audit quality by introducing new perspectives, enhancing scrutiny, and increasing attention to potential errors or irregularities. New auditors may bring different expertise or methodologies into the auditing process, leading to a more thorough examination of financial statements (Hall et al., 2023). To provide a comprehensive understanding of this topic, it is crucial to consider reliable research and evidence sources. Some studies have shown that audit quality can improve after an auditor switch; (Lu, 2006) in contrast, other studies have found that audit judgments and opinions are not significantly different after a switch in auditors.

Lennox (2000) demonstrates that the use of predicted opinions rather than actual opinions reveals a tendency for audit opinions to be more favorable to management after an auditor switches. However, existing research on opinion buying concentrates mainly on the switching activities of the auditor's clients and compares the audit quality of previous and new auditors. This limited approach overlooks a full range of potential problems. To fill this gap, it is vital to research the circumstances in which auditor independence may be jeopardized even if there is no switch in auditors (Hunt et al., 2021).

Audit quality remains a critical focus in the financial reporting landscape, particularly in light of concerns regarding financial statement falsification and the role of auditors in maintaining integrity and professionalism. Zaafaranie et al. (2024) investigated the impact of audit fees, tenure, and turnover on audit quality in publicly traded insurance companies listed on the Indonesian Stock Exchange (2018–2022).

Their findings indicate that, while audit fees significantly enhance audit quality, audit tenure and turnover do not exhibit notable effects. Similarly, Elizabeth et al. (2023) explored the effects of frequent auditor switching and concluded that it was associated with lower audit quality.

However, strong internal and external monitoring can mitigate these negative effects, highlighting the detrimental impact of frequent auditor changes on the audit market, and the need for regulatory oversight. Harianja et al. (2022) examined the influence of audit fees, audit delays, and auditor switching on audit quality in Indonesian state-owned companies (2016–2020), employing Kasznik's model to measure audit quality. Their study found that audit fees and delays significantly affected audit quality, whereas auditor switching had no significant influence. Collectively, these studies emphasize the critical role of audit fees and monitoring mechanisms in improving audit quality while providing mixed evidence on the implications of auditor switching.

2.3 .The role of machine learning

Machine learning techniques can be used to identify companies that are more likely to switch auditors and to investigate whether there is a correlation between the likelihood of switching auditors and lower audit quality. This approach can help regulators identify audits that are currently underway and at risk of declining quality (Hunt et al., 2021). Machine learning techniques must be properly trained and tested to ensure accurate predictions and prevent overfitting. Machine learning models learn from training data and are evaluated using out-of-sample data.

Therefore, training and testing are essential components of machine learning. The training phase of machine learning involves exposing the algorithm to a labeled dataset, allowing it to learn the patterns and relationships within the data. Through this process, the algorithm adjusts its internal parameters to optimize its performance. Once the training was complete, the testing phase was conducted using a separate dataset that the algorithm had not seen before. This out-of-sample testing evaluates the ability of the algorithm to generalize its learning and make accurate predictions based on new, unseen data. It helps to identify if the model has overfitted the training data, which means that it has learned the specific patterns of the training set but fails to perform well on new data. Overfitting can lead to a poor performance when applied to real-world scenarios. By following this training and testing process, Machine learning models can learn from the data and make accurate predictions on new, unseen instances. This ensures that the models generalize well and are reliable in real-world applications (Janiesch et al., 2021). The process described in this study was implemented for a sample from 2002 to 2021. The objective was to use auditor switch modeling as the target variable, based on previous research.

Audit quality, an essential aspect of financial reporting, is deeply influenced by auditor characteristics including expertise and independence. In Iran, audit quality is often tied to the size and reputation of audit firms, as larger firms tend to have more resources and a higher level of expertise. Aghaei Chadegani et al. (2013) observed that the quality of audits in Iran is largely determined by the size and reputation of the audit firm, with larger firms more likely to deliver higher-quality audits due to their advanced capabilities. However, the switching of auditors may compromise audit quality, particularly during the initial engagement period when new auditors face pressures related to establishing client relationships. Furthermore, Ostadjafari et al. (2024) find that auditor switching in the initial years often leads to fee discounting, a factor that could negatively affect audit quality. This phenomenon occurs because in the early stages of an engagement, auditors may have reduced bargaining power and are more likely to offer lower fees to retain clients. While this fee discounting may benefit clients in the short term, it can place pressure on auditors, potentially compromising audit quality. The dynamic between audit fees and quality is particularly relevant in Iran, where market conditions and regulatory oversight may not fully safeguard audit quality, particularly when competition among auditors leads to aggressive pricing (Aghaei Chadegani et al., 2013; Ostadjafari et al., 2024). This study investigates the presence of differences in opinion between auditors and companies, specifically focusing on situations where the possibility of switching the auditor exists, but no actual switch has been observed. Machine learning techniques were employed to identify cases in which a switch in the auditor could occur but the company decided to retain the current auditor. In addition, this study examines the audit quality of these companies (Hunt et al., 2021). Based on these investigations, the following hypothesis is proposed:

Hypothesis 1: Companies that retain their auditor despite the possibility of auditor switch experience a decrease in audit quality.

3. Method

3. Predicting the probability of switching auditors

A training and test dataset consisting of 1,995 observations was utilized to calculate the variable known as the auditor switching probability (PROB_SWITCH). This variable represents the likelihood that auditors will switch within the dataset. For each company in year T-1, we measured the following variables:

- A company's total assets are expressed as LN_AT, which is the natural logarithm of its assets.
- INVT_RECT: sum of receivables and inventory divided by total assets.
- DACC: Estimation of discretionary accruals using the modified Jones model.
- CASH: sum of cash and cash equivalents divided by total assets.
- ROA: Ratio of income before extraordinary items to total assets.
- LOSS: When ROA is less than zero, LOSS is set to 1, otherwise it is set to 0.
- AT_GROW: the change in total assets divided by the total assets of the previous year
- ACQUIRE: When the cash outflows related to acquisitions of total assets exceed ten percent, the ACQUIRE variable is set to 1; otherwise, it is set to 0.
- CFEARLY: If a company is in its introduction or growth stage of its lifecycle, CFEARLY is 1; otherwise, it is 0.
- CFMATURE: The CFMATURE indicator is set to 1 if the company is in its mature stage, and 0 otherwise.
- When the independent auditor issues a modified opinion, MODOP is set to 1 and if not, it is set to 0.
- BIGN: an indicator variable that is set to 1 if the company is audited by a big audit organization and 0 otherwise.
- SWITCH: Our target variable, an indicator variable that equals 1 if the company switches its auditor in the current year (year t) compared to the previous year (year t-1), and 0 otherwise. Descriptive statistics for the training and testing samples are presented in Table 1.

