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ARTICLE

Audit characteristics and the likelihood of fraudulent financial reporting

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Abstract

Purpose – To analyze the relationship between audit characteristics and the likelihood of fraudulent financial reporting within companies.

Theoretical framework – Agency theory.

Design/methodology/approach – A descriptive, documentary study with a quantitative approach using rough set theory, k-means clustering, and logistic regression methods. The sample consists of 211 Brazilian companies listed on the [B]3 from the Refinitiv database from 2016 to 2021.

Findings – The results suggest that audits by the Big Four reduce the likelihood of fraudulent-looking financial reports (FLFRs) in Brazil, providing greater security to stakeholders. However, changing auditors and the financial independence of the audit firm do not significantly impact the detection of FLFRs. Furthermore, qualified opinions increase the likelihood of FLFRs by 3.625 times and abstentions from an opinion increase the likelihood by 62.22 times. These types of opinions are thus highlighted as the main indicators for identifying FLFRs.

Practical & social implications of research – Considering the number of publicly traded companies that comprise the [B]3 and the volume of shares traded daily in Brazil, understanding the relationship between audit characteristics and FLFRs is crucial for navigating the Brazilian organizational landscape.

Originality/value – Drawing from a global trend, this article offers an in-depth analysis of the investments of the "Big Three" as shareholders in Brazilian companies. The paper also discusses the intensification of financialization and its connection to the growth of institutional investors as shareholders in large corporations.

Keywords: Audit characteristics, financial statements, fraudulent-looking reports.

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1 Introduction

Suspected fraudulent financial reports have called into question the integrity of the global financial market, underscoring the importance of auditing as a vital means of safeguarding stakeholders and fostering corporate transparency. In Brazil, high-profile cases such as Enron Tropical (1990), Daslu (2000), Petrobras (2014), and Americanas (2023) underscore the importance of this issue, particularly in emerging markets that face distinctive regulatory and governance challenges. In an international context, suspicious cases occurred with Enron (2001), WorldCom (2002), and Nortel Networks (2004).

According to Martins and Ventura Jr. (2020), agency theory, formalized by Jensen and Meckling (1976), offers an essential theoretical perspective for understanding cases of fraud. The theory addresses conflicts of interest between agents and principals, and when combined with information asymmetry, it can create incentives for opportunistic behavior (Araujo et al., 2024). Examples of such behavior include accounting manipulation and concealing financial data (Martins & Ventura Jr., 2020; Araujo et al., 2024). This is because information disclosed by an organization can directly affect the price of its shares on the capital market (Amiram et al., 2018). Thus, managers may be tempted to present data indicating constant growth and profitability, even if it does not reflect the company's reality (Richardson et al., 2022).

In this context, it is necessary for the information disclosed by organizations to undergo independent audit analysis (Tonye & Boloumbele, 2023). Audits play a fundamental role in protecting the interests of stakeholders and reducing the likelihood of fraudulent financial reporting (Khaksar et al., 2022). Big Four audits are recognized for offering higher-quality services due to their extensive experience. This increases the reliability of financial reports and reduces the chances of irregularities (Azghandi et al., 2023).

Switching audit firms is also an effective way to detect fraud because it enables a more impartial review of financial reports by new professionals (De Fond et al., 2002). They increase the verifiability of information and encourage managers to reduce information asymmetry, thereby increasing the reliability of financial reports (Romanus et al., 2008; De Fond et al., 2002).

Another critical aspect is audit independence. When auditors perform their duties without management influence, they can more easily identify distortions in financial reports, thus reducing the likelihood of fraudulent reports (Khaksar et al., 2022). Another important indicator is the type of opinion issued by the auditors. Qualified opinions, adverse opinions, or abstentions can indicate inconsistencies in the information provided by the company (Khaksar et al., 2022). Therefore, the type of opinion can indicate that the information provided by the organization is distorted.

Therefore, analyzing accounting fraud cases in Brazil through the lens of agency theory underscores the importance of robust auditing mechanisms that mitigate conflicts of interest and enhance organizational transparency. Independent verification of financial reports protects stakeholders and strengthens the stability and credibility of the financial market. This is because the results presented in financial reports can directly influence share price fluctuations (Amiram et al., 2018; Tonye & Boloumbele, 2023).

Law (2011) and Martins and Ventura Jr. (2020) point out that when companies are involved in fraud, as was the case with Enron Tropical, Daslu, Banco PanAmericano, Petrobras, JBS, and most recently, Americanas, the trust that stakeholders place in the financial information made available by these organizations is seriously compromised. These fraudulent practices damage a company's credibility and are difficult to identify, especially in contexts with low internal control or insufficient investor monitoring (Araujo et al., 2024).

In this scenario, certain auditing characteristics play a crucial role in identifying potentially fraudulent financial reports, mitigating risks, and strengthening corporate transparency. Furthermore, Associação Brasileira das Entidades dos Mercados Financeiro e de Capitais (2022) points out that the Brazilian capital market has experienced significant growth, with operations quadrupling in the last 25 years. This growth reinforces the importance of robust auditing mechanisms to sustain trust and integrity in this expanding environment.

Keeping this in mind, the purpose of this study is to analyze the relationship between audit characteristics and the likelihood of suspicious financial reports in publicly traded companies that comprised the [B]3 – Brasil, Bolsa e Balcão index between 2017 and 2021. The main findings of this study contribute to the existing literature by showing that the type of opinion issued by auditors increases the likelihood of fraudulent-looking financial reports (FLFRs).

The results reveal that the type of opinion issued by auditors significantly impacts the likelihood of FLFRs. Specifically, auditors who issue qualified opinions increase the likelihood of suspicious reports by 3.625 times, signaling potential inconsistencies in disclosed financial information. Additionally, an opinion with an abstention has an even more significant effect, increasing the likelihood of FLFRs by 62.22 times. These findings underscore the critical role of these opinions in identifying potential financial irregularities.

