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A REVIEW OF THE RESEARCH ON DATA MINING TECHNIQUES IN THE DETECTION OF FRAUD IN FINANCIAL STATEMENTS

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ABSTRACT

Financial statement fraud is a type of fraud that contributes to the biggest losses for businesses. In today's business environment it has become possible to detect financial statement fraud by using data mining methods, which has in turn led to more research in the past 15 years. The first step in the successful implementation of a system for detecting financial statement fraud using data mining methods is defining financial ratios that can be powerful indicators in the detection of financial statement fraud. Of 110 financial and non-financial ratios analysed in the previously published research, eight (8) can be identified as being the most significant for forming a model for the detection of fraud in financial statements using data mining methods.

Key words: *financial statement frau; detection of fraud in financial statement; financial ratios*

1. INTRODUCTION

Financial statement fraud implies "*the deliberate misrepresentation of the financial condition of an enterprise accomplished through the intentional misstatement or omission of amounts or disclosure in the financial statements to deceive financial statement users*" (as defined by the *Association of Certified Fraud Examiners*, ACFE).

Of the three primary categories of fraud classified by the *Association of Certified Fraud Examiners* (corruption, asset misappropriation, and financial statement fraud), financial statement fraud caused the greatest losses for businesses. [1, p. 11]. Its influence on a vast number of stakeholders is inevitable, since, in only one year, it caused a median loss of $975,000, took approximately 24 months to uncover and represented 9.5% of the fraud cases analysed [1]. In the long run financial statement fraud can also directly and significantly influence the economy.

In today's environment, in which great amounts of information and data are accessible, it has become possible to develop data mining methods. *Data mining is the process of investigating and analysing large amounts of data with the aid of automatic or semi-automatic methods with the goal of uncovering meaningful patterns.* [2].

This is a relatively new field of computer science which combines statistics, artificial intelligence and data management methods. Although in practice data mining is commonly applied in banking (e.g. credit rating assessment), sales (e.g. cross-selling techniques), and medicine (e.g. early detection of diseases), it can also be used for the detection of different kinds of fraud in business. Transparency and public access to financial statements are the necessary preconditions for the use of data mining methods for automatically detecting businesses for which there are indications of financial statement fraud. For this kind of detection it is essential to be familiar with the characteristics (models) of fraud and to define indicators which suggest that they exist. After defining indicators which suggest financial statement fraud exists it is possible to connect these with data mining methods that, in the end, result in the creation of a model that will detect potential financial statement fraud.

There are two main critiques of the research that has been carried out to date related to the detection of fraud by data mining methods; firstly, a shortage of publically available data that would be the basis for carrying out research and secondly, a lack of methods and techniques that have been well-researched and published [3].

This paper reviews the key studies in the field of financial statement fraud detection using data mining methods carried out in the past 15 years. The aim of this paper, on the basis of the results of previous studies, is to confirm the hypothesis that financial analysis ratios are powerful indicators in the detection of financial statement fraud. Furthermore, the analysis proves that certain ratios are particularly significant in the detection of financial statement fraud.

2. ANALYSIS OF PREVIOUS STUDIES

During the past 15 years a great number of papers have been published in the field of financial statement fraud detection using data mining methods. The following published studies were analysed in this paper:

Table 1 – A summary of previous research on the use of data mining methods in the detection of financial statement fraud (according to year of publication)

Reference:	Study:
[4]	Persons, O. S. (1995). Using financial statement data to identify factors associated with fraudulent financial reporting. *Journal of Applied Business Research (JABR), 11*(3), 38-46.
[5]	Beasley, M. S. (October 1996). An empirical analysis of the relation between the board of director composition and financial management fraud. *Accounting Review, 71*(4), 443-465.
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[15]	Skousen, C. J., Smith, K. R., & Wright, C. J. (2009). Detecting and predicting financial statement fraud: The effectiveness of the fraud triangle and SAS No. 99. *Corporate Governance and Firm Performance (Advances in Financial Economics), 13*, 53-81
[16]	Chen, W.-S., & Du, Y.-K. (August 2009). Using neural networks and data mining techniques for the financial distress prediction model. *Expert Systems with Applications, 36*(2), 4075-4086.
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[18]	Ravisankar, P., Ravi, V., Rao, G., & Bose, I. (2011). Detection of financial statement fraud and feature selection using data mining techniques. *Decision Support Systems, 50*(2), 491-500.

