INSTRUMENTAL CONTEXT OF A FORENSIC ACCOUNTING INVESTIGATION: A SYSTEMATIC REVIEW OF THE CURRENT LITERATURE

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Abstract: *The aim of the manuscript is to provide a review of the studies on the professional methodology of a forensic accounting investigation. The review presents various types of analyses that could prove to be effective in detecting and proving fraud such as industry analysis, financial analysis, nonfinancial data analysis, and internal control. A considerable part of this review is dedicated to the exhibit of several statistical and data mining techniques, as nowadays a forensic accounting investigation implies the work with and analysis of huge amounts of data. As this research is a descriptive one, the methodology used for elaborating this paper comprised an extensive literature review on the given subject, including a wide range of specialized works such as articles, researches, surveys, statistics, books, websites etc., and due to research's nature, it made use of the content analysis method. There is a wide-range of technical instruments available for a forensic accounting investigation that goes from financial analyses to business intelligence. It is the forensic accountant prerogative to choose the appropriate methods and tools according to the nature of the investigation, its complexity and its purpose, as some of them proved to be more useful than others. There has to be used several methods which can validate each other's results and together lead to a final conclusion on the occurrence or dimension of fraud.*

Keywords: *forensic accounting, systematic review, financial and nonfinancial analyses, statistics models and techniques*

JEL Classification: M40, M41, M21

General working framework of a forensic accounting investigation

The forensic accounting investigation is similar in many ways to a financial audit, meaning that it includes the basic steps: a planning stage, a gathering evidence period, a review of the process and a report to the client. Unlike the audit of the financial information, the purpose of the forensic accounting investigation is to discover if the alleged fraud actually took place, to identify the involved perpetrators, to quantify the amount of the fraud, to report the findings to the client and to present them in court, if necessary.

Based on this there can be found a more detailed generic working framework for this kind of forensic investigation, which could contain the following steps:

Assessing the potential investigation. Before accepting the job the forensic accountant must meet the client in order to understand the issues and the context. It is very important for these

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meetings to happen, because based on the information the investigator has to consider if the firm has the necessary skills and experience to accept the job. As this kind of investigation is highly specialized, it requires a thorough knowledge of fraud investigation techniques, the legal framework, interviewing and interrogation techniques and methodologies of securing the gathered evidence. Moreover, this information gathered in the beginning helps the investigator to determine where he should focus his investigation and therefore this can save time and money for the client, as these would be cut to minimum (Manning, 2005).

Considering ethical and commercial aspects. In this stage it is important to deal with or rule out some ethical aspects, for example if the company which requires the investigation is also an audit client. In this case the investigating firm might be exposed to self-review, advocacy, management threats to objectivity or conflict of interests. More, this meeting is appropriate for negotiating the fees aspects for offered specialized work and likely the involvement of senior and experienced members of the investigating firm.

Performing initial investigation. Prior to a detailed plan of action it is usually preferable to be developed an initial operational plan which will help the investigator to articulate subsequent planning based on a deeper understanding of the case (Peshori, 2015). In this step the forensic accountant also should gather more detailed information about the company which could point him the major existing risks like: insufficient internal control, deficiencies in accounting performance, high personnel fluctuation, fiscal and juridical risks, social conflicts, big losses, etc. (Popa et al., 2009). It is essential for the forensic accountant to understand and well-know the business under investigation, since every entity is unique under various aspects like organizational, operational, procedural, etc., and therefore the approach should be adapted to it.

Planning in detail the investigation. As a consequence of the previous steps, it is in order to be elaborated the specific course of action which includes setting of the objectives to be achieved and of the appropriate methodologies to be followed. The work has to be planned accordingly. The objectives of this kind of investigation may include:

- identifying the type of fraud or irregularities that have occurred
- determining the period of time of their occurrence
- determining the techniques and methods used for concealing them
- identifying the involved fraudster(s)
- assessing and quantifying the financial losses
- gathering the evidences needed in the court's proceedings
- providing the specialized advice for preventing the fraud reoccurrence (Peshori, 2015).

Gathering evidence. For gathering detailed and relevant evidence such as documents, economic information, unaccounted records, it is necessary for the investigator to know and fully understand the specific type of fraud and the way it was committed. Ultimately, the gathered evidence should prove the identity of the fraudster(s), the mechanics of the fraud scheme and the extent of the financial loss. Various techniques can be use in this step, such as: testing controls to collect evidence for the identification of the weaknesses which allowed the fraud to be carried out; using analytical procedures for comparing trends over time or different segments of the business; using computer assisted audit techniques; discussing and interviewing the employees etc..