Table 1. *The descriptive statistics*

	N	Mean	SD	p25	p50	p75
SWITCH	1995	0.196	0.397	0.000	0.000	0.000
LN_AT	1995	13.418	1.489	12.330	13.270	14.370
INVT_RECT	1995	0.645	0.244	0.480	0.650	0.800
DACC	1995	0.060	0.115	-0.060	0.010	0.070
CASH	1995	0.040	0.039	0.010	0.030	0.050
ROA	1995	0.125	0.155	0.030	0.100	0.210
LOSS	1995	0.129	0.335	0.000	0.000	0.000
AT_GROW	1995	0.253	0.516	0.030	0.160	0.330
ACQUIRE	1995	0.014	0.118	0.000	0.000	0.000
CFEARLY	1995	0.535	0.499	0.000	1.000	1.000
CFMATURE	1995	0.269	0.443	0.000	0.000	1.000
MODOP	1995	0.594	0.491	0.000	1.000	1.000
BIGN	1995	0.236	0.424	0.000	0.000	0.000

3.1. Introduction to artificial intelligence and machine learning

Machine learning is a type of artificial intelligence that allows software applications to learn from data and make predictions without the need for explicit programming. Machine learning algorithms use historical data as inputs to predict new output values. This was performed by identifying the patterns and relationships between the variables in the data (Sarker, 2021).

This process, known as machine learning, enables the identification of intricate patterns and relationships that humans find challenging by using traditional statistical techniques. Machine learning is a type of design science that distinguishes itself from the natural and social sciences by focusing on the development of practical tools to assist in solving significant problems. On the other hand, natural and social sciences focus on theory development and testing (Deng et al., 2020; Kogan et al., 2019; Sarker, 2021).

Machine learning techniques have attracted the attention of accounting and auditing researchers to investigate various issues such as fraud detection (Cecchini et al., 2010; Jones, 2017; Whiting et al., 2012) and bankruptcy prediction (Bao et al., 2020; Bertomeu et al., 2020; Perols et al., 2017; Perols & Lougee, 2011).

Machine learning techniques for predicting fraud in financial statements are especially pertinent to this study because they are data-driven ways of recognizing rare occurrences that can have a major effect on the financial standing and reputation of organizations.

Machine learning is a type of artificial intelligence that allows software applications to learn from data and make predictions without the need for explicit programming. Machine learning algorithms use historical data as inputs to predict new output values. This was performed by identifying the patterns and relationships between the variables in the data (Sarker, 2021).

This process, known as machine learning, enables the identification of intricate patterns and relationships that humans find challenging by using traditional statistical techniques. Machine learning is a type of design science that distinguishes itself from the natural and social sciences by focusing on the development of practical tools to assist in solving significant problems. On the other hand, natural and social sciences focus on theory development and testing (Deng et al., 2020; Kogan et al., 2019; Sarker, 2021).

Machine learning techniques have attracted the attention of accounting and auditing researchers to investigate various issues such as fraud detection (Cecchini et al., 2010; Jones, 2017; Whiting et al., 2012) and bankruptcy prediction (Bao et al.,

2020; Bertomeu et al., 2020; Perols et al., 2017; Perols & Lougee, 2011).

Machine learning techniques for predicting fraud in financial statements are especially pertinent to this study because they are data-driven ways of recognizing rare occurrences that can have a major effect on the financial standing and reputation of organizations.

Machine learning algorithms are ideal for prediction tasks as they can learn from data to recognize patterns and associations that can be employed to forecast future occurrences. Machine learning is a type of artificial intelligence that allows computers to learn from data without explicit programming. Machine learning algorithms play a crucial role in extracting valuable insights from diverse types of data, including cybersecurity, business, and social media data. Predictive analytics, which incorporates machine learning techniques, utilizes historical and current data to estimate future outcomes. It leverages statistical techniques and models to understand potential future occurrences. Machine learning is a potent technique that can be employed to enhance prediction tasks by learning from data and making precise forecasts (Gu et al., 2020; Sarker, 2021). Logistic regression and other traditional statistical models are often used in accounting research to estimate parameters. However, these models may not be effective for out-of-sample predictions because they make strong assumptions about the data-generation process. However, Machine learning methods are more flexible and require fewer assumptions, making them more suitable for out-of-sample predictions (Mullainathan & Spiess, 2017). Also, they are more flexible and suitable for approximating complex data generation processes (Gu et al., 2020).

Our procedure for estimating the probability of switching auditors in the current year is designed to be timely, and utilizes data from previous years. The only information we require are whether a firm has switched its current auditor. We used the train_test_split function in the scikit-learn library to randomly split our dataset into training and testing sets. This function allows us to split arrays or matrices into random subsets, which is useful for training and evaluating Machine learning models. We used the train_test_split function to split our dataset into training and testing sets. The training set was allocated 75% of the data, and the testing set was allocated 25% of the data. This split ensured that the distribution of classes in both sets was representative of the entire dataset. To achieve this, we set the stratification parameter as the target variable, which maintains the proportion of each class in both the training and testing sets. Using the train_test_split function, we can ensure that our training and testing data are independent and unbiased, enabling us to accurately evaluate the performance of our estimation procedure. This function considers input validation, shuffling of the data, and stratified splitting, if specified.

We used a predictive model to estimate the probability of switching auditors. The model was trained on a dataset of historical data and was able to accurately predict the probability of auditor switching in a dataset that had not been seen before. We used the predict-proba method from the scikit-learn library to calculate the probability estimates (PROB_SWITCH) for each class label. This method takes a trained model and input data as inputs and outputs a list of probability estimates for each class label. It is important to consider that the accuracy and reliability of the probability estimates depend on the chosen predictive model and quality of the input data. Therefore, it is crucial to use appropriate evaluation techniques to assess the performance and validity of a model. Scikit-learn provides several methods for model evaluation, including score methods specific to each estimator and metric functions for assessing prediction errors.