The results of this study build upon Martins and Ventura Jr.'s (2020) research by incorporating consolidated analysis models adapted to the Brazilian market. The study employed the bankruptcy predictability model adjusted by Altman et al. (1979) and the fraudulent financial reporting probability model proposed by Beneish (1999). By applying the Z-score and M-score, this study explores these tools within a framework that considers the characteristics of audit firms, providing a more comprehensive and current approach.

The results of this research expand on the findings of Khaksar et al. (2022), who analyzed companies from Iran – an emerging country, much like Brazil – with a focus on volatility, political risk, and uncertainty. Thus, this research not only complements but also expands upon the existing literature, offering a more comprehensive and practical understanding of the unique characteristics of these economic contexts.

In addition to these literary and methodological contributions, the results of this research are useful for investors and market regulators because it was possible to identify the probabilities of fraudulent reporting, bankruptcy, and result manipulation. Additionally, it was found that certain characteristics of audit firms are effective in identifying FLFRs.

2 Theoretical background and development of hypotheses

According to Azghandi et al. (2023), Big Four audits demonstrate a greater understanding of regulatory compliance and governance. As a result, these companies tend to mitigate information asymmetry by carrying out their work in a way that allows for greater diversification of services (Khaksar et al., 2022). Big Four audits are recognized both nationally and internationally because the organizations they audit present reports that convey greater reliability to stakeholders. Research by Khaksar et al. (2022) indicates that organizations audited by the Big Four are less likely to disclose fraudulent financial reports. Similarly, Gontara et al.'s (2023) study revealed that Big Four audits reduce the likelihood of fraudulent activity. Therefore, it is expected that Big Four audits will also reduce the likelihood of FLFRs in the Brazilian organizational scenario. Therefore, the first hypothesis of the research is formulated:

2.1 H_1: Having the Big Four conduct an audit reduces the likelihood of suspicious financial reports

A change in audit firms is another factor that supports the detection of fraudulent financial reports (Khaksar et al., 2022). According to Karami et al. (2017), changing audit firms leads to verification and comparison of information prepared by organizations, which makes it possible to detect asymmetry in disclosed financial information. When auditors with different skills and knowledge analyze the information, they may identify possible distortions (Mukhlasin, 2018). As audit firms adopt different working metrics, an auditor evaluating an organization for the first time tends to exercise greater caution, increasing the likelihood of identifying asymmetric financial information (De Fond et al., 2002). Companies adopting different working metrics cause auditors to assess organizations with greater caution, which increases the likelihood of identifying asymmetric financial information (De Fond et al., 2002). Thus, it is expected that changing audit firms in the Brazilian organizational scenario will increase the chances of detecting FLFRs. Thus, the second hypothesis of the research is presented:

2.2 H_2: Switching audit firms increases the likelihood of identifying suspicious financial reports

De Fond et al. (2002) state that work performed by independent auditors increases the likelihood of identifying FLFRs within organizations. Independence enables the audit firm to perform its duties clearly and objectively, ensuring that the auditor is completely independent from the audited company (De Fond et al., 2002). When the audit firm is independent, the auditor has greater freedom to identify possible information asymmetry in financial reports (Khaksar et al., 2022).

In this sense, the auditor presents his or her opinion without being influenced by the relationship between the auditing and audited companies. This characteristic increases audit firms' chances of detecting fraudulent financial reports in organizations (Khaksar et al., 2022). Consequently, there is a perception that the financial independence of audit firms increases the likelihood of detecting FLFRs. Thus, the third hypothesis of the research is presented:

2.3 H_3: An independent audit firm is more likely to detect suspicious financial reports

The audit report communicates the auditor's findings to stakeholders and plays a crucial role in alerting users of financial reports to potential issues (De Fond et al., 2002). This indicates that the auditor's opinion is directly related to the occurrence of FLFRs in organizations (Khaksar et al., 2022). There are four types of audit opinions: unqualified, qualified, adverse, and withheld.

An unqualified audit opinion indicates that the auditor did not identify any distortions in the information and therefore suggests a lower probability of fraudulent financial information (De Fond et al., 2002). Conversely, a qualified, adverse, or no opinion indicates that the financial reports contain asymmetric information and may have problems (De Fond et al., 2002).

Thus, qualified opinions indicate specific problems in financial reports, while adverse opinions or abstentions suggest significant informational asymmetry and reflect greater difficulties in validation by the auditors. Therefore, these types of opinions are expected to be associated with a greater likelihood of FLFRs. This leads to the fourth research hypothesis:

2.4 H_4: Having a qualified, adverse, or withheld opinion increases the likelihood of suspicious financial reporting

Table 1 illustrates the expected relationships between the research variables.

3 Methodological procedures

3.1 Sample and data collection

The initial sample for the study consists of 472 Brazilian companies listed on the [B]3 – Brasil, Bolsa e Balcão. Data were collected from the Refinitiv database; however, financial institutions were excluded from the analysis because they have a different operating structure from non-financial companies. The analysis period covered the 2017-2021 financial years (see Supplementary Data 1 – Database). However, the selected interval is seven years because the 2016 financial year was used to calculate changes from 2017 onwards (change from 2017 compared to 2016).

The period from 2017 to 2021 was chosen because financial information and audit reports for Brazilian publicly traded companies were available, intact, and comparable during this time. This time frame ensures the collection of consistent data following the adoption of International Financial Reporting Standards (IFRS) in Brazil, which promotes greater uniformity and quality in financial reporting. This time period also allows for the appropriate application of the Altman et al. (1979) insolvency prediction model and Beneish (1999) earnings manipulation model, as both require complete annual information to calculate financial variables. This respects the methodological consistency required by the models (see Supplementary Data 2 – Variables).

As a result, the final subsample used in the analysis included 211 companies. The study's variables were calculated and organized in Microsoft Excel® spreadsheets. After collection, the data were imported into SPSS® software to apply the statistical techniques used in the research. The analyses were carried out in four stages: (1) calculation of the Altman et al. (1979) and Beneish (1999) indices, (2) application of rough set theory, (3) segmentation of the companies via k-means clustering, and (4) testing of the hypotheses using logistic regression.