Reference:	Study:
[19]	Dechow, P. M., Ge, W., Larson, C. R., & Sloan, R. G. (March 2011). Predicting Material Accounting Misstatements. *Contemporary accounting research, 28*(1), 17-82.
[20]	Sen, I., & Terzi, S. (2012). Detecting falsified financial statements using data mining: empirical research on finance sector in Turkey. *Maliye Finans Yazilari, 1*(96), 76-94.
[21]	Ujal, M., Amit, P., Hiral, P., & Rajen, P. (2012). Detection of Fraudulent Financial Statement in India: An Exploratory Study. *GFJMR, 4*, 1-19.
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The process of data mining itself goes through separate phases, defined by the methodology, which, in the end, result in the detection of new information. Although there are a number of methodologies, the most common is CRISP_DM (*Cross-Industry Process for Data Mining*), which encompasses the following phases:

i) understanding the problem and the data, which consists of defining the outcome of the project (business understanding) and becoming familiar with the available data with the goal of detecting useful data that are essential for forming a hypothesis (data understanding);

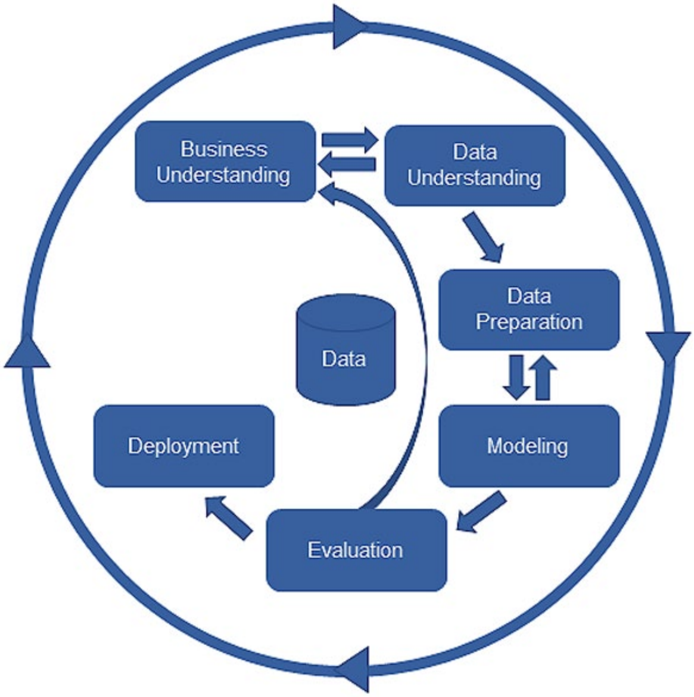
ii) data preparation, which implies building a final version of a useful database from the initial database. This in turn implies the transformation and cleaning-up of data, in addition to selecting tables, fields and attributes;

iii) modelling, which implies selecting techniques, since a number of data mining techniques may be appropriate for the same type of problem;

iv) evaluation, which implies a review of the executive steps for the creation of the model, in order to ensure that the model properly achieves the business objectives;

v) deployment, which implies organising and presenting the obtained knowledge in order for it to be implemented by the user.

Figure 1 – CRISP – DM Data mining methodology



Source: [26]

While carrying out data mining, according to previous research and an analysis of the CRISP-DM model, it is essential to do the following:

i) define good quality input that can indicate fraud, during the data preparation phase. This implies defining red flags and their influence on the detection of fraudulent financial statements. Red flags, as a rule, pertain to the selection of key financial analysis indicators and individual positions on the balance sheet and profit and loss (income) statement that are more exposed to fraud ([4], [9], [10], [11], [12], [14], [18], [20], [21], [22], [25]). In a minority of the studies, red flags pertained to specific non-financial ratios ([5], [6], [7], [8], [13], [15], [16], [17], [19];

ii) select a data mining method in the modelling phase for the purpose of detecting financial statement fraud.