3.2 .Model Evaluation

In this study, we utilized the Random Forest Classifier Model from Scikit-learn, which is a popular Python library for machine learning. This library provides easy-to-use tools for data analysis and modeling, including classification, regression, and clustering algorithms. Ensemble methods combine the predictions of several base estimators built with a given learning algorithm to improve the generalist generality/robustness over a single estimator. Two famous examples of ensemble methods are gradient-boosted trees and random forests. The sklearn.ensemble module includes two averaging algorithms based on randomized decision trees: the random forest algorithm and the extra-tree method. Both algorithms are perturb-and-combine techniques specifically designed for trees. This implies that a diverse set of classifiers is created by introducing randomness in the classifier construction. The prediction of the ensemble is given as the average prediction of the individual classifiers. In random forests, each tree in the ensemble is built from a sample drawn with replacement from the training set. In random forests, Furthermore, when splitting each node during the construction of a tree, the best split is found through an exhaustive search of the features values of either all input features or a random subset of size the purpose of these two sources of randomness is to decrease the variance of the forest estimator. Individual decision trees typically exhibit a high variance and tend to overfit. The injected randomness in forests yields decision trees with decoupled prediction errors. By taking the average of these predictions, some errors can be cancelled out. Random forests achieve reduced variance by combining diverse trees, sometimes at the cost of a slight increase in bias. In practice, variance reduction is often significant, yielding an overall better model. In contrast to the original publication, the scikit-learn implementation combines classifiers by averaging their probabilistic prediction instead of letting each classifier vote for a single class. (Pedregosa et al., 2011)

Utilizing a Random Forest Classifier model has numerous advantages, particularly for classification tasks. This model offers high accuracy by creating an ensemble of decision trees and aggregating their outputs, reducing the risk of overfitting and enhancing predictive performance. It is robust, handles diverse data types effectively, and performs well even with substantial noise or missing values in the dataset. Furthermore, it can highlight which features are most critical for classification, aiding a deeper understanding of the data. The Random Forest model is versatile and applicable for both classification and regression tasks, making it a valuable tool in the machine learning arsenal. Additionally, it generalizes well to new data by averaging the outcomes of multiple trees, avoiding overreliance on any single tree.

The train_test_split function in scikit-learn's sklearn. model selection module is used to randomly split arrays or matrices into training and test subsets for machine learning model training. This tool provides a simple way to split data into training and testing sets, with a variety of customization options available. The train_test_split function in the sklearn.model_selection module was used to divide the data into training and testing sets with 25% of the data reserved for testing. The train_test_split function can be used to split the data into training and testing subsets, which allows us to evaluate the accuracy of different Machine learning techniques and compare the performance of various models in the training process (Pedregosa et al., 2011).

We employed receiver operating characteristic (ROC) curves to evaluate the performance of each classifier and determine the optimal model for our classification task. Receiver operating characteristic (ROC) curves are visual aids used to evaluate the effectiveness of the binary classifiers. This enables us to observe the balance between the true positive rate (TPR) and false positive rate (FPR) for various classification thresholds. The area under the receiver operating characteristic curve (AUC) is a commonly used metric for assessing classifier performance and is used to compare the performances of our models.

3.2.1 .receiver operating characteristic (ROC) curve

An ROC curve is a graph that illustrates the balance between the true positive rate (sensitivity) and false positive rate (1-specificity) for different cutoff points used to classify data. Before assessing an ROC curve, we must comprehend the concepts of sensitivity and specificity. Sensitivity gauges how accurately a model forecasts positive results, whereas specificity evaluates how accurately a model predicts negative results. When comparing the results of a specific test between two populations, it is uncommon to find that the two groups are entirely different (Metz, 1978) .

In the context of auditor switching, a true positive is a company that has switched auditors, and is correctly classified as having switched. A false negative is a company that has switched auditors, but is incorrectly classified as not having switched. A true negative indicates a company that has not switched auditors and is correctly classified as not having switched. A false positive is a company that has not switched auditors, but is incorrectly classified as having switched. The goal of any classification test is to minimize the number of false positives and negatives. However, it is impossible to eliminate all errors; therefore, there will always be some cases that are misclassified. The calculation methods (TP, FP, TN, and FN) are presented in Table 2.

Table 1. *The calculation methods of TP, FP, TN, and FN*

	Auditor switch				
Test	Yes		No		Total
Positive	True Positive (TP)	a	False Positive (FP)	c	a + c
Negative	False Negative (FN)	b	True Negative (TN)	d	b + d
Total		a + b		c + d	

Here, is an example of the ROC curve.

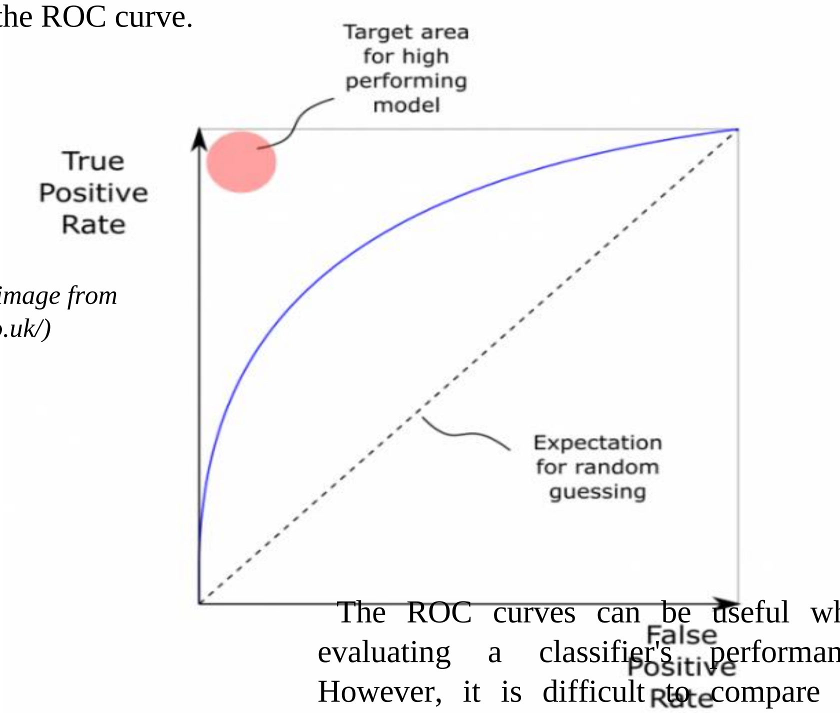

Figure 1. *ROC curve (image from https://deparkes.co.uk/)*

The ROC curves can be useful when evaluating a classifier's performance. However, it is difficult to compare the performance of different classifiers using the ROC curve alone. This is because the ROC curve is a two-dimensional graph and it can be difficult to visually compare the curves of different classifiers. The area under the curve (AUC) is often used as a common method of summarizing ROC curves. Classifiers are measured by their accuracy, which is called the AUC. A classifier with an AUC of 0.5 is no better than random guessing, while a classifier with an AUC of 1 perfectly classifies all of the data. AUC values generally indicate the classifier's accuracy .

$$AUC = \int_{x=0}^{1} TPR\left(FPR^{-1}(x)\right)dx$$

All packages, modules, and functions used in this research are presented in Table 3.