Table 1
Relationships investigated in the research

Variable	Expected Influence	Author(s)
Size of the Big Four audit firm	-	Reichelt and Wang (2010); Khaksar et al. (2022)
Change of audit firm *Aud-Change*	+	Khaksar et al. (2022); Azghandi et al. (2023)
Independence of the audit firm *Fi-Ind*	+	Khaksar et al. (2022)
Type of auditor's opinion *Modify* QOT; AOT; NOT	+	Reichelt and Wang (2010); Habib and Bhuiyan (2011); Camargo and Flach (2016).

Legend: QOT Qualified opinion type; AOT Adverse opinion type; NOT No opinion type. **Source:** Prepared by the authors (2025).

3.2 Analysis models

To measure the likelihood of financial problems and insolvency among the analyzed companies, we applied the Altman et al. (1979) model, which is suitable for the Brazilian context and widely used in Brazilian accounting literature. The model calculates the Z-score from four financial indicators, the formulas of which were applied according to the original structure: X_1 corresponds to working capital divided by total assets, X_3 to return on assets (ROA), X_4 to market value over total liabilities, and X_5 to asset turnover. As in previous studies by Altman et al. (1979) and Martins and Ventura Jr. (2020), X_2 was excluded from the analysis because it did not accurately reflect Brazilian reality.

To identify companies with signs of accounting distortion, the Beneish (1999) model was applied to determine their propensity to manipulate earnings. The variables used follow the adapted Brazilian methodology, as validated in recent studies (Martins & Ventura Jr., 2020). Combining these two models not only allows us to assess companies' financial health, but also to identify potential manipulation of results, thereby increasing the predictive capacity for detecting fraudulent financial reports (Martins & Ventura Jr., 2020).

Rough set theory (RST) was used to identify the audit characteristics most associated with the occurrence of FLFRs. This technique enables us to work with incomplete and uncertain data by identifying patterns and relationships between conditional and decisional attributes. We chose RST due to its flexibility in handling large volumes of unbalanced data and its ability to generate clusters of relevant attributes based on observation similarity.

After applying the Altman and Beneish models, the results were grouped using k-means clustering, an unsupervised learning technique that segments companies into homogeneous groups based on the likelihood of fraud. Five clusters were chosen based on theoretical criteria to balance the interpretation of the centroids and the dispersion of the data. Clusters 1 to 4 were considered for the model because they had a higher probability of information suspected to be fraudulent, while cluster 5 was excluded due to its low probability.

Five clusters were defined based on recommendations in the literature (Hair et al., 2009), taking into account intra-group variability and the interpretability of the results. This approach was complemented by an analysis of centroid behavior. The logistic regression model with unbalanced panel data was then applied, taking into account the selected audit and control variables. This technique was chosen because it is appropriate for modeling dichotomous dependent variables, and it allows for the inclusion of sector and year fixed effects. This increases the robustness of the analysis and controls for unobserved factors.

3.3 Rough set theory

To select the audit characteristics most closely resembling fraud, we used a data mining technique based on rough set theory (RST). RST provides a foundation for understanding how audit characteristics influence the detection of potential fraudulent financial reports.

RST, a technique first presented by Pawlak in 1982, was introduced as an extension of set theory aimed at studying intelligent systems characterized by insufficient and incomplete information (Zonatto et al., 2011). According to Hein and Kroenke (2010), RST is a data mining technique applicable to various fields of study, including organizational studies.

Zonatto et al. (2011) note that a variety of users with different interests analyze the financial information made available by organizations, especially in the stock market. Pawlak (1982) explains that data processing and mining start with an information matrix. The rows of the matrix represent experiments or objects of research, and the columns describe variables or attributes collected. Table 2 illustrates the data table model developed by Hein and Kroenke (2010).

RST is developed through a set of options described by the research and applied based on the selected attributes – in this case, the audit characteristics – by comparing them with each other in the context of Brazilian companies listed on the [B]3 – Brasil, Bolsa e Balcão. This allows us to identify the audit characteristics that best predict fraudulent financial reports in Brazilian organizations.

To support the data calculation metric, a previous study that used RST in accounting is presented. Zonatto et al. (2011) sought to identify the characteristics of companies that best explain adherence to international accounting standards in the electricity sector among companies listed on the BM&F Bovespa. The study used an exploratory methodology and RST to determine if a financial declaratory nucleus existed that could explain this adherence (Zonatto et al., 2011).

The results of the study indicated that factors such as company size, financing needs, debt levels, fixed assets, and return on equity best explain adherence to

Table 2
Structure of an information matrix

	Attribute 01	Attribute 02	...	Attribute R
Objective 1	V_{11}	V_{12}	...	V1r
Objective 2	V_{21}	V_{22}	...	V2r
			...	...
Objective M	Vm1	Vm2	...	Vmr

Source: Based on Hein and Kroenke (2010).

international accounting standards among the analyzed companies (Zonatto et al., 2011). In this context, we conclude that applying the RST technique to analyze the data in this study is feasible and appropriate. This allows us to identify the audit characteristics that best predict the occurrence of fraudulent financial reports in Brazilian organizations.

3.4 Audit characteristics

Table 3 describes how the information was collected. Notably, the information on the auditing company was manually collected from the audit report and reference form, both of which contain information provided by the company itself. The reference form was accessed via the website of the Brazilian Securities and Exchange Commission (CVM).

3.5 Data analysis procedure

To analyze the influence of audit characteristics on fraud detection and meet the research objective, logistic regression models with unbalanced panel data were used. The probability of fraudulent-looking financial reports ($FLFR_{it}$) occurring is a dichotomous variable equal to 1 if the company belongs to clusters 1 to 4 and 0 otherwise. Equation 1 describes the model of fraud occurrence and the characteristics of audits after applying the rough set analysis technique.

$$\boldsymbol{In}\left(\frac{\boldsymbol{P}\left(\boldsymbol{FLFR_{it}}=1\right)}{1-\boldsymbol{P}\left(\boldsymbol{FLFR_{it}}=1\right)}\right)=\beta_0+\beta_1 QOT_{it}+\beta_2 WOT_{it}+\beta_3 BIGFOUR_{it} \\ +\beta_4 FIINDy_{it}+\beta_5 AUDCHANGEy_{it}+\sum YearFixedEffect+ \\ \sum SectorFixedEffect+\varepsilon_{it} \quad (1)$$

Big Four$_{it}$ indicates that the auditing firm is one of the four largest in the world; *AudChange*$_{it}$ refers to a change of auditing firm; *FiInd*$_{it}$ indicates that the auditing firm is independent, as well as the type of auditor's opinion. There are two types: a qualified opinion (QOT) and a withheld opinion (WOT). Note that no reports with an adverse opinion were found for the companies in the sample.