Reporting. There has to be prepared a report for the client which will contain the findings of the investigation, including a summary of the evidence, a conclusion regarding the amount of the financial loss as a consequence of the fraud, the way the fraudster(s) was able to set up the fraud scheme and which regulations were bypassed. Also, the report may include the recommendations for improvements of the regulations so future reoccurrence of similar fraud to be prevented.

Court proceedings. If it is the case and the investigation findings lead to legal proceedings against the suspect(s), the forensic accountant will have to present in court the gathered evidence and to explain how the suspect was identified. It is very important in this case that the forensic accountant is capable to present the evidence in a clear and professional manner and is able to adapt the professional language and to simplify accounting complex issues, so that non-accountants present in the court to understand the evidence and its implications. As expert witnesses, the forensic accountants should always remember that their opinions "are only as good as their reputation and integrity. They should never sell their opinions to the highest bidder, but rather should give their honest opinions at all times" (Albrech et al., 2012).

These steps are presented more like a working guideline than a mandatory plan of action and such they should be considered. Each step can be completed or detailed, steps can be added or eliminated depending on the case. The control-flow perspective of this working phases is presented in the Figure no.1.

Figure no.1 Forensic Accounting investigation process flow (remade)
(*Source*: Peshori, 2015, pp. 34)

The working stages presented above are of a general nature, but since every investigation of fraud or fraud suspicion is unique and happens in a certain context, a forensic accountant has to create and develop some particular situation-oriented procedures for each particular case.

Financial and nonfinancial analyses

There are several types of analyses which a forensic accountant can use during an investigation. They can provide valuable information for assessing the possible fraud, for identifying the problematic area(s), measuring the fraud financial dimension, and ultimately to gather evidence to support his findings.

Industry analysis. The industry analysis “provides benchmarking data to financial analysts and other users of accounting information” (Alexander et al., 2007). Therefore, the industry data can provide valuable information as the companies that are active in the same industry or economic branch tend to handle and to report the financial and non-financial data in comparable manner, with respect to the laws and regulations of every country and considering the reports and statics issued about that industry issued by the government or other public or private institutions. In Manning’s opinion by “comparing a business entity with others can identify problem areas, i.e., inventory, receivables, payables, sales, etc.” (Manning, 2005).

Financial analysis. Financial statements are a very valuable source of information about a business entity as they provide comparable information about present and past accounting periods. Wells states that the conversion of the financial statements numbers into ratios or percentages allows us to analyse them based on their relationship with each other. In a fraud investigation the determination of the reason for relationships and changes in the amounts are relevant because these determinations are red flags that may rise questions for the forensic investigator and point him in the direction of the possible fraud. This kind of analysis is done usually by using three techniques: ratio analysis, vertical analysis and horizontal analysis (Wells, 2011).

a) Ratio analysis – it is a “means of measuring the relationships between two different financial statements amounts” (Wells, 2011). If the financial ratios highlight significant fluctuations from one year to another or over a longer period of time, these changes have to be examined, and their causes have to be determined. There can be many reasons for these fluctuations, like changes in the economic conditions, management strategy etc., fraud being only one of them (Manning, 2005).

As there are many financial ratios which can be used for drawing conclusions for different purposes, researchers tried to identify those financial ratios that are more likely to indicate a possible fraud. For example, below, in Table no.1, there are the results of a study made by Kanapickiene and Grundieve (2015).

Table no.1

Potential fraud indicator financial ratios in Lithuanian companies

Category	Financial Ratios
Profitability ratios (Return of sales)	• gross profit to sales (GP/SAL) • operating profit to sales (OP/SAL) • net profit to gross profit (NP/GP)
Profitability ratios (Return of investment)	• gross profit to total assets (GP/TA) • net profit to equity (NP/EQ)
Liquidity ratios	• inventories to current liabilities (INV/CL) • cash to total liabilities (CASH/TL) • cash to current liabilities (CASH/CL)
Solvency ratios	• all the ratios of this group, except for the total liabilities

	to equity (TL/EQ)
Activity ratios	• all the ratios of this group, except for the inventories to sales (INV/SAL), the cost of sales to inventories (CS/INV)
Structure ratios (Total assets structure ratios)	• all ratios of this group, except for accounts receivable to total assets (REC/TA)
Structure ratios (Current assets structure ratios)	• the inventories to current assets (INV/CA) • the cash to current assets (CASH/CA)
Structure ratios (Property structure ratios)	• the current liabilities to total liabilities (CL/TL)

(*Source*: Kanapickiene and Grundiene, 2015, pp. 323-325)

The researchers conducted an empirical research on 165 sets of financial statements of Lithuanian companies, 40 sets being fraudulent financial statements and 125 sets being non-fraudulent financial statements, and determined that the certain financial ratios were indeed more efficient in detecting fraud.