Table 2. *Packages and functions used in the scikit Learn library*

Purpose	Packages and modules	Functions
Data preprocessing and standardization	sklearn. preprocessing	MinMaxScaler
split data into training and test subsets	sklearn. model_selection	train_test_split
Model Evaluation	sklearn. metrics	roc_auc_score
ROC curve	sklearn. metrics	roc_curve
Model Evaluation	sklearn. Model _selection	ross_val_score
Random Forest Classifier Model	sklearn. ensemble	RandomForestClassifier

3.3 .Ensemble methods

Ensemble methods are powerful machine learning strategies that combine the predictions of individual base models to enhance accuracy and reliability. Ensemble methods aim to combine weak models to create a stronger ensemble. Averaging the base model predictions or training them sequentially to focus on errors can be used to create ensemble methods. These methods are powerful for improving machine learning model accuracy and robustness, and have been successful in various machine learning tasks (Pedregosa et al., 2011) .

Random Forests constructs multiple decision trees to form a forest by training different subsets of training data. Each tree was built by sampling subsets of observations (bootstrap samples) with replacement, and selecting the most optimal split at each node. The final prediction in the Random Forests is obtained through majority voting for classification or averaging for regression, where each tree's prediction contributes to the final outcome. This model had the AUC level (96.33%), indicating that it is highly accurate in its predictions and has a strong ability to discriminate between the positive and negative classes (Pedregosa et al., 2011). figure 4 shows ROC curve of this model.

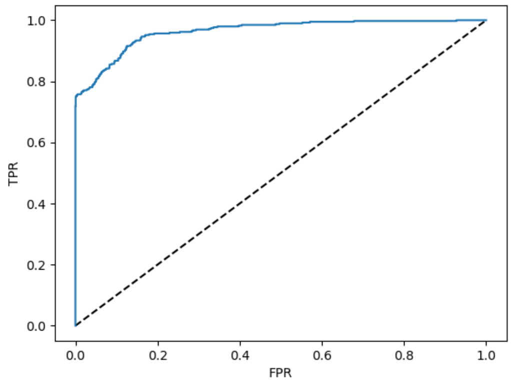

Figure 2. *shows ROC curve of "Random Forest Classifier" model (image from result)*

4. Data collection

To explore the effects of a potential auditor switch on audit quality, we employ the following model.

$$\begin{aligned} AQ_{it} = \beta_0 + \beta_1 PROB\_SWITCH_{it} &+ \beta_2 LN\_AT_{it} + \beta_3 LEV_{it} \\ &+ \beta_4 ROA_{it} + \beta_5 LOSS_{it} \\ &+ \beta_6 INVT\_RECT_{it} \\ &+ \beta_7 CFEARLY_{it} \\ &+ \beta_8 CFMATURE_{it} \\ &+ \beta_9 AT\_GROW_{it} \\ &+ \beta_{10} CFO_{it} + \beta_{11} BIGN_{it} \\ &+ IndustryFE + YearFE \\ &+ \varepsilon_{it} \end{aligned}$$

Audit quality (AQ) measures have commonly been used in previous studies (Aobdia, 2016; Brown & Knechel, 2016; Mohammadrezaei & Faraji, 2019; Tan & Young, 2015). Audit quality as an abstract concept (structure) should be examined from different perspectives. The different dimensions and aspects of this concept have unique strengths and weaknesses in all studies, particularly in the Iranian environment. It is difficult to measure audit quality because the amount of certification and confirmation provided by the auditor cannot be seen (DeFond & Zhang, 2014). To evaluate audit quality, three variables, namely AudFailA, AudFailB, and 'new modified report (NMR),' are utilized as follows:

To assess audit quality, De Fund and Zheng (2014) proposed using the restatement of financial statements, with the exception of restatement due to tax as an indicator. This indicates that the previous year's audit may have failed to detect significant distortions or errors, leading to a need for restatement in the following year. Barnes and Renart (2013) proposed two types of audit error: alpha and beta. Specifically, they define the first type of audit error (alpha error) as the incorrect rejection of an acceptable report due to the problem of non-continuance of business, but not going bankrupt in the next financial year. The second type of audit error (beta error) is the incorrect acceptance of an unacceptable report in the current financial year, which leads to bankruptcy in the next fiscal year. It is important to note that these definitions may not be directly relevant in our country as the criteria for an acceptable or unacceptable report may vary based on local laws and regulations. In 2019, Mohammad Rezaei et al. modified audit error criteria to suit Iran's research environment. They introduced a criterion that has fewer errors in measuring audit quality than the restatement of financial statement criteria. The authors defined the first type of audit error (AudFailA) as the "issuance of an unacceptable audit report in the current fiscal year by auditors and failure to restatement financial statements in the next fiscal year." The second type of audit error (AudFailB) was defined as the "issuance of an acceptable audit report in the previous fiscal year and restatement financial statements in the current year." With this new definition, the possible objections of auditing professional activists to this standard have been largely resolved (Barnes & Renart, 2013; DeFond & Zhang, 2014; Mohammadrezaei & Faraji, 2019)

In the context of financial reporting in Iran, the variable of 'new modified report' can be utilized as a metric for assessing audit quality, taking into account the prevailing environmental conditions. The term 'new modified report' refers to situations in which the auditor is a modified report in the current year, despite the entity having received a favorable opinion in the previous fiscal year. A study conducted by Mohammadrezaei et al. (2018) indicate that approximately 10 percent of modified audit reports can be categorized as new modified reports (Mohammadrezaei & Faraji, 2019; MohammadRezaei et al., 2018).

4. Finding

The primary variable in our analysis is the probability of auditor switching, which we denote PROB_SWITCH. This variable represents the likelihood that a firm will switch auditors from year t-1 to t. LEV is another variable that we consider that measures debt divided by total assets. We also consider CFO, which is the cash flow from operations divided by the total assets. All other variables are as previously defined.

To ensure the robustness of our analysis, we use two practices to reduce the impact of outliers and account for potential correlations between observations within companies:1) The first and 99th percentiles are used to winsorize all continuous variables. This means that we replace any values that fall outside the 1st and 99th percentiles with values at those percentiles. This helps to reduce the impact of outliers on our results. 2) Standard errors are clustered by company. Thus, we calculated the standard errors of our estimates separately for each company. Therefore, the correlation between observations from the same company and observations from other companies is easier to explain. This approach allows us to account for any outliers that may exist in the data, which could potentially skew our results.

Our sample was refined to focus on companies without auditor switching to estimate their probability of switching auditors. Consequently, we removed 392 observations that switched auditors between years t-1 and t. We obtained 1,603 observations as a result of this approach, and we provide their descriptive statistics in Table 4.