Table 3
Independent research variables

Variable	Description	Author(s)
Big Four	A dichotomous variable of company size. It is considered 1 if the audit firm is one of the Big Four and 0 otherwise.	Reichelt and Wang (2010); Khaksar et al. (2022)
Aud-Change	If the auditor switched in the year under review, the value is one; otherwise, it is zero.	Khaksar et al. (2022); Azghandi et al. (2023)
Fi-ind	Financial independence is equal to the sum of fees received from each client by each audit firm per year, divided by the sum of total fees received by auditors in each sector. If this index is greater than 0.5, it indicates a lack of independence and is equal to zero. If it is less than 0.5, however, it is equal to one and indicates financial independence.	Khaksar et al. (2022)
QOT	If the auditor's opinion is qualified, the value is 1; otherwise, the value is 0.	Reichelt and Wang (2010); Habib and Bhuiyan (2011); Camargo and Flach (2016).
AOT	If the auditor's opinion is adverse, the value is 1; otherwise, the value is 0.	
WOT	If the auditor's opinion is withheld, the value is 1; otherwise, the value is 0.	

Legend: QOT: Qualified Opinion Type; AOT: Adverse Opinion Type; WOT: Withheld Opinion Type.
Source: Prepared by the authors (2025).

4 Analysis and discussion of results

To analyze the relationship between audit characteristics and the likelihood of fraudulent financial reports in the companies, the study variables were first analyzed using descriptive statistics. Then, rough set theory and regressions were applied to test the research hypotheses.

4.1 Descriptive statistics

Table 4 shows the descriptive statistics for the numerical variables in the Altman et al. (1979) and Beneish (1999) models. These statistics include the mean, median, standard deviation, sample variance, range, minimum, maximum, and coefficient of variation. As mentioned earlier, this study's dependent variables include the likelihood of fraudulent financial reporting, which is calculated using the aforementioned models.

According to the Beneish (1999) model, the organizations have no evidence of fraudulent financial reporting, as the averages of the calculation metrics DSRI, GMI, AQI, SGI, DEPI, SGAI, and LVGI are close to 1. However, TATA showed discrepant values (-0.0443), indicating possible information asymmetry.

The Altman et al. (1979) model comprises formulas X_1, X_3, X_4 and X_5, which have the most discrepant mean values and may indicate possible problems in the organizations' financial reports. However, this discrepancy can be explained by the fact that the model considers not only the possibility of financial problems in organizations but also the probability of fraudulent financial reports.

4.2 Rough set theory analysis

The rough set analysis was performed using 10 random samples to more reliably analyze the quality of the approximation, given that the dataset is highly imbalanced. The rough set analysis used 10 stratified random samples with replacement to balance the distribution of classes with and without FLFRs. This approach aimed to minimize the effects of imbalance since all classes were proportionally represented in the samples. This enabled a more robust and reliable evaluation of the approximation quality. Table 5 describes the quality of the approximation according to the condition attributes for each random sample.

Table 5 shows the quality of the approximation for various combinations of the condition attributes opinion, change, big, find, and modify, when used alone or in combination. The values shown represent the quality of the approximation and demonstrate the degree of precision. Higher values suggest that the attribute has a greater capacity to make correct decisions.

Attributes referring to the Big Four audit and find can be interchanged since working with {opinion, big} or {opinion, find} produces a very close approximation. For example, in the first sample, which includes all the variables (opinion, change, big, find, and modify), the approximation quality is 12.1% (0.121). With the variables {opinion, big} or {opinion, find}, the approximation quality is nearly identical at 11.7% (0.117). Table 6 describes the nuclei according to the sample.

Table 4
Descriptive statistics of numerical variables for the possibility of fraudulent financial reporting

Descriptive Statistics	Mean	Median	Standard deviation	Sample variance	Interval	Minimum	Maximum	Coefficient of variation
DSRI	1.1231	0.9843	1.0872	1.1820	27.9597	0	27.9597	96.7999
GMI	0.9497	0.9849	3.6570	13.3738	147.8504	-62.4288	85.4216	385.0574
AQI	1.0802	0.9930	0.8828	0.7794	23.9707	0.0060	23.9767	81.7328
SGI	1.1618	1.1010	0.5953	0.3543	14.5312	0.0357	14.5670	51.2377
DEPI	1.0858	0.9893	1.1546	1.3331	34.7001	0	34.7001	106.3404
LVGI	1.0283	1.0123	0.2052	0.0421	2.8812	0.1562	3.0375	19.9574
TATA	-0.0443	-0.0314	0.1585	0.0251	3.4812	-2.3663	1.1148	-358.2224
SGAI	1.0635	0.9695	0.8611	0.7416	18.1840	0.0459	18.2299	80.9702
X1	0.0785	0.1186	0.4638	0.2151	6.9442	-3.5631	3.3810	590.6961
X3	0.0318	0.0507	0.1660	0.0275	2.9116	-1.6357	1.2759	522.0024
X4	48.6493	0.7936	1520.1278	2310788.56	49377.05	-0.4217	49376.632	3124.6677
X5	0.6534	0.5606	0.4991	0.2491	3.8540	0.0035	3.8575	76.3871

Source: Research data (2025).