Dalnial, Kamaluddin, Sanusi and Khairuddin (2014) also realized a research for identifying the financial ratios which are significant to detect fraudulent financial reporting. This study was done on a sample of 65 fraudulent companies and 65 non-fraudulent companies of Malaysian Public Listed Firms, with data available between 2000 and 2011, and some of the results are presented in Table no.2.

Table no.2

Potential fraud indicator financial ratios in Malaysian companies

Category	*Financial Ratios*	*Observations*
Financial leverage	• total debt to total equity (TD/TE) • total debt to total asset (TD/TA)	• positive figures expected • the higher the leverage, the higher the probability violations and ultimately of fraud
Profitability	• net profit to revenue (NP/REV)	• negative values expected • the lower the profit, the higher tendency to overstate the revenue or expenses, so the higher probability of fraud
Asset composition	• current assets to total assets (CA/TA) • receivables to revenue (REC/REV) • inventory to total assets (INV/TA)	• positive values expected • the higher the amounts, the higher the risk of overstatements, thus the higher probability of fraud
Liquidity	• working capital to total assets (WK/TA)	• negative values expected • the lower firm's liquidity, the higher probability of fraud
Capital turnover	• revenue to total assets (REV/TA)	• negative figures expected • the higher difficulty to generate sales, the higher probability of fraud

(*Source*: Dalnial *et al.*, 2014, pp. 63-64)

The results of the two researches present both similarities and differences. There are some financial ratios found in both of the studies like the profitability ratios, the assets structure ratios, but probably due to the different methodologies the financial ratios are sometimes defined or chosen differently. Still, there is one financial ratio that is found in both studies, but the conclusion about it was contradictory, that is the total debt/equity which seems to be a useful indicator in the case of Malaysian companies, but not in the case of Lithuanian firms. This simple difference shows us that it is very important for the forensic accountant to be very careful in choosing the right financial indicators in his analysis.

Other financial ratios are also indicated in the literature: gross margin ratio = gross profit/net sales Albrech et al. (2012), Peshori (2015), Manning (2005); earning per shares = net income/number of shares of stock Manning (2005); operating performance margin = net income/total sales Albrech et al. (2012), Lenard and Alam, (2009).

A system for analysing a company, or different subdivisions of a company, made of a combination of several ratios, is the DuPont system of analysis, developed for an internal operating control using control charts (Carey and Essayyard, 2005). It is based on the combination of three indicators: 1) the net profit margin, 2) total assets turnover and 3) an equity multiplier (used for indicating the amount of leverage), and it is useful for determining the return on company's equity (ROE). (Mayo, 2012). The classic formula for DuPont system is: Return on equity = (Net profit/Sales) x (Sales/Assets) x (Assets/Equity) = Net profit/Equity.

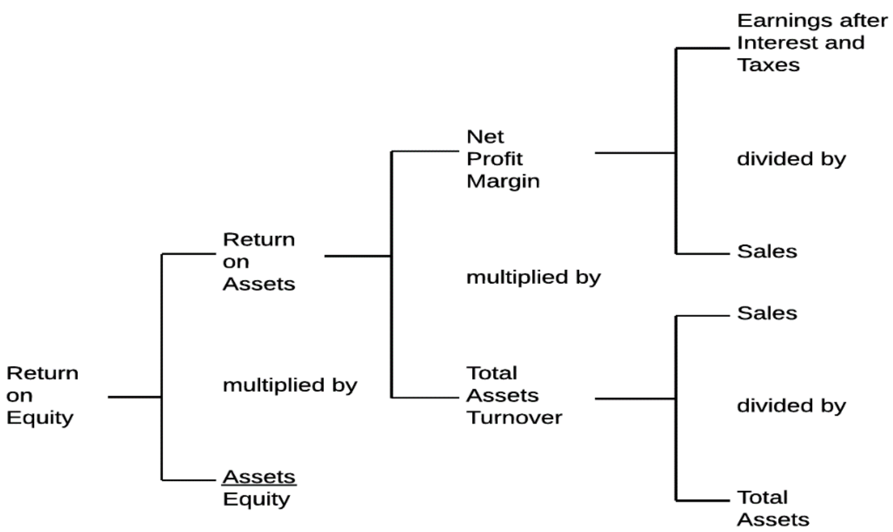

Figure no.2 The DuPont System of Financial Analysis (remade)

(*Source*: Mayo, 2012, pp. 201)

Using the general layout of the system depicted in Figure no.2 the forensic accountant can identify the internal sources of company's problems and also, if necessary, in some situations, this system provides a way of comparing of companies from one industry with companies from other companies (Mayo, 2012).

b) Vertical analysis – it is a method used for analysing the relationships between all the items on the income statement, balance sheet, or statement of cash flows expressed in terms of percentages. In the balance sheet for the total assets are allocated 100% on one side, and on the other side there are allocated 100% for all the liabilities and equity; in the income statement 100% are allocated for the net sales; all the other elements are expressed as percentage of these. "This method often is referred to as common sizing financial statements" (Wells, 2011).

c) Horizontal analysis – it is technique through which there are analysed and compared the percentage changes in the financial statement from one year to the next. The first period is considered as base, and the changes in the subsequent periods are computed as percentage of the base period (Wells, 2011).