Table 3. *the descriptive statistics*

Stats	N	Mean	SD	p25	p50	p75
PROB_SWITCH	1603	0.102	0.089	0.038	0.081	0.131
AudFailA+ AudFailB	1603	0.273	0.446	0.000	0.000	1.000
AudFailA	1603	0.808	0.394	1.000	1.000	1.000
AudFailB	1603	0.289	0.453	0.000	0.000	1.000
NMR	1603	0.900	0.300	1.000	1.000	1.000
LN_AT	1603	13.452	1.551	12.293	13.289	14.442
LEV	1603	0.671	0.258	0.512	0.647	0.771
ROA	1603	0.997	0.122	0.030	0.088	0.168
LOSS	1603	0.124	0.329	0.000	0.000	0.000
INVT_RECT	1603	0.644	0.241	0.482	0.643	0.802
CFEARLY	1603	0.548	0.498	0.000	1.000	1.000
CFMATURE	1603	0.257	0.437	0.000	0.000	1.000
AT_GROW	1603	0.268	0.352	0.040	0.161	0.342
CFO	1603	0.033	0.109	0.018	0.080	0.147
BIGN	1603	0.284	0.451	0.000	0.000	1.000

Table 5 presents the results of Eq. (1), and supports our hypothesis. Columns 1, 2, 3, and 4 show the results obtained from the logistic regression models combining AudFailA and AudFailB, AudFailA, AudFailB, and NMR, respectively. We consistently find evidence in columns 1, 2, and 3, indicating a negative association between the probability of switching auditors and audit quality. Specifically, the coefficient on PROB_SWITCH is -1.83 ($p < 0.05$) in Column 1, -0.83 ($p < 0.1$) in Column 2, and -1.29 ($p < 0.1$) in Column 3 and -2.12 ($p < 0.1$) in Column 3. As a result, Table 5 strongly supports our hypothesis and suggests that audit quality declines as companies continue to work with incumbent auditors and are more likely to switch auditors. This indicates that companies with a high likelihood of switching auditors yet choosing to retain their current auditors often experience lower audit quality. This phenomenon can be attributed to several factors, including financial reporting challenges and the reluctance to invest in high-quality audit services. In other words, companies with a high likelihood of switching auditors but choosing to retain their current auditors may experience lower audit quality because of financial reporting challenges and reluctance to invest in high-quality audit services. The persistence of lower audit quality in these companies may also be influenced by the auditors' familiarity with the client's operations, potentially leading to complacency or reduced scrutiny.

Table 5. *results of Eq. (1)*

	AudFailA+AudFailB	AudFailA	AudFailB	NMR
prob_switch	-1.83**	-0.83***	-1.29***	-2.12***
	(0.94)	(0.85)	(1.43)	(1.91)
LN_AT	-0.24**	0.16***	-0.28**	0.01
	(2.15)	1.73	(2.28)	0.03
LEV	-0.94**	-0.01	-0.92**	0.36
	(2.23)	(0.04)	(2.08)	0.79
ROA	1.35	1.08	1.32	-0.22
	1.22	0.98	1.18	(0.07)
LOSS	-0.76**	-0.42	-0.72***	0.04
	(2.11)	(1.56)	(1.83)	0.09
INVT_RECT	-0.10	0.48	-0.11	0.41
	(0.23)	1.20	(0.23)	0.67
CFEARLY	0.20	0.07	0.26	-0.26
	1.02	0.36	1.30	(1.11)
CFMATURE	0.04	-0.14	0.15	-0.06
	0.17	(0.58)	0.67	(0.17)
AT_GROW	-0.20	0.00	-0.23	0.41
	(0.97)	0.01	(1.08)	0.99
CFO	-0.66	0.94	-0.59	0.61
	(0.75)	0.92	(0.65)	0.49
BIGN	0.02	-0.34	-0.12	-0.35
	0.07	(1.20)	(0.43)	(0.51)
Coefficient estimates above, z-statistic below. Robust standard errors are clustered by company with year and industry fixed effects. *, **, * indicate significance at p < 0.01, p < 0.05, and p < 0.10, respectively.**				

Additionally, the decision to retain an auditor despite a high likelihood of switching could signal a lack of commitment to robust financial governance, further contributing to the observed decline in audit quality. This situation underscores the importance of regular evaluations of auditor-client relationships to maintain high standards of financial reporting and oversight.

5.1. Additional analyses for large and small companies

We investigate whether our main findings exhibit more robust patterns in larger companies, which might potentially result in lower audit fees when they decide to switch auditors. We posit that audit fees hold significant weight for large companies when making decisions to switch auditors. A considerable increase in audit fees can prompt companies to consider alternative auditing firms. The cost of audits can be substantial given the complexity of large companies' financial operations. Consequently, if they perceive that the current auditor fees are unreasonably high, they may seek more cost-effective alternatives. There are two types of companies in the sample: larger companies whose total assets exceed the median value and smaller companies whose total assets are below the median. Table 6 presents the results of our analysis using three different measures of audit quality: AudFailA+AudFailB, AudFailA, and AudFailB.

Larger companies are represented by Columns 1 and 2, and smaller companies in Columns 3 and 4.

Column 4 shows that the impact of PROB_SWITCH is not statistically significant. However, Column 1 shows a significant association ($p < 0.01$).

Similarly, PROB_SWITCH has an insignificant coefficient in Column 2 and Column 5. The coefficient of PROB_SWITCH in Column 6 is not significant, whereas it is significant in Column 3 ($p < 0.01$).

For larger companies, switching auditors is associated with increased misstatement likelihood, but not for smaller ones. In general, we found that large companies were primarily affected by more severe audit-quality issues related to switching probabilities.

Table 6. *Additional analyses for large and small companies*

	AudFailA+ AudFailB big	AudFailA big	AudFailB big	AudFailA+ AudFailB small	AudFailA small	AudFailB small
prob_switch	-1.37*	0.08	-1.37*	(0.73)	(1.61)	(1.47)
	(1.25)	0.06	(1.25)	(0.52)	(1.26)	(0.98)
LN_AT	-0.51**	0.22	-0.51**	(0.12)	0.02	(0.15)
	(2.39)	1.47	(2.39)	(0.64)	0.10	(0.73)
LEV	(0.22)	0.32	(0.22)	-1.55**	(0.87)	-1.7*
	(0.30)	0.68	(0.30)	(2.41)	(1.61)	(2.64)
ROA	2.31	1.63	2.31	1.77	0.72	1.64
	1.28	0.80	1.28	1.33	0.59	1.22
LOS	-0.99***	(0.54)	-0.99***	(0.33)	(0.36)	(0.24)
	(1.68)	(1.28)	(1.68)	(0.65)	(0.88)	(0.42)
INVT_RECT	(0.52)	0.68	(0.52)	0.49	0.64	0.66
	(0.75)	1.20	(0.75)	0.84	0.99	1.02
CFEARLY	0.42	0.71**	0.42	(0.22)	-0.52***	(0.12)
	1.21	2.57	1.21	(0.84)	(1.84)	(0.42)
CFMATURE	(0.30)	0.14	(0.30)	0.01	(0.50)	0.23
	(0.74)	0.39	(0.74)	0.03	(1.59)	0.76
AT_GROW	(0.29)	(0.12)	(0.29)	(0.03)	(0.29)	0.08
	(0.98)	(0.39)	(0.98)	(0.05)	(0.63)	0.16
CFO	(1.93)	2.10	(1.93)	0.69	0.31	0.84
	(1.32)	1.22	(1.32)	0.78	0.30	0.93
BIGN	(0.50)	-0.75**	(0.50)	0.78**	0.39	0.51
	(1.09)	(2.04)	(1.09)	2.19	1.10	1.34

Coefficient estimates above, z-statistic below. Robust standard errors are clustered by company with year and industry fixed effects. *, **, *** indicate significance at p < 0.01, p < 0.05, and p < 0.10, respectively.