The reason for including non-financial data in this type of research is based on research carried out by Dong et al. [27], who stress that conventional audit practice unsuccessfully detects financial statement fraud primarily because the existing audit procedures and academic research are focused on statistical analyses of structured financial ratios and on data related to market activity. On the other hand, some research suggests that non-financial ratios are not significant in the formation of data mining models [24].

In addition to financial and non-financial ratios, the existing research also focuses on large quantities of textual information about individual companies that are publically available [28]. This focus on mining not only financial ratios but also the textual format of financial statements makes the model more complex and in the end can result in less successful detection of financial statement fraud. Consequently, this paper focuses solely on the financial ratios that can help detect financial statement fraud.

As a rule, previous research (14) is based on the analysis of a large number of financial analysis indicators that the literature suggests could be significant in detecting financial statement fraud. As a second step, these studies, using various tests for the assessment of statistical significance (Kruskal-Wallis test, t-test, ANOVA test, Mann-Whitney U test), define financial analysis indicators that have a significant influence on the detection of financial statement fraud in relation to those which do not.

Furthermore, the analysed indicators have been segmented into seven (7) groups, as follows:

i. activity ratios;
ii. liquidity ratios;
iii. profitability ratios;
iv. solvency ratios;
v. assets structure ratios;
vi. cash flow ratios; and
vii. other ratios.

Table 2 – A summary of important and unimportant activity ratios with respect to financial statement fraud detection

Ratios:	Important	Unimportant	TOTAL
Activity ratios	34	29	63
Did profit before taxation increase by more than 10%?	1		1
Did accounts receivables increase by more than 10%?	1		1
Long-term assets turnover (t)	1	1	2
Capital and reserves turnover (t)	1		1
Receivables turnover (t)	1	1	2
Total assets turnover (t)	5	7	12
Inventory turnover (t)		1	1

Ratios:	Important	Unimportant	TOTAL
Accounts receivables current year (t) to accounts receivables previous year (t-1) ratio	3		3
EBIT (t) to total assets (t) ratio	2	1	3
COGS (t) to inventory (t) ratio	2		2
Accounts receivables (t) to sales (t) ratio	5	5	10
Change of accounts receivables to sales (t)	1		1
Change of accounts receivables to total assets (t)	1		1
Inventory (t) to sales (t) ratio	2	5	7
Increase of sales	2	1	3
Increase of assets	2		2
Sales (t)	1	1	2
Sales minus margin (t)		1	1
Change of the accounts receivables to sales ratio over 2 consecutive years		1	1
Change of the inventory to sales ratio over 2 consecutive years		1	1
Average change in total assets over a period of 2 years		1	1
Average accounts receivable payment days (t)	2		2
Average accounts payables payment days (t)		1	1
Difference in the change of sales compared to industry average		1	1
Operating profit (t) to total assets (t) ratio	1		1

Source: Author

Activity ratios measure the ability of a company to convert various forms of assets into sales and/or cash, and they are focused on the ability of management to use their assets to generate sales and cash assets. The elements of financial statements, among those used to calculate activity ratios, that can be manipulated to carry out financial statement fraud are sales, accounts receivables and inventory. The basic presumption is that, when recording fictitious sales, the sales and accounts receivables positions will increase, while the inventory value may or may not be a product of manipulation. In the case of the sale of products, it is to be expected that only the values of accounts receivables and sales will increase, while the inventory value most likely will not be a product of manipulation but rather the true value of inventory will be reported.

Confirmation of such a conclusion can be seen in the fact that in five (5) of the studies ([9], [15], [14], [18], [21]) the inventory to sales ratio is considered to be a key indicator in the detection of financial statement fraud.

Another key indicator, which has been confirmed in seven (7) earlier studies ([10], [12], [15], [4], [18], [22], [23]), relates to the sales to total asset ratio. In order to increase sales it is necessary to invest in both short and long term assets. An increase in sales without a coinciding increase in assets is only possible over a shorter period of time, which is why some of the studies suggest that the sales to long-term assets ratio is an essential indicator to observe ([16], [18]). Since income from fictitious sales cannot be collected in such cases, accounts receivables, as a rule, are higher than normal. Accordingly, an increase in the average accounts receivable payment days is to be expected, which is suggested by one of the studies [11].