Albrech et al. (2012) give us an example of how vertical and horizontal analysis worked in the case of ESM Government Securities, Inc., a brokerage firm specialized in buying and selling debt securities. These analyses were prepared by Steve Albrech using ESM's actual financial statements for a period of years. The red flags appeared in the case of two accounts "securities sold under agreement to repurchase (repo) account" and "securities purchased under agreement to resell (reverse repo) account". These two accounts were large enough to hide fraud, their balances were identical in 3 of the 4 years and, moreover, the numbers in the financial statements changed randomly, the changes were significant from one year to another and often they were in opposite directions, which it was considered strange as stable companies are expected to have consistent changes from year to year (Albrech et al., 2009). The data for the two analyses are found in Table no.3 and Table no.4.

Table no.3

ESM-Government – Vertical Analysis (remade)

	$ Year 1	**%**	**$ Year 2**	**%**	**$ Year 3**	**%**	**$ Year 4**	**%**
Assets								
Cash	$99,000	0.000	$1,767,000	0.001	$1,046,000	0.001	$339,000	0.000
Deposits	25,000	0.000	25,000	0.000	25,000	0.000	25,000	0.000
Receivables from brokers and dealers	725,000	0.000	60,000	0.000	1,084,000	0.001	2,192,000	0.001
Receivables from customers	33,883,000	0.024	40,523,000	0.027	21,073,000	0.022	16,163,000	0.006
Securities purchased under agreement to resell	1,367,986,000	0.963	1,323,340,000	0.867	738,924,000	0.781	2,252,555,000	0.840
Accrued interest	433,000	0.000	433,000	0.000	1,257,000	0.001	7,375,000	0.003
Securities purchased not sold at market	17,380,000	0.010	161,484,000	0.106	182,674,000	0.193	402,004,000	0.150
Total assets	$1,420,531,000		$1,527,632,000		$946,083,000		$2,680,653,000	
Liquidity and equity								
Short-term bank loans	$5,734,000	0.005	$57,282,000	0.037	$80,350,000	0.085	$91,382,000	0.034
Payable to brokers and dealers	1,721,000	0.001	478,000	0.000	3,624,000	0.004	5,815,000	0.000
Payable to customers	2,703,000	0.002	4,047,000	0.003	1,426,000	0.002	3,683,000	0.000
Securities sold under agreement to repurchase	1,367,986,000	0.963	1,323,340,000	0.867	738,924,000	0.781	2,457,555,000	0.917
Accounts payable and accrued expenses	272,000	0.000	796,000	0.000	591,000	0.001	1,377,000	0.000
Accounts payable – parent and affiliates	33,588,000	0.020	127,604,000	0.084	95,861,000	0.101	92,183,000	1.014
Common stock	1,000	0.000	1,000	0.000	1,000	0.000	1,000	0.000
Additional contributed capital	4,160,000	0.040	4,160,000	0.003	4,160,000	0.004	4,160,000	0.000

Retained earnings Total liabilities and equity	4,366,000 $1,420,531,000	0.040	9,924,000 $1,527,632,000	0.006	21,146,000 $946,083,000	0.022	24,497,000 $2,680,653,000	0.010

(*Source*: Albrech *et al*., 2012, pp. 189)

Table no.4

ESM-Government – Horizontal Analysis (remade)

	Year 1 to Year 2	**Year 2 to Year 3**	**Year 3 to Year 4**
Assets			
Cash	1,684%	(40%)	(67%)
Deposits	0	0	0
Receivables from brokers and dealers	(91)	1,706	102
Receivables from customers	19.5	(48)	(23)
Securities purchased under agreement to resell	(3)	(44)	205
Accrued interest	0	190	487
Securities purchased not sold at market	829	13	120
Total assets	7.5	(38)	183
Liquidity and equity			
Short-term bank loans	898	40	14
Payable to brokers and dealers	(72)	658	33
Payable to customers	50	(64)	158
Securities sold under agreement to repurchase	(3)	(44)	232
Accounts payable and accrued expenses	192	(100)	55
Accounts payable – parent and affiliates	279	(25)	(4)
Common stock	0	0	0
Additional contributed capital	0	0	0
Retained earnings	127	113	21