Furthermore, the analysis reveals that the main results are concentrated among larger companies, indicating that the relationship between audit

quality and probability of switching auditors is more pronounced in larger companies. This finding suggests that larger companies may have more complex financial reporting requirements and greater scrutiny from stakeholders, making audit quality a more critical factor in their decision-making process. Smaller companies, on the other hand, might have simpler audit needs or be more constrained by cost considerations when selecting auditors. The stronger relationship between audit quality and probability of auditor switching in larger companies could also reflect their greater resources and ability to change auditors when dissatisfied with the quality of service provided. Therefore, based on these findings, it can be concluded that companies with a higher likelihood of switching auditors but who ultimately continue to work with their current auditors have poor audit quality.

6. Conclusion

It is a fundamental aspect of audit quality to ensure that financial statements faithfully represent a company's financial position and performance, as well as to ensure that financial statements accurately reflect a company's economic reality. By upholding independence, auditors contribute to the overall transparency, reliability, and trustworthiness of financial information, which is vital for effective decision making and the functioning of financial markets. Previous research on opinion shopping has found that auditors' independence is undermined when clients can switch auditors at any time to more favorable audit opinions or less conservative accounting practices. However, even more concerning are situations in which auditors aim to retain their current clients by creating pressure. compromise on auditor independence without an observable auditor switch is a significant concern. It not only undermines the reliability of financial information but also poses a threat to the integrity of financial markets. Efforts should be made to identify and mitigate these threats to ensure the independence and quality of auditing practices. In our investigation, we examine the consequences of this situation by analyzing the quality of audits conducted among companies that have a higher likelihood of switching auditors but ultimately do not proceed with the switch. Specifically, it seeks to determine whether these companies perform lower-quality audits. As has been proposed in the literature on opinion shopping, we propose that a decrease in audit quality indicates compromised auditor independence.

In our study, we employed machine learning techniques, specifically the Random Forest Classifier, to compute auditor switching probability. This probability was subsequently utilized as an independent variable in the regression analysis, with audit quality serving as the dependent variable. The area under the ROC curve (AUC) is a widely used metric for classifier performance and was used to compare the performances of our models. AUC provides a single scalar value that represents the overall discrimination ability of a classifier across all possible classification thresholds. It ranges from 0.5 (random guessing) to 1.0 (perfect classification), with higher values indicating a better model performance. Using the AUC metric, we objectively assessed and ranked the effectiveness of our different models in distinguishing between classes. The Random Forest Classifier Model achieved the highest AUC level of 96.33, indicating a high level of accuracy in its predictions and a strong ability to distinguish between the positive and negative classes. We applied the Random Forest Classifier to a dataset comprising various firm characteristics and audit-related variables to estimate the likelihood of auditor switching (PROB_SWITCH). The Random Forest algorithm was chosen because of its robustness and superior performance in classification tasks, particularly in predicting audit-related outcomes. The computed PROB_SWITCH values were then incorporated into a regression model to examine their relationship with audit quality .

Audit quality is a critical component of financial reporting that ensures the accuracy and reliability of a company's financial statements. The relationship between auditor switching probability and audit quality has been extensively studied, revealing that companies with a higher probability of changing auditors often experience lower audit quality. This relationship between the probability of auditor switching and audit quality has significant implications for investors, regulators, and other stakeholders who rely on financial statements for decision making. This phenomenon is particularly evident in firms that retain incumbent auditors despite indications of potential auditor changes. This situation can create a challenging environment for both auditors and companies, potentially leading to increased financial reporting risk.

Furthermore, the analysis reveals that the main results are concentrated among larger companies, indicating that the relationship between audit quality and probability of switching auditors is more pronounced in larger companies. Therefore, based on these findings, it can be concluded that companies with a higher likelihood of switching auditors but who ultimately continue to work with their current auditors have poor audit quality. This finding suggests that larger companies may face more scrutiny and pressure to maintain high-quality audits, making them more sensitive to audit-quality issues. This study highlights the importance of monitoring audit quality, particularly in larger organizations, to ensure the integrity of financial reporting and maintain stakeholder confidence. A similar conclusion was reached by Hunt et al. (2021), which reinforces the credibility of the results. The alignment between these studies enhances the overall validity of the observed phenomenon and highlights a potential trend or pattern that warrants further exploration in future research.

6.1 .Auditor and regulator implications of the findings

Our research provides critical insights into the auditing profession by focusing on opinion shopping and auditor switching behaviors. While traditional studies emphasize companies that switch auditors to secure favorable opinions, our study investigates companies that, despite a high likelihood of switching, retain their incumbent auditors. This overlooked scenario can mask potential audit quality impairments, thereby escaping the scrutiny of regulators and investors. Our findings enrich the academic literature by highlighting the complexities of auditor-client dynamics and the pressures that influence audit outcomes. For regulators, we propose a machine learning-based approach to predict auditor-switching likelihood, offering a proactive tool to detect engagements in which auditors may face undue pressure without an actual switch. For audit firms, understanding why clients consider but do not switch auditors can inform strategies to preserve audit quality and independence. Methodologically, our application of machine learning, particularly Random Forest algorithms, marks a significant advancement in audit research by improving the ability to identify quality risks. These insights suggest that policymakers should adopt enhanced oversight mechanisms and leverage technology to bolster audit integrity. Overall, our research shows that machine learning has the potential to revolutionize the auditing field. Using these techniques, auditors, regulators, and audit firms can make informed decisions, identify potential risks, and improve audit quality.