Table 5
Approximation quality according to condition attributes by random sample

Condition attributes	1	2	3	4	5	6	7	8	9	10
Opinion, Change, Big, Find, Modify	**0.121**	**0.089**	**0.084**	**0.103**	**0.070**	**0.075**	**0.107**	**0.107**	**0.084**	**0.103**
change, big, find, modify	0.121	0.047	0.056	0.061	0.042	0.000	0.075	0.065	0.047	0.061
opinion, big, find, modify	0.121	0.089	0.084	0.103	0.070	0.075	0.107	0.107	0.084	0.103
opinion, change, find, modify	0.117	0.075	0.084	0.103	0.028	0.075	0.103	0.103	0.070	0.103
opinion, change, big, modify	0.117	0.051	0.075	0.070	0.061	0.009	0.075	0.070	0.070	0.070
opinion, change, big, find	0.121	0.089	0.084	0.103	0.070	0.075	0.107	0.107	0.084	0.103
big, find, modify	0.121	:	:	:	:	:	:	:	:	:
change, big, find	0.121	:	:	:	:	:	:	:	:	:
opinion, big, find	0.121	0.089	0.084	0.103	0.070	0.075	0.107	0.107	0.084	0.103
opinion, change, find	:	:	0.084	0.103	:	0.075	:	:	:	0.103
find, modify	0.117	:	0.056	0.061	:	0.000	:	:	:	0.061
big, modify	0.117	:			:		:	:	:	
big, find	0.005	0.005	0.000	0.000	0.000	0.075	0.000	0.005	0.005	0.000
change, find	0.117	:	0.056	0.061	:	0.000	:	:	:	0.061
change, big	0.117	:	:	:	:		:	:	:	
opinion, change	:	:	0.070	0.070	:	0.000	:	:	:	0.070
opinion, find	**0.117**	**0.075**	**0.084**	**0.103**	**0.028**	**0.075**	**0.103**	**0.103**	:	**0.103**
opinion, big	**0.117**	**0.051**	**0.075**	**0.070**	**0.061**	**0.009**	**0.075**	**0.070**	**0.070**	**0.070**
opinion, modify	:	:	0.070	0.070	:	0.000	:	:	:	0.070

Source: Research data (2025).

Table 6 supplements Table 5 by displaying the core attributes of each of the ten samples. These samples represent the most relevant combinations for classifying the data, as they are the subset with the highest quality of approximation. Based on the ten random samples, the main Y-reductions of the variables in P = {opinion, change, big, find, modify} are {opinion, big} and {opinion, find}. Given this, the nucleus of P in five of the ten samples is composed of $Nucleus_{\emptyset}$ ({opinion, big, find}) = {opinion, big} $\cap$ {opinion, find} = {opinion}. Thus, the variable representing the types of auditors' opinions is the most significant attribute. Therefore, this attribute cannot be disregarded since its absence implies lower-quality approximations.

Of the ten established rules, seven are deterministic. However, only one is used to separate companies suspected of fraud. Clearly, these rules have fewer observations than the non-deterministic rules. However, it is possible to simplify the rules using the {opinion, big} or {opinion, find} sets, which yield a similar level of approximation. Therefore, to proceed with the logistic model, only the most prevalent variables in the nuclei were selected.

Table 6
Nucleus of the ten samples

Nucleus	Sample
big, find	1
opinion, big, find	2
opinion, find	3
opinion, find	4
opinion, big, find	5
opinion, find	6
opinion, big, find	7
opinion, big, find	8
opinion, big, find	9
opinion, find	10

Source: Research data (2025).

4.3 Identification of the probability of manipulation of results

In this research, Altman et al. (1979) Z-score was calculated and applied to predict the likelihood of financial problems in organizations. Altman et al. (1979) developed a bankruptcy prediction model suitable for Brazil's organizational landscape. Using the financial

Table 7
Calculation of the possibility of insolvency identification in organizations (Altman et al., 1979)

X_1	(*Current Assets* $_{it}$ - *Current Liabilities* $_{it}$)	X_4	*Market Value* $_{It}$
	Total Assets $_{it}$		*Total Liabilities* $_{it}$
X_3	*Profit Before Interest and Tax* $_{it}$	X_5	*Sales* $_{it}$
	Total Assets $_{it}$		*Total Assets* $_{it}$

Legend: X_1 is working capital, weighted by total assets; X_3 is return on assets (*ROE*); X_4 is the market value to total liabilities ratio; and X_5 is asset turnover.
Source: Prepared by the authors based on Altman et al. (1979).

characteristics of organizations, the authors developed an equation that can indicate insolvency in organizations and predict financial reports suspected of fraud. The metrics used to calculate the four regressor variables are shown in Table 7.

To conduct this study, we first estimated the Altman et al. (1979) model, considering the 211 companies in the sample between 2017 and 2021. The calculation metric proposed by Altman et al. (1979) is shown in Equation 2[1]. To identify the probability of insolvency P (Zi = 1), z_i refers to companies in judicial reorganization.

$$P_i = P\left(Z_i = 1\right) = \frac{1}{1+e^{-\left(-X - X_{1t} + X_{3t} + X_{4t} + X_{51}\right)}} \quad (2)$$

Next, as applied by Martins and Ventura Jr. (2020), the Beneish (1999) model was used to measure the likelihood of fraudulent financial reporting. This model distinguishes companies that manipulate or are predisposed to manipulating results (Beneish, 1999; Beneish et al., 2013). The M-score was calculated using the Beneish (1999) model, as shown in Table 8.

Similar to the model proposed by Altman et al. (1979), the Beneish (1999) model aimed to estimate coefficients for a specific sample of organizations experiencing continuity issues. Thus, Beneish's model also applied a logistic regression to the 211 companies in the sample that published their financial reports between 2017 and 2021. It should be noted that, with this technique, the number of clusters is chosen; in this case, five clusters