(*Source*: Albrech *et al.*, 2012, pp. 188)

Cash flow analysis. The cash-flow statement, while containing the inflows and outflows of cash, serves as a link between the balance sheet and the income statement (Manning, 2005). Although it seems more difficult to temper with the cash flow statement than with the other two financial statements, the researchers identified several methods that were used to manipulate the cash flow data: maximizing the inflow of money from operating activities and minimizing the outflow of money from operating activities (Dimitrijevic, 2015). Schilit and Perler state that there are 4 methods, which they called “shenanigans”, through which the cash flow can be altered: 1. shifting financing cash inflows to the operating section; 2. shifting normal operating cash out-flows to the investing section; 3. inflating operating cash flow using acquisitions or disposals; 4. boosting operating cash flow using unsustainable activities (Schilit and Perler, 2010).

Nonfinancial data analysis. This type of analysis is useful in order to support, compare and cross verify the financial data analysis results whenever the results appear to be out of order. In their study made for investigating if comparing financial data to nonfinancial measures (NMFs) could be helpful in assessing fraud risk, Brazel, Jones, Zimbelman found, for example, that “fraud firms have greater difference in percent change in revenue growth and percent change in NFMs than their non-fraud competitors” (Brazel et al., 2009).

Substantial differences between the financial data analysis results and nonfinancial data analysis results should rise questions for the forensic investigator and determine him to pursue with further inquiries. Manning states that there is a direct relationship data provided in the financial statements and the movement of the physical assets and goods, and therefore he points out the following logical correlations between financial and nonfinancial data aspects that should be reviewed, as they presented in Table no.5.

Table no.5

Logical relationships between changes in the financial and nonfinancial data

No.	Changes	Logical effects
1.	Sales increase	Accounts receivable should increase
2.	Sales increase	Inventory should increase
3.	Profits increase	Cash should increase
4.	Sales increase	Cost of outbound freight should increase
5.	Purchases increase	Cost of inbound freight should increase
6.	Manufacturing volume increases	Per-unit cost should decrease
7.	Manufacturing volume increases	Scrap sales and purchases discount should increase
8.	Inventory increases	Storage space must be available
9.	Sales increase	Usually other expense accounts should increase proportionately
10.	Over-aged receivables could indicate a slow payment of the customer or a fraud.	

(*Source*: Manning, 2005, pp. 422)

These are only a few general correlations that can be made in a risk fraud analysis and they are by no means exhaustive. As each case is particular, the forensic accountant should take into consideration the results from the previous analyses, the context, the particularities of the industry, and then follow the path that could give him more reliable answers.

Internal controls. Internal control comprises systematic measures and procedures that should provide reasonable assurance that errors and irregularities are deterred and detected in a timely manner. Manning states that as among the objectives of the internal control are: the execution of the transactions with the management's authorization, the properly recording of the transactions, the assets are safeguard and there is a periodical comparison between the actual assets and the accounting recording, the forensic accounting should review them in order to identify problem areas (Manning, 2005).

Statistics models and techniques

There are several statistics models that can be helpful in a forensic accounting investigation due to the fact that they allow working with and analysing large amounts of data.

Risk of bankruptcy analysis. The models initially developed for predicting bankruptcy and financial stress proved to be useful in detection fraud also. Although they don't indicate fraud all by themselves, they can rise questions for the forensic accountant. Several of these models are presented below.

a) The Altman Model. It is a statistic-mathematical model which uses the following equation:

$$Z = 0.012\ X_1 + 0.014\ X_2 + 0.033\ X_3 + 0.0006\ X_4 + 0.999\ X_5$$

The terms of this equation represent: X_1 = working capital/total assets, showing the measure of the entity's flexibility; X_2 = retained profit/total assets, representing the total assets' auto-financing rate; X_3 = earnings before interest and taxes/total assets, expressing the economical rate of return; X_4 = market value of shares/total debt, pointing the entity's borrowing capacity; for the companies not listed on the stock market, the market value of shares equals the social capital, X_5 = turnover/total assets, measuring the asset turnover. According to this model, if the Z-score is above 3.0 the company is healthy and sound. If the Z-score is below 1.8, the company is predicted to be a bankrupt one. If the Z-score is between the two mentioned values, the company finds itself in the grey area, in a possible temporary financial distress situation and further investigation must be done

(Achim and Borlea, 2012). In a research done by Lenard and Alam on 60 companies, 30 fraudulent entities and 30 non-fraudulent, they found out that the Altman's model had an overall prediction accuracy in identifying fraudulent firms of 30.8% (Lenard and Alam, 2009).