7. Limitation

As general consideration for data interpretation of the current manuscript, some limitations of current research need to be considered. The major limitation for our current study was the limited number of primary datasets. Limitation in the primary data is a common limitation in verity of studies. This limitation can effect on the final results or training of the algorithm. However, it needs to be considered that, the current study is just a primary study in this field and needs to be improved by future more comprehensive studies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Aghaei Chadegani, A; Mohamed, Z; Jari,A. (2013). *The Determinant Factors of Auditor Switch Among Companies Listed on Tehran Stock Exchange.* International Research Journal of Finance and Economics ISSN 1450-2887, Issue 80 (2011). https://ssrn.com/abstract=2227597

Aobdia, D. (2016). *The validity of publicly available measures of audit quality: Evidence from the PCAOB inspection data.* Social Science Research Network (SSRN). http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2629305

Aobdia, D. (2019). *Do practitioner assessments agree with academic proxies for audit quality? Evidence from PCAOB and internal inspections.* Journal of Accounting and Economics, 67(1), 144-174. https://doi.org/10.1016/j.jacceco.2018.09.001

Bao, Y., Ke, B., Li, B., Yu, Y. J., & Zhang, J. (2020). *Detecting accounting fraud in publicly traded US firms using a machine learning approach.* Journal of Accounting Research, 58(1), 199-235. https://doi.org/10.1111/1475-679X.12292

Barnes, P., & Renart, M. A. (2013). *Auditor Independence and Auditor Bargaining Power: Some S panish Evidence Concerning Audit Error in the Going Concern Decision.* International Journal of Auditing, 17(3), 265-287. https://doi.org/10.1111/ijau.12003

Bayo Flees, R., & Mouselli, S. (2023). *The impact of qualified audit opinion on stock returns: an empirical study at Amman stock exchange*. Journal of Financial Reporting and Accounting, 21(3), 633-653. https://doi.org/10.1108/JFRA-02-2021-0056

Beardsley, E. L., Imdieke, A. J., & Omer, T. C. (2021). *The distraction effect of non-audit* *services on audit quality.* Journal of Accounting and Economics, 71(2), 101380. https://doi.org/10.1016/j.jacceco.2020.101380

Bertomeu, J., Cheynel, E., Floyd, E., & Pan, W. (2020). *Using machine learning to detect misstatements.* Review of Accounting Studies, 1-52. https://doi.org/10.1007/s11142-020-09563-8

Board, P. C. A. O. (2013). Improving the transparency of audits: Proposed amendments to PCAOB auditing standards to provide disclosure in the auditor's report of certain participants in the audit. In: PCAOB Washington, DC.

Brown, S. V., & Knechel, W. R. (2016). *Auditor–client compatibility and audit firm selection.* Journal of Accounting Research, 54(3), 725-775. https://doi.org/10.1111/1475-679X.12105

Budisantoso, T., & Kurniawan, H. (2022). *The contagion effect of decreasing audit's quality on financial statement audit engagement: the Indonesian case.* Asia-Pacific Journal of Business Administration, ahead-of-print(ahead-of-print). https://doi.org/10.1108/APJBA-11-2020-0393

Calocha, R., & Herwiyanti, E. (2020). *Factors that affect audit quality.* Journal of Contemporary Accounting, 2, 35-48. https://doi.org/10.20885/jca.vol2.iss1.art4

Cecchini, M., Aytug, H., Koehler, G. J., & Pathak, P. (2010). *Detecting management fraud in public companies.* Management Science, 56(7), 1146-1160. https://doi.org/10.1287/mnsc.1100.1174

CHEN, F., PENG, S., XUE, S., YANG, Z., & YE, F. (2016a). *Do Audit Clients Successfully Engage in Opinion Shopping? Partner-Level Evidence.* Journal of Accounting Research, 54(1), 79-112. https://doi.org/https://doi.org/10.1111/1475-679X.12097

Chen, F., Peng, S., Xue, S., Yang, Z., & Ye, F. (2016b). *Do audit clients successfully engage in opinion shopping? Partner‐level evidence.* Journal of Accounting Research, 54(1), 79-112. https://doi.org/10.1111/1475-679X.12097

Chen, P. F., He, S., Ma, Z., & Stice, D. E. (2012). *Qualified audit opinions and debt contracting.* Available at SSRN. https://hdl.handle.net/1783.1/7932

Chung, H., Kim, Y., & Sunwoo, H.-Y. (2021). *Korean evidence on auditor switching for opinion shopping and capital market perceptions of audit quality.* Asia-Pacific Journal of Accounting & Economics, 28(1), 71-93. https://doi.org/10.1080/16081625.2020.1845000

Chung, H., Sonu, C. H., Zang, Y., & Choi, J.-H. (2019). *Opinion shopping to avoid a going concern audit opinion and subsequent audit quality.* Auditing: A Journal of Practice & Theory, 38(2), 101-123. https://doi.org/10.2308/ajpt-52154

Commission, E. (2010). Green paper: Audit policy: Lessons from the crisis. Publications Office of the European Union.

Cowle, E. N., Decker, R. P., & Rowe, S. P. (2023). *Retain or Rotate: The Association between Frequent Auditor Switching and Audit Quality.* Accounting Horizons, 1-23. https://doi.org/10.2308/horizons-2022-018

DeFond, M., & Zhang, J. (2014). *A review of archival auditing research.* Journal of accounting and economics, 58(2-3), 275-326. https://doi.org/10.1016/j.jacceco.2014.09.002

Deng, C., Ji, X., Rainey, C., Zhang, J., & Lu, W. (2020). *Integrating Machine Learning with Human Knowledge.* iScience, 23(11), 101656. https://doi.org/https://doi.org/10.1016/j.isci.2020.101656

Dhaliwal, D. S., Lamoreaux, P. T., Lennox, C. S., & Mauler, L. M. (2015). *Management Influence on Auditor Selection and Subsequent Impairments of Auditor Independence during the Post-SOX Period.* Contemporary Accounting Research, 32(2), 575-607. https://doi.org/https://doi.org/10.1111/1911-3846.12079

Elizabeth N. Cowle, Ryan P. Decker, Stephen P. Rowe. (2023). *Retain or Rotate: The Association between Frequent Auditor Switching and Audit Quality.* Accounting Horizons 1 September 2023; 37 (3): 79–101. https://doi.org/10.2308/HORIZONS-2022-018

Fakhari, H., & Amiri, E. (2020). *Causes and Consequences of Audit Opinion Shopping.* Accounting and Auditing Studies, 9(36), 5-26. https://doi.org/10.22034/iaas.2020.128133

Gu, S., Kelly, B., & Xiu, D. (2020). *Empirical asset pricing via machine learning.* The Review of Financial Studies, 33(5), 2223-2273. https://dx.doi.org/10.2139/ssrn.3159577

Harianja, A., & Sinaga, J. T. G. (2022). *The effect of audit fee, audit delay, and auditor switching on audit quality.* JASa (Jurnal Akuntansi, Audit Dan Sistem Informasi Akuntansi), 6(1), 23-31.