Table 8
Variables used in the Beneish (1999) model

AQI	1 - ((*Current Assets* $_{it}$ + *Fixed Assets* $_{(it)}$)/*Total Assets* $_{it}$)	*DSRI*	*Accounts Receivable* $_{it}$/ *Revenues* $_{it}$
	1 - ((*Current* Assets $_{it-1}$ + *Fixed Assets* $_{(it-1)}$)/*Total Assets* $_{it-1}$)		*Accounts Receivable* $_{it-1}$/ *Revenues* $_{it-1}$
DEPI	*Depreciation* $_{it}$/ (*Depreciation* $_{it}$ + *Fixed Assets* $_{it}$)	*GMI*	*Gross Margin* $_{it}$
	Depreciation $_{it-1}$/ (*Depreciation* $_{it-1}$ + *Fixed assets* $_{it-1}$)		*Gross Margin* $_{it-1}$
SGAI	*Selling and Administrative Expenses* $_{it}$/ *Revenues* $_{it}$	*SGI*	*Revenue* $_{it}$
	Selling and Administrative Expenses $_{it-1}$/ *Revenues* $_{it-1}$		*Revenue* $_{it-1}$
TATA	(*Net Income* $_{it}$ - *Cash from Operations* $_{it}$)/ *Total Assets* $_{it}$	*LGVI*	*Total liabilities* $_{it}$/ *Total assets* $_{it}$
	(*Net Income* $_{it-1}$ - *Cash from Operations* $_{it-1}$)/ *Total* Assets $_{t-1}$		*Total liabilities* $_{it-1}$/ *Total assets* $_{it-1}$

Legend: DSRI > 1 indicates possible inflation of company revenues to improve results; GMI > 1 indicates a deterioration in gross margin; AQI > 1 indicates a tendency to capitalize and defer expenses that should have been recognized on the income statement; SGI > 1 indicates that growing companies are more likely to manipulate results under pressure to achieve earnings targets; DEPI > 1 indicates that assets may be depreciated at a lower rate to increase earnings; SGAI > 1 indicates possible manipulation of results to defer expenses; LVGI > 1 indicates an increase in leverage and possible manipulation of results due to default; TATA > 1 indicates possible manipulation of results due to accruals.
Source: Beneish (1999) and Beneish et al. (2013).

were chosen. As expected, the FLFR information was grouped into a single cluster, as shown in Table 9. Figure 1 shows the clusters used to detect similarities with fraudulent reports.

As shown in Figure 1, the results of the Altman et al. (1979) and Beneish (1999) models were

Table 9
Results of the k-means cluster analysis

Column	1	2	3	4	5
Altman et al. (1979)	0.86307	0.18719	0.22989	0.52049	0.04608
Beneish (1999)	0.80272	0.14408	0.50664	0.1626	0.05729
Observations by cluster	**4.00**	**72.00**	**6.00**	**25.00**	**948.00**

Source: Research data (2025).

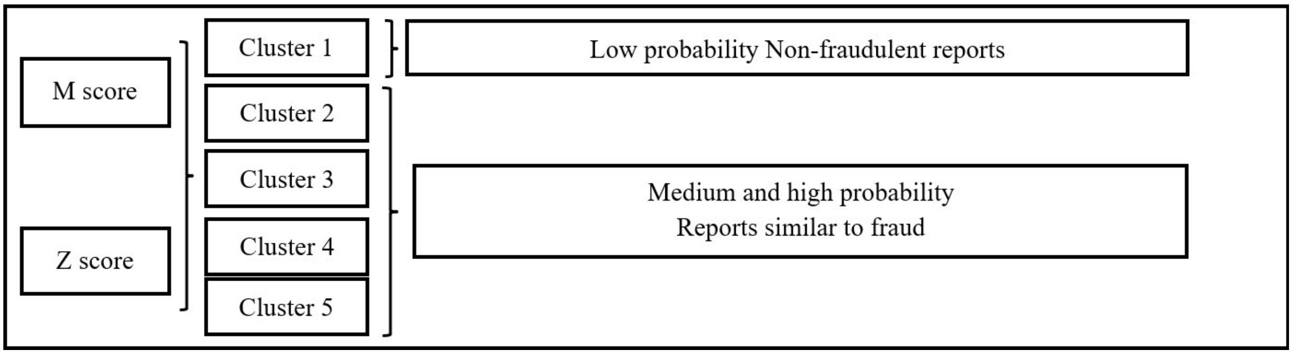

Figure 1. Procedure used to detect similarities with fraudulent reports
Source: Prepared by the authors (2025)

segmented using the K-means clustering technique. This technique groups observations into subsets (clusters), so companies in the same cluster are more similar to each other than to companies in other clusters, considering the analyzed indicators. For this study, five clusters (k = 5) were defined. This number was chosen based on theoretical criteria and analysis of intra-group variability. This number of clusters enabled adequate separation between companies with a higher or lower probability of FLFR occurrence.

The K-means clustering process stems from the following mathematical problem: Given sets *S1, S2, ..., Sk* containing *n* observations in clusters, note that each observation must belong to one and only one of the clusters. The goal is to partition the observations into k clusters so that the total variation within each cluster, summed across all k clusters, is minimized. In this sense, Δ is the distance between elements within a cluster (Equation 3).

$$Minimize_{(S1.......Sk)} \left\{ \sum_{k=1}^{k} \Delta(S_k) \right\} \quad (3)$$

The elements can be segmented into k clusters so that the total variation within the clusters, $\Delta\ (S_k)$, added across all clusters, $\sum_{k=1}^{k} \Delta(S_k)$, is minimized. After applying the k-means clustering model, five groups can be identified that determine the likelihood of fraudulent financial reports. The clustering process using the k-means algorithm involved the following steps. First, five centroids (average values) representing the clusters were randomly defined. Then, each company was allocated to the cluster whose centroid was closest based on the Euclidean distance between the Altman and Beneish score values.

The centroids were recalculated iteratively until the allocations stabilized, which minimized the sum of the squared distances within each cluster. The following clusters were identified at the end of the process:

Clusters 1 to 4: Companies with different levels of probability of FLFR occurrence. The centroids indicate high to moderate risk.

Cluster 5: Companies with a low probability of FLFR occurrence. This cluster serves as a reference group.

Table 9 describes the results of the cluster analysis

As shown in Table 9, cluster 1 had the highest probability of fraudulent information, with values exceeding 80%. Clusters 2, 3, and 4 had more moderate probabilities. Cluster 5 contains the largest number of observations with a low probability of fraudulent financial reporting. Therefore, we chose to use information from clusters 1 to 4 because their probabilities are higher than that of cluster 5's centroid. Thus, clusters 1 to 4 represent the observations with the highest probability of containing suspicious fraudulent information.