b) Conan & Holder Model. It is a model appropriate for the industrial companies with a number of 10 up to 500 employees. It also based on a Z model, but with a different structure:

$$Z = 16\ X_1 + 22\ X_2 - 87\ X_3 - 10\ X_4 + 24\ X_5,$$

where X_1 = receivables plus cash/current liabilities, representing the quick ratio; X_2 = permanent capital/liabilities and equity, expressing the firm's financial stability; X3 = financial expenses/turnover, measuring the financing level of sales from external resources; X_4 = salaries expenses/value added, representing the employees payment level; X_5 = operating profit/value added. If the Z-score is above 9, the company is solid. If the Z-score is below 4, the company is in a difficult financial situation. The between Z-score is indicating an uncertain financial situation, which needs to be further investigated (Achim and Borlea, 2012).

c) Robertson Model. A third Z model was created by Professor Robertson which identified four elements that could alter an entity's financial health: market stability, decrease of the profit, shortcoming of the working capital and escalation of the loans. The function of this model is the following:

$$Z = 3.0\ X_1 + 3.0\ X_2 + 0.6\ X_3 + 0.3\ X_4 + 0.3\ X_5,$$

where X_1 = (turnover-total assets)/turnover; X_2 = gross result of the period/total assets; X_3 = (current assets-total liabilities)/total liabilities; X_4 = (owners' equity-loans)/total liabilities; X_5 = (liquid assets – account overdraft)/loans. This Z-score targets the changes that appear in the company's financial statements from one period to another. If Z-score drops with 40% or more in one year, the causes of this reduction have to be found. If the Z-score is 40% or above in two years in a row, the company is on its way to bankruptcy (Achim and Borlea, 2012).

d) Ohlson's model of logistic regression. It is a model of: $1/(1 + e^{-Y})$. Lenard and Alam tested in their study the efficiency of this model in identifying fraudulent companies and they used for Y the following expression:

$$Y=-1.32-0.407(LOGTA) +6.03(TLTA)-1.43(WCTA) +0.0757(CLCA)$$
$$-2.37(NITA)-1.83(FUTL) +0.285(INTWO)-1.72(OENEG),$$

where LOGTA = log of total assets; TLTA = total liabilities/total assets; WCTA = working capital/total assets; CLCA = current liabilities/current assets; NITA = net income/total assets; FUTL = funds provided by operations/total liabilities; INTWO = 1 if net income is negative for the last two years and 0 if otherwise; OENEG = 1 if total liabilities are greater than total assets and 0 if otherwise. A score above 0.038 is an indication of a bankrupt company. In the study this method had 50% accuracy of prediction of the fraudulent companies (Lenard and Alam, 2009).

Even if this type of risk assessment models does not necessarily indicate fraud, a score that indicates a high risk of bankruptcy also could indicate the possibility of it, as in this situation some companies are more tempted to commit fraud, or some of them became bankrupt as a result of fraud. It should be determined if the financial distress is a consequence of certain conditions, like market, management policies, etc., or it is indeed somehow connected to fraud.

Risk of fraud in financial statements analysis. As the rise of fraud grow in the society some models were developed in order to help the professionals to detect fraud more easily. Some of these models are presented below.

a) Logistic regression model of fraud detection in financial statements tested by Kanapickiene and Grundiene on Lithuanian companies that allowed them to calculate the probability of fraud by the following equation:

$$P = 1/(1+e^{5.768-4.263xINV/TA-0.029xSAL/FA-4.766xTL/TA-1.936xCACH/CL}),$$

where INV/TA = inventories/total assets; SAL/FA = sales/fixed assets; TL/TA = total liabilities/total assets; CACH/CL = cash/current liabilities. P indicates the probability of fraud in financial statements (from 0 to 1), that is, P> 50% indicates that the financial statements are fraudulent and P<50% indicates that the financial statements are not fraudulent (Kanapickiene and Grundiene, 2015).

b) Benford's Law. It is statistical and mathematical instrument which helps to detect fraud, errors, or biases in reported financial numbers, by looking for frequencies or similar recurring patterns, as accounting data has a notable conformity to Bendford's Law. Still, this method alone does not detect fraudulent financial reporting, but deviations from it should make the analyst to question the validity, the accuracy or the integrity of the reported data (Nigrini, 2012).

c) Relative Size Factor (RSF). The RSF test is a "test for reasonableness within a specific grouping of data sets … and it identifies outliers within the group where the amount is too small to be considered as an anomaly" (Gee, 2015). This factor is "measured as the ratio of the largest number to the second large number in the given set of data", and it stresses the unusual fluctuations, fraudulent or not, which are to be investigated further (Peshori, 2015).