In relation to revenue recognition, there is a parallel increase in sales and accounts receivables; consequently, in situations of financial statement fraud, ratios related to accounts receivables positions from earlier statements have been found to be significant indicators of fraud. The accounts receivables to sales ratio and the receivables turnover in particular were found to be significant, as has been suggested by seven (7) of the previous studies ([10], [11], [22], [8], [15], [23], [25]).

Table 3 - A summary of important and unimportant liquidity ratios in detecting financial statement fraud

Ratios:	Important	Unimportant	TOTAL
Liquidity ratios	10	14	24
Current ratio (t)	5	2	7
Cash ratio (t)		1	1
Quick ratio (t)	1	2	3
Net working capital (t)		1	1
Net working capital to total assets (t) ratio	2	7	9
Inventory (t) to short term liabilities (t) ratio	1	1	2
Net working capital leverage (t)	1		1

Source: Author

Liquidity ratios relate to the ability of a business to meet its financial obligations when they become due, and therefore these ratios are calculated on the basis of particular current assets elements (inventory, accounts receivables, current financial assets, cash and cash equivalents), and current liabilities. Among the particular liquidity ratio positions observed, financial statement fraud directly influences the following:

- inventory value: there is an increased inventory value in situations where there hasn't been a corresponding value adjustment of, for example, long-term inventory;
- accounts receivables: there is an increased value in accounts receivables in situations where there hasn't been a value adjustment for bad debts

(e.g. in cases where clients file for bankruptcy or initiate pre-bankruptcy proceedings), or in cases of fictitious sales;

- current liabilities: there is a decrease in the value of current liabilities in situations where not all expenses have been recorded in the appropriate reporting period.

The liquidity ratio which most strongly detected fraud in seven (7) of the previous studies ([10], [9], [12], [11], [22], [23], [25]) was the net working capital to total assets ratio[1].

Table 4 - A summary of important and unimportant solvency ratios in detecting financial statement fraud

Ratios:	Important	Unimportant	TOTAL
Solvency ratios	29	19	48
Logarithm of total debt (t)	3		3
Debt to equity (t) ratio	7	3	10
Total debt to total assets (t) ratio	2	11	13
Total assets (t) to total capital and reserves (t) ratio	3		3
EBIT to total interest costs (t) ratio		2	2
Capital and reserves to total debt (t) ratio	2	1	3
Retained earnings (t) to total assets (t) ratio	2	1	3
Long-term debt (t) to total capital and reserves (t) ratio	1	1	2
Long-term debt (t) to total debt (t) ratio	1		1
Long-term debt (t) to total assets (t) ratio	5		5
Short-term debt (t) to total assets (t) ratio	1		1
Total debt (t)	2		2

Source: Author

Solvency ratios measure the degree of indebtedness of a business, that is, they measure how much the business finances itself through its own sources (capital and reserves) and how much from external sources (current and long-term liabilities). A higher degree of external financing may increase the probability of financial statement fraud, since the risk is transferred from the owner of the capital onto the creditors [9]. In eleven (11) of the studies ([9], [12], [11], [4], [22], [14], [15], [23], [21], [25], [24]), the total debt to total assets ratio was suggested as the key indicator to detect fraudulent financial statements.

1 Working capital is calculated as total short term assets minus total short-term debt.

Table 5 - A summary of important and unimportant asset structure ratios in detecting financial statement fraud

Ratios:	Important	Unimportant	TOTAL
Assets structure ratios	28	18	46
Logarithm of total assets (t)	3	2	5
Cash and cash equivalents (t)	1	1	2
Cash and cash equivalents (t) to short-term assets (t) ratio	2	1	3
Long-term assets (t) to total assets (t) ratio	1	1	2
Net long-term assets (t) to total assets (t) ratio		1	1
Accounts receivables (t)	2		2
Long-term material assets (t) to total assets (t) ratio	2		2
Short-term assets (t) to total assets (t) ratio	1	5	6
Accounts receivables (t) to total assets (t) ratio	4	1	5
Accounts receivables (t) to total assets of previous year (t-1) ratio		1	1
Cash and cash equivalents (t) to total assets (t) ratio	5		5
Inventory (t) to total assets (t) turnover	5	4	9
Total assets (t)	2		2
Change in short-term assets minus the change in cash and cash equivalents, change in short-term debt, depreciation, deferred assets, plus retained earnings compared to total assets (t)		1	1