4.4 Results of the research hypotheses

Table 10 shows the results of the logistic regression related to the four hypotheses of this study, controlling for sector and year. The data show that the coefficient of determination (Nagelkerke's R^2) was 30.50%, indicating a good relative fit of the regression in the analyzed context. The choice of this metric is due to the adjustment of the Cox and Snell R^2 scale, which leaves the scale between 0 and 1 (Nagelkerke, 1991), facilitating the interpretation of the proportion explained by the model. Additionally, the VIF statistic determines if there are exact or nearly exact linear relationships between the variables. In this study, the obtained values were within the range of 1.728 (Hair et al., 2009). These results show that there is no evidence of multicollinearity, which reinforces the validity of the independent variable analysis.

Regarding H_1, the results suggest a significant relationship between the independent variable, "Big Four," and the dependent variable, "possibility of FLFRs occurring." This finding supports the hypothesis that Big Four audit firms reduce the likelihood of FLFRs by 81.8% (1 - 0.182). Thus, the research results underscore the Big Four's role as mitigators of information asymmetry, contributing to more transparent financial reporting. This effect can be attributed to these auditors' high level of expertise in areas such as regulatory compliance and corporate governance, which is favored by their global operations and extensive market experience.

These findings are supported by previous literature. For example, Khaksar et al. (2022) investigated the Iranian organizational context and analyzed the relationship between audit firm size and fraud detection. They found that the Big Four significantly reduce the likelihood of fraudulent financial reports. Similarly, Gontara et al. (2023) found a positive, significant relationship between Big Four audits and the quality of French companies' financial reports.

According to Gontara et al. (2023), the Big Four play a significant role in producing transparent reports that mitigate information asymmetry and increase trust in the corporate environment. Thus, the results of this study align with previous empirical studies, supporting

Table 10
Regression results for the research hypotheses

Independent Variables	Coefficient	Wald	EXP (B)	VIF	95% C.I. for EXP (B)	
					Lower	Upper
MODIFY WOT	**4.131*** **	**4,152**	**62,222**	**1,034**	**12,386**	**312,591**
MODIFY QOT	**1.288*** **	**5,826**	**3,625**	**1,042**	**1,481**	**8,872**
BIG	**-1.703*** **	**49,216**	**0,182**	**1,728**	**0,102**	**0,324**
FIND	-0.502	7,792	0,605	1,748	0,332	1,103
CHANGE	-0.565	15,991	0,179	1,812	0,323	1,189
2018	-0.063	16,985	0,939	1,593	0,487	1,809
2019	-0.299	16,985	0,741	1,588	0,373	1,471
2020	-0.378	16,985	0,685	1,584	0,343	1,369
2021	-1.148	16,985	0,317	1,579	0,139	1
Educational Services	0.258	4,509	2,810	1,089	0,443	3,782
Basic Materials	0.568	11,834	1,295	1,382	0,7	4,456
Essential Products	0.177	17169	1,766	1,413	0,415	3,429
Non-essential products	0.957	12,359	1,193	1,153	0,603	11,237
Energy	-17.746	6,005	2,603	1,179	0	0
Medical Assistance	0.967	7,596	0,000	1,512	1,017	6,805
Industry	1.556	15,546	2,631	1,359	1,742	12,903
Real Estate	0.545	11,022	4,741	1,140	0,443	6,715
Technology	-1.461	7,226	0,389	1,538	0	0
Model sig.			0.000			
Negelkerke's R^2			0.305			
Observations			1.055			

Legend: VIF: Variance Inflation Factor; Sig.: Significance.
Notes: Significance levels: *** p<0.01.
Source: Research data (2025).

the thesis that audits conducted by Big Four companies positively impact the reliability of financial reports. The second research hypothesis (H_2) proposed that changing the audit firm would increase the likelihood of identifying FLFRs. However, the results of the empirical analysis did not support this hypothesis, suggesting that replacing the audit firm alone is insufficient to increase the likelihood of identifying FLFRs.

This result contradicts some existing literature. Karami et al. (2017) argue that changing auditors could favor the detection of financial irregularities since newly hired firms tend to use different methods in their verification processes. Additionally, Mukhlasin (2018) and Khaksar et al. (2022) argue that changing audit firms introduces professionals with different profiles and skills. This broadens the analytical perspectives and procedures applied and potentially increases the chance of identifying financial asymmetries.

Despite the theoretical evidence, the data from this study indicate that replacing the auditing firm alone is not an effective way to improve FLFR detection. It is important to note that factors such as accumulated experience, technical knowledge, and familiarity with the audited company's sector play a decisive role in the quality of the audit work. According to DeFond et al. (2002), auditors' performance is directly associated with their ability to understand the specificities and nuances of analyzed information, as well as identify distortions or asymmetries.

Given this, the results suggest that changing the auditing firm alone may have limited impact on detecting financial reports suspected of fraud. For this process to be effective, the new firm must have in-depth knowledge of the audited company's sector and a qualified technical team experienced in identifying financial discrepancies. This reinforces the idea that, while organizational changes in the choice of auditor may be appropriate in certain contexts, the new firm's technical preparation and familiarity with the environment in which it will operate largely determine the effectiveness of these changes.

Regarding the third research hypothesis (H_3), it was assumed that an independent audit firm would be more likely to detect FLFRs. However, the obtained results did not confirm this expectation. The Find variable coefficient was -0.502, and the estimated odds ratio was 0.605. These results indicate that audit independence does not significantly contribute to identifying financial reports suspected of fraud. Thus, H_3 was rejected. These results contrast with the findings of other studies. For example, Khaksar et al. (2022) identified a positive and significant relationship between audit firm independence and the ability to detect fraudulent financial reports. The authors argue that independence fosters greater objectivity and impartiality in analyzing financial information, facilitating the detection of inconsistencies and fraudulent practices.

However, in the Brazilian organizational context, the results of this study suggest that audit independence, although an essential requirement for reliable work, alone is insufficient to significantly increase the likelihood of detecting FLFRs. Contextual factors, such as regulatory complexity, high information asymmetry, and the quality of the audited companies' internal controls, can hinder this process. Additionally, factors such as the auditors' experience, technical proficiency, and familiarity with the economic sector in which they operate play a decisive role in the effectiveness of the analysis and identification of financial distortions.