d) Beneish M-score. It is a statistical model, develop by Messod Beneish and tested on 74 companies that manipulated their earnings and 2,332 companies considered non-fraudulent, in the period 1982-1992, regarding the tempered and non-tempered financial reporting. The model for detection of earnings manipulation is: $M_i = \beta' X_i + \varepsilon_i$, where M is a variable coded with 1 for manipulators and 0 for the others, X is the matrix of explanatory variables: days' sales in receivables index (DSRI), gross margin index (GMI), asset quality index (AQI), sales growth index (SGI), depreciation index (DEPI), sales, general and administrative expenses (SGAI), leverage index (LVGI), total accrual to total assets (TATA), and ε_i is vector of residuals. The results show that the M-score depends on the variables which point out the area where the manipulation might have appeared (Beneish, 1999). In 2012 Beneish, Lee and Nichols published another study in which they tested the Beneish M-score on a sample of 41,544 companies, for the period 1993-2009, based on the previous model, but taking into account changed financial regulations. The used model was the following:

$$\text{MSCORE} = -4.84 + .920{*}\text{DSR} + .528{*}\text{GMI} + .404{*}\text{AQI} + .892{*}\text{SGI} + .115{*}\text{DEPI} - .172{*}\text{SGAI} + 4.679{*}\text{ACCRUALS} - .327{*}\text{LEVI}$$

Table no.6

Variables used in MSCORE (remade)

Variable Name	Description	Rationale
DSR	$(\text{Receivables}_t[2]/\text{Sales}_t[12]/(\text{Receivables}_{t-1}/\text{Sales}_{t-1})$ [Numbers in squared brackets are COMPUSTAT[5] codes]	Captures distortions in receivables that can result from revenue inflation
GMI	Gross Margin_{t-1}/ Gross Margin_t, where Gross Margin is 1 minus Costs of Goods Sold [#8]/ Sales	Deteriorating margins predispose firms to manipulate earnings
AQI	$[1-(\text{PPEt}+\text{CA}_t)/\text{TAt}]\ /[1-(\text{PPE}_{t-1}+\text{CA}_{t-1})/\text{TA}_{t-1}]$, where PPE is net [#8], CA are Current Assets [#4]and TA are Total Assets [#6]	Captures distortions in other assets that can result from excessive expenditure capitalization

[5] A database of financial, statistical and market information on active and inactive global companies throughout the world. It includes data, industry classification, key market identifiers etc.

SGI	$Sales_t$[12]/$Sales_{t-1}$	Managing the perception of continuing growth and capital needs predispose growth firms to manipulate sales and earnings
DEPI	Depreciation Rate $_{t-1}$/ Depreciation $Rate_t$, where depreciation rate equals Depreciation [#14-#65]/(Depreciation+PPE [#8])	Captures declining depreciation rates as a form of earnings manipulation
SGAI	(SGA_t [189]/$Sales_t$ [12])/(SGA $_{t-1}$/Sales $_{t-1}$)	Decreasing administrative and marketing efficiency (larger fixed SGA expenses) predisposes firms to manipulate earnings
LEVI	$Leverage_t$ /Leverage $_{t-1}$, where Leverage is calculated as debt to assets [(#5+#9)/#6]	Increasing leverage tightens debt constraints and predisposes firms to manipulate earnings
Accruals to total assets	(Income Before Extraordinary Items [18]- Cash from Operations[308])/ Total $Assets_t$[6]	Capture where accounting profits are not supported by cash profits

(*Source*: Beneish *et al.*, 2012, pp. 31)

The results provide evidence that this model can be used successfully in identifying fraud in the financial reporting. This M-score was tested again by Tarjo and Nurul Herawati on 35 fraudulent companies and 35 non-fraudulent companies. The logit regression model used in their study was:

$$FRAUD = \beta_0 + \beta_1 DSRI + \beta_2 GMI + \beta_3 AQI + \beta_4 SGI + \beta_5 DEPI + \beta_6 SGAI + \beta_7 TATA + \beta_8 LVGI + \varepsilon_{i},$$

where FRAUD = dummy variable (1 for fraudulent companies and 0 for non-fraudulent companies; DSRI = sales index; GMI = gross margin index; AQI = assets quality index; SGi = sales growth index; DEPI = depreciation index; SGAI = sales and general administration expenses index; TATA = total accrual; LVGI = leverage index; and ε_i = residual. The results show that from de 35 fraudulent companies 27 were correctly identified, meaning that there was a classification accuracy of 77.1%, and from the 35 non-fraudulent companies 28 companies were accurately identified, meaning that there was an accuracy of 80% (Tarjo and Herawati, 2015).

Data mining. It is a term used “to describe knowledge discovery in databases” and it “is a process that uses statistical, mathematical, artificial intelligence and machine-leaning techniques to extract and identify useful information and subsequent knowledge from large databases” (Turban et al., 2007). It includes functions like “knowledge extraction, data archelogy, data exploration, data pattern processing, data dredging, and information harvesting. All these activities are conducted automatically and allow quick discovery even by non-programmers” (Turban et al., 2007). Data mining techniques are also known as business intelligence.