https://doi.org/10.36555/jasa.v6i1.1709
Hall, C., Judd, J. S., & Sunder, J. (2023). *Auditor conservatism, audit quality, and real consequences for clients.* Review of Accounting Studies, 28(2), 689-725.
https://doi.org/10.1007/s11142-021-09653-1
Hu, N., Xu, J., & Xue, S. (2022). *Regulatory risk and auditors' reporting conservatism: Evidence from Chinese comment letters.* Journal of Accounting and Public Policy, 41(6), 106997.
https://doi.org/https://doi.org/10.1016/j.jaccpubpol.2022.106997
Hunt, J. O. S., Rosser, D. M., & Rowe, S. P. (2021). *Using machine learning to predict auditor switches: How the likelihood of switching affects audit quality among non-switching clients.* Journal of Accounting and Public Policy, 40(5), 106785.
https://doi.org/https://doi.org/10.1016/j.jaccpubpol.2020.106785
Janiesch, C., Zschech, P., & Heinrich, K. (2021). *Machine learning and deep learning.* Electronic Markets, 31(3), 685-695.
https://doi.org/10.1007/s12525-021-00475-2
Jones, S. (2017). *Corporate bankruptcy prediction: a high dimensional analysis.* Review of Accounting Studies, 22(3), 1366-1422.
https://doi.org/10.1007/s11142-017-9407-1
Kogan, A., Mayhew, B. W., & Vasarhelyi, M. A. (2019). *Audit data analytics research—An application of design science methodology.* Accounting Horizons, 33(3), 69-73.
https://doi.org/10.2308/acch-52459
Krishnan, J. (1994). *Auditor switching and conservatism.* Accounting Review, 200-215.
https://www.jstor.org/stable/248267
Lennox, C. (2000). *Do companies successfully engage in opinion-shopping? Evidence from the UK.* Journal of accounting and economics, 29(3), 321-337.
https://doi.org/10.1016/S0165-4101(00)00025-2
Lu, T. (2006). *Does opinion shopping impair auditor independence and audit quality?* Journal of Accounting Research, 44(3), 561-583.
https://doi.org/10.1111/j.1475-679X.2006.00211.x
Metz, C. E. (1978). *Basic principles of ROC analysis.* Seminars in Nuclear Medicine, 8(4), 283-298.
https://doi.org/https://doi.org/10.1016/S0001-2998(78)80014-2
Mohammadrezaei, F., & Faraji, O. (2019). *The Dilemma of Audit Quality Measuring in Archival Studies: Critiques and Suggestions for Iran's Research Setting.* Journal of Accounting and Auditing Review, 26(1), 87-122.
https://doi.org/10.22059/acctgrev.2018.256781.1007884
MohammadRezaei, F., Mohd-Saleh, N., & Ahmed, K. (2018). *Audit firm ranking, audit quality and audit fees: Examining conflicting price discrimination views.* The International Journal of Accounting, 53(4), 295-313.
https://doi.org/10.1016/j.intacc.2018.11.003
Mullainathan, S., & Spiess, J. (2017). *Machine learning: an applied econometric approach.* Journal of Economic Perspectives, 31(2), 87-106.
DOI: 10.1257/jep.31.2.87
Newton, N. J., Persellin, J. S., Wang, D., & Wilkins, M. S. (2015). *Internal Control Opinion Shopping and Audit Market Competition.* The Accounting Review, 91(2), 603-623.
https://doi.org/10.2308/accr-51149
Ostadjafari, M; Faraji, O; Arabzadeh,M; Jabbary,H; Ghanimati, H. (2024). *Factors Affecting Auditor Switching with an Emphasis on Auditor Characteristics: A Meta-Analysis Approach.* International Journal of Finance and Managerial Accounting. ISSN 2588-4379, Volume 9, Issue 34 - Serial Number 34 (2024).
https://doi.org/10.30495/ijfma.2022.67587.1857
Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., & Dubourg, V. (2011). *Scikit-learn: Machine learning in Python.* the Journal of machine Learning research, 12, 2825-2830.
http://scikit-learn.sourceforge.net/
Perols, J. L., Bowen, R. M., Zimmermann, C., & Samba, B. (2017). *Finding needles in a haystack: Using data analytics to improve fraud prediction.* The Accounting Review, 92(2), 221-245.
https://doi.org/10.2308/accr-51562
Perols, J. L., & Lougee, B. A. (2011). *The relation between earnings management and financial statement fraud.* Advances in Accounting, 27(1), 39-53.
https://doi.org/10.1016/j.adiac.2010.10.004
Sarker, I. H. (2021). *Machine Learning: Algorithms, Real-World Applications and Research Directions.* SN Computer Science, 2(3), 160.
https://doi.org/10.1007/s42979-021-00592-x
Securities, & Commission, E. (1988). *Disclosure Amendments to Regulation SK, Form 8-K and Schedule 14A regarding changes in*

accountants and potential opinion shopping situations. Financial Reporting Release(31), 1140-1147.

Senate, U. (1976). Accounting Establishment: A Staff Study. Report of the Subcommittee on Reports, Accounting, and Management of the Committee on Government Operations.(Metcalf Committee Report). Washington, DC: US Government Printing Office. In: Metcalf Committee Report). Washington, DC: US Government Printing Office ….

Tan, C. E., & Young, S. M. (2015). *An analysis of "Little r" restatements.* Accounting Horizons, 29(3), 667-693. https://doi.org/10.2308/acch-51104

Van Brenk, H., Majoor, B., & Wright, A. M. (2021). *The Effects of Profit-Sharing Plans, Client Importance, and Reinforcement Sensitivity on Audit Quality.* Auditing: A Journal of Practice & Theory, 40(1), 107-131. https://doi.org/10.2308/AJPT-18-118

Whiting, D. G., Hansen, J. V., McDonald, J. B., Albrecht, C., & Albrecht, W. S. (2012). *Machine learning methods for detecting patterns of management fraud.* Computational Intelligence, 28(4), 505-527. https://doi.org/10.1111/j.1467-8640.2012.00425.x

Xie, Z., Cai, C., & Ye, J. (2010). *Abnormal audit fees and audit opinion–Further evidence from China's capital market.* China Journal of Accounting Research, 3, 51-70. https://doi.org/10.1016/S1755-3091(13)60019-2

Yuejun, T. (2011). *Audit fees, motivation of avoiding loss and opinion shopping: Test for moderating effect based on evidences of Chinese stock market from 2001 to 2008.* China Finance Review International, 1(3), 241-261. https://doi.org/10.1108/20441391111144103

Zaafaranie, S. D., Wati, N. N., Angga, A., & Rosnidah, I. (2024). *The Influence of Audit Fees, Audit Tenure, and Auditor Switching on Audit Quality.* Indonesian Interdisciplinary Journal of Sharia Economics (IIJSE), 7(3), 5350-5364. https://doi.org/10.31538/iijse.v7i3.5375