Regarding the fourth research hypothesis (H_4), the results showed a positive correlation between issuing qualified and non-qualified opinions and detecting fraudulent financial reports, thus confirming the hypothesis. These findings align with the specialized literature, as noted by Khaksar et al. (2022) and DeFond et al. (2002). These scholars point out that these types of opinions typically indicate relevant distortions or inconsistencies in the information organizations present.

A qualified opinion indicates that the auditor believes the financial statements generally comply with applicable accounting principles (Reichelt & Wang, 2010; Camargo & Flach, 2016). However, it highlights one or more specific aspects that, while relevant, do not entirely compromise the reliability of the financial reports (Habib & Bhuiyan, 2011). Conversely, an opinion with an abstention is issued when the auditor cannot gather sufficient evidence to form a conclusive opinion on the financial statements. This is usually due to the absence or limitation of essential information, which makes it impossible to adequately assess the organization's financial situation (Reichelt & Wang, 2010; Habib & Bhuiyan, 2011; Camargo & Flach, 2016).

According to DeFond et al. (2002), issuing a "no opinion" indicates a high level of information asymmetry, suggesting that the auditor encountered significant barriers when attempting to access the necessary data to perform their work. In such contexts, an inability to issue an opinion suggests that the information provided by the company may be incomplete, inconsistent, or conceal substantial irregularities.

Table 11
Result of hypothesis testing

Hypotheses	Relationship Found	Conclusion
H_1. Being audited by the Big Four decreases the likelihood of suspicious financial reports.	Negative and significant	H_1 Not rejected
H_2. Changing audit firms increases the likelihood of detecting suspicious financial reports.	Positive and not significant	H_2 Rejected
H_3. The independence of the audit firm increases the likelihood of detecting suspicious financial reports.	Negative and not significant	H_3 Rejected
H_4. The type of opinion (qualified, adverse, or abstention) increases the likelihood of suspicious financial reporting.	Positive and significant	H_4 Not rejected

Source: Prepared by the authors (2025).

Table 11 presents the result of hypothesis testing. The results of this research reinforce this understanding by showing that audit reports containing qualified opinions or abstentions are more frequently associated with a higher probability of FLFRs in the Brazilian organizational context. These reports increase the chances of FLFRs by 6,100.222% (62.222%-1) and 200.625% (3.625%-1), respectively. These types of opinions reflect the auditor's difficulty in fully validating the company's financial information. They suggest potential mismanagement, flaws in internal controls, or attempts to conceal fraud.

Thus, this study shows that the impact of audit firms' independence in detecting suspected fraudulent financial reports is limited in the Brazilian scenario. Furthermore, the study's findings emphasize the importance of monitoring audit reports, particularly those with caveats or disclaimers. These types of opinions can alert stakeholders and regulators to potential financial or organizational vulnerabilities and are essential for identifying fraudulent financial reports.

5 Conclusion

This study examined how audit characteristics influence the detection of fraudulent financial reports in Brazil using the combined application of the Altman et al. (1979) and Beneish (1999) models with rough set theory (RST) and logistic regression. The results significantly contribute to auditing and financial fraud literature by showing that audits performed by Big Four firms reduce the likelihood of FLFRs, and that the qualified opinion and abstention from opinion types are strong predictors of financial report inconsistencies.

This study contributes to academic knowledge by examining the relationship between audit characteristics and FLFRs in an emerging country, a topic that has not been widely explored in the international literature. For the first time in Brazil, it integrates the models of Altman et al. (1979) and Beneish (1999) with rough set theory, offering a robust methodological approach to predicting financial fraud. The study also corroborates and extends existing international research, including that of Khaksar et al. (2022) and Gontara et al. (2023), to the Brazilian regulatory and economic environment.

From a corporate governance standpoint, the practical implications are that auditors should pay attention to the issuance of modified opinions (caveats and disclaimers), as these are strong indications of potential irregularities. This reinforces the need for rigorous auditing procedures in situations involving limited scope and inconsistent information. Additionally, regulatory institutions can use these types of opinions as metrics to intensify inspections of companies that receive modified audit reports. Finally, companies and stakeholders should consider hiring Big Four firms to mitigate informational asymmetry and establish internal governance and compliance mechanisms that reduce the likelihood of receiving a modified opinion, thereby preserving their reputation and market stability.

This study has several limitations. First, the sample focused on non-financial, publicly traded companies in Brazil, which limits the generalizability of the results to other sectors or countries. Also, relying exclusively on financial metrics from the Altman et al. (1979) and Beneish (1999) models may prevent the identification of qualitative factors associated with financial fraud. Additionally, the results are limited to the period from 2017 to 2021 and may not reflect subsequent regulatory changes or auditing practices.

With this in mind, future research should test the proposed model in specific sectors, such as financial institutions and privately held companies, given their relevance in the economic context. Additionally, the timeframe should extend beyond the period of the COVID-19 pandemic to verify potential changes in auditing firms' behavior and the quality of financial reports. Another suggestion is to explore including qualitative variables such as corporate governance structure, compliance mechanisms, and audit committee performance. Finally, the effectiveness of other data mining and artificial intelligence methods in detecting fraudulent reports in environments with high information asymmetry should be investigated.

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Notes

[1]Equations 1 and 2 have the same logistic regression structure but are applied in different contexts. Equation 1 is the primary model for FLFR detection, and Equation 2 is used to construct the Z-score, similar to the M-score. These scores serve as the basis for cluster formation and are later used as dependent variables in the main model.

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SUPPLEMENTARY MATERIAL

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The authors declare that artificial intelligence (AI) platforms were utilized in various stages of this research to enhance accuracy, efficiency, and overall quality. The specific contributions of AI to this work include **(X) Enhancing Readability and Proofreading – Grammarly.**
The author(s) declare that after using this tool/service, the author(s) reviewed and edited the content as needed and take (s) full responsibility for the content of the publication.

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