Source: Author

Asset structure ratios compare particular asset elements to total assets. As with liquidity ratios, the basic presumption is that in cases of financial statement fraud particular positions of current assets are overvalued. The short term assets to total assets ratio was identified in five (5) of the previous studies ([4], [18], [22], [23], [24]) as the key indicator in the detection of financial statement fraud, while the inventory to total assets ratio was identified in four (4) of the previous studies ([22], [18], [14], [23]).

Table 6 - A summary of important and unimportant profitability ratios in detecting financial statement fraud

Ratios:	Important	Unimportant	TOTAL
Profitability ratios	23	29	52
Profit before taxation (t)	1	1	2
Profit before taxation (t) to operating profit (t) ratio	1		1
Gross margin ratio (t) = (sales – COGS)/sales)		1	1
EBIT (t)		1	1

Ratios:	Important	Unimportant	TOTAL
Profit after taxation (t)	1	1	2
Net profit margin (t)	4	5	9
Current year profit after taxation (t) to previous year profit after taxation (t-1) ratio	1		1
Profit before taxation (t) to EBIT (t) ratio	1		1
Profit before taxation (t) to sales (t) ratio	3	1	4
Profit before taxation (t) to total assets (t) ratio	3	4	7
Current year profit before taxation (t) to previous year profit before taxation (t-1) ratio	1		1
Profit after taxation (t) to profit before taxation (t) ratio	2		2
Profit after taxation (t) to long-term assets (t) ratio	2	1	3
Profit tax (t) to sales (t) ratio	1		1
Operating costs (t) to sales (t) ratio		1	1
Return on long-term debt and capital and reserves		1	1
Interest costs (t) to operating costs (t) ratio		1	1
ROA (t)	2	8	10
ROCE (t)		1	1
Increase of operating profit		1	1
Operating profit (t) to sales (t) ratio		1	1

Source: Author

Profitability ratios compare profit (before or after taxation) with particular positions on the balance sheet or profit and loss account. Since the aim of financial statement fraud is to achieve a positive result (i.e. show a profit), which, without manipulation, would probably have been negative (i.e. shown a loss), the previous research suggests that this group of ratios is very important in the detection of fraud. In the studies that were analysed, no less than twenty-one (21) different ratios were identified as significant in detecting fraud. In eight (8) of the studies ([10], [12], [9], [18], [14], [15], [21], [25]) the key indicator in this group was shown to be ROA (return on assets)[2,3], while net profit margin was identified as another key indicator in five (5) of the studies ([10], [14], [18], [22], [23]).

2 Return on assets = net profit for the current period/total assets

3 In addition to net return on assets, which compares net profit for the current reporting period with total assets, the studies that were analysed suggest that gross return on assets (which compares profit before tax in a particular reporting period with total assets) is also a significant indicator in the detection of financial fraud. Since the difference between these two ratios is only in relation to the current profit tax, studies which suggest either of these two as important indicators were encompassed here.

Table 7 - A summary of important and unimportant cash flow ratios in detecting financial statement fraud

Ratios:	Important	Unimportant	TOTAL
Cash flow ratios	3	4	7
Operating cash flow (t) minus net cash flow (t), profit distribution (t) and capital expenditures (t)		1	1
Operating cash flow (t-1)	1		1
Operating cash flow (t)	1		1
Operating cash flow (t) to short-term debt (t)		1	1
Increase of operating cash flow	1		1
Operating profit minus operating cash flow (t) to total assets ratio		1	1
Operating profit minus WACC for previous 3 years to short-term assets (t-1)		1	1

Source: Author

Cash flow ratios compare cash flow, primarily operating cash flow, with particular positions on the balance sheet. Since cash flow ratios were included in only three of the fourteen (14) studies analysed and were considered significant in the detection of financial statement fraud in only two, it can be concluded that these ratios haven't been shown to be that significant in the detection of financial statement fraud.

Table 8 - A summary of other important and unimportant ratios in the detection of financial statement fraud

Ratios	Unimportant	Important	TOTAL
Other ratios	12	22	34
Altman Z Score Model	2	7	9
Number of audit committee members		1	1
Number of Management board members	1		1
Number of Management board members that have left company 2 years prior to fraud		1	1
Has there been a change of auditors during the last 2 years prior to fraud?		1	1
Was the audit done by a Big 4 company?	1		1
Was the audit opinion unqualified?		1	1
Does the audit committee have a person with financial expertise?		1	1
Does the company have internal audits?		1	1
Have there been any court proceedings?		1	1
Is the CEO also president of the supervisory board?	1	1	2

Ratios	Unimportant	Important	TOTAL
Logarithm of book value of assets as of the end of the financial year (t)		1	1
Market value of the company (t) to book value of the debt (t) ratio	1		1
Retained earnings to total profit (t) ratio	2		2
Percentage of members of audit committee that are independent		1	1
Percentage of shares owned by management and supervisory board members	1		1
Percentage of shares owned by management board members		1	1
Sales abroad to total sales (t) ratio		1	1
Percentage of supervisory board members outside the company		1	1
Percentage of substantial shareholders in total ownership structure	1		1
Size of the company (t)		1	1
Total percentage of shares owned by third parties		1	1
Number of supervisory board members outside the company	1		1
Percentage of pledged shares owned by management and supervisory board members	1		1

Source: Author

Other ratios are based on various forms of non-financial information, however, in the studies analysed, only the Altman Z score model has been shown to be an important indicator in the detection of financial statement fraud.

3. CONCLUSION

Research carried out by the ACFE suggests that financial statement fraud is a type of fraud that causes the greatest losses for businesses. As a result of the relatively large number of cases of financial statement fraud in the past 15 years (Enron, WorldCom, Parmalat...), there has been an increased interest by the public and the academic community in ensuring that financial statement fraud is detected early in the current business environment. The aim of this paper was to analyse previous research on the application of data mining methods in the detection of financial statement fraud, focusing on financial analysis indicators that can detect fraud in financial statements.

It can be concluded that of the 110 financial and non-financial ratios analysed in the previous research, only eight (8) financial analysis indicators can successfully be used to detect financial statement fraud, as can be seen in the following table:

Table 9 - A summary of key financial analysis indicators for detecting financial statement fraud

Ratios:	Financial analysis indicators:
Activity ratios	Inventory to sales ratio
	Sales to total assets ratio
	Accounts receivables to sales ratio
Liquidity ratios	Working capital to total assets ratio
Solvency ratios	Total debt to total assets ratio
Profitability ratios	ROA (Profit after taxation / total assets)
	Net profit margin (Profit after taxation / sales)
Other ratios	Altman Z Score Model

Source: Author

Since the previous research pertains to different geographic regions, and different time periods, this review suggests that financial statement fraud can be detected early by focusing on only eight financial analysis indicators.

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PREGLED ISTRAŽIVANJA PRIMJENE TEHNIKA RUDARENJA PODACIMA PRILIKOM OTKRIVANJA LAŽIRANJA FINANCIJSKIH IZVJEŠTAJA

SAŽETAK RADA

Lažiranje financijskih izvještaja predstavlja oblik prijevare koja polučuje najveće gubitke za poslovne subjekte. Današnje poslovno okruženje osigurava da se primjenom metoda rudarenja podacima (eng. data mining methods) detektiraju lažiranja financijskih izvještaja, što je ujedno i dovelo do većeg broja istraživanja posljednjih 15-tak godina. Kao prvi korak u uspješnoj implementaciji sustava detekcije primjenom metoda rudarenja podacima, pokazatelji financijske analize snažni su indikator pri otkrivanju lažiranja financijskih izvještaja. Analizom četrnaest (14) prethodno objavljenih radova detektirano je 110 financijskih i nefinancijskih pokazatelja, od čega je osam (8) pokazatelja financijske analize moguće izdvojiti kao najvažnije u formiranju modela detekcija lažiranja financijskih izvještaja, primjenom metoda rudarenja podacima.

Ključne riječi: *lažiranje financijskih izvještaja; otkrivanje prijevara u financijskim izvještajima; pokazatelji financijske analize*