Taking into consideration that an investigation for fraud detection in financial accounting implies large and complex data volumes Sharma and Panigrahi (2012) offers us a graphical conceptual framework based on a literature review of existing knowledge on data mining and fraud detection research. This conceptual framework pictured in Figure no.3 is set on two layers, first comprising six data mining application classes of classification, and the second comprising the supporting data mining techniques.

The six data mining application classes of classification and the supporting data mining techniques are briefly presented below:

- classification - it builds and uses a model useful for distinguishing between objects of different classes by identifying the common features, using categorical labels. This kind of classification is used frequently in detection of credit card, health care and automobile insurance, and corporate fraud, being one of the most common learning models for the application of data mining in fraud detection. The most common techniques of classification are Neural Networks, Naïve Bayes technique and Decision Trees.
- clustering – it is used to segregate objects into conceptually meaningful groups (clusters), the objects in the cluster being similar to one another, but very different form the objects in other clusters. One of the most common used technique is Naïve Bayes.
- prediction – it is used for numeric and ordered future values estimations based on the patterns of the data set and the most common used techniques are Neural Networks.
- outlier detection – it is used for detecting the data that have different characteristics and are inconsistent with the other data from the set. They are called outliers and their detection is fundamental in data mining.
- regression – it is a statistical method used to outline the relationships between independent and dependent variables. It makes use of logistic regression and linear regression and it can be found in the detection of the credit card, crop and automobile insurance, and corporate fraud.
- visualization – it refers to the easily understandable presentation of the data and to the methods of conversion of the data characteristics into clear patterns that allows the users to easily comprehend the results of the data mining process.
- regression models – most of them are based on logistic regression which is a generalized linear model and it is used mainly for solving problems in insurance and corporate fraud.
- neural networks – they are non-linear statistical data modelling tools, widely applied and advantageous due to its characteristics: it is adaptive, it can generate robust models and the classification process can be changed. It is used to credit card, automobile insurance and corporate fraud.
- Naïve Bayes – it uses a simple probabilistic classifier based on Bayes conditional probability rule[6] and it is used mostly in banking and financial fraud detection and claim fraud detection.
- decision trees – it is a tree structured decision support tool, made of nodes which represent tests on attributes and branches which represent possible consequences. It is used to credit card, automobile insurance and corporate fraud.
- Bayesian belief network – it represents a set of random variables and their conditional interdependencies and it is used successfully in developing models for credit cards, automobile insurance and corporate fraud.
- nearest neighbour method - it is a classification approach based on similarity.
- fuzzy logic – it is a mathematical technique that assigns data to a particular group based on the possibility that might be part of that group.
- genetic algorithm – it is used in classifier systems for representing and modelling the auditor’s behaviour in the fraud setting.
- expert systems – they increase the detecting ability of the investigators and help them to discriminate better among situations with different levels of management fraud-risk (Sharma and Panigrahi, 2012).

[6] It is the probability of observing event A given that event B is true

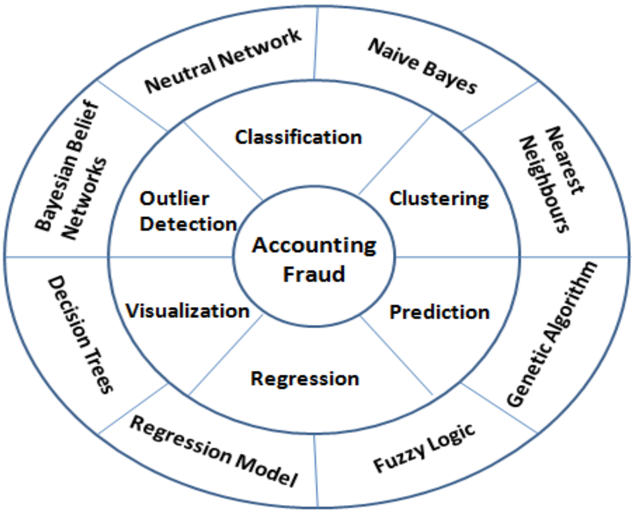

Figure no.3 The Conceptual Framework for Application of Data Mining to Financial Accounting Fraud Detection

(*Source*: Sharma and Panigrahi, 2012, pp. 38)

For successfully using the data mining in a forensic accounting investigation there are several steps that should be follow. Each step has a very clearly defined limits and it is relevant in the process architecture. The flow of the data mining process considering the characteristics of the presented fraud detection techniques for financial accounting fraud is presented in the Figure no.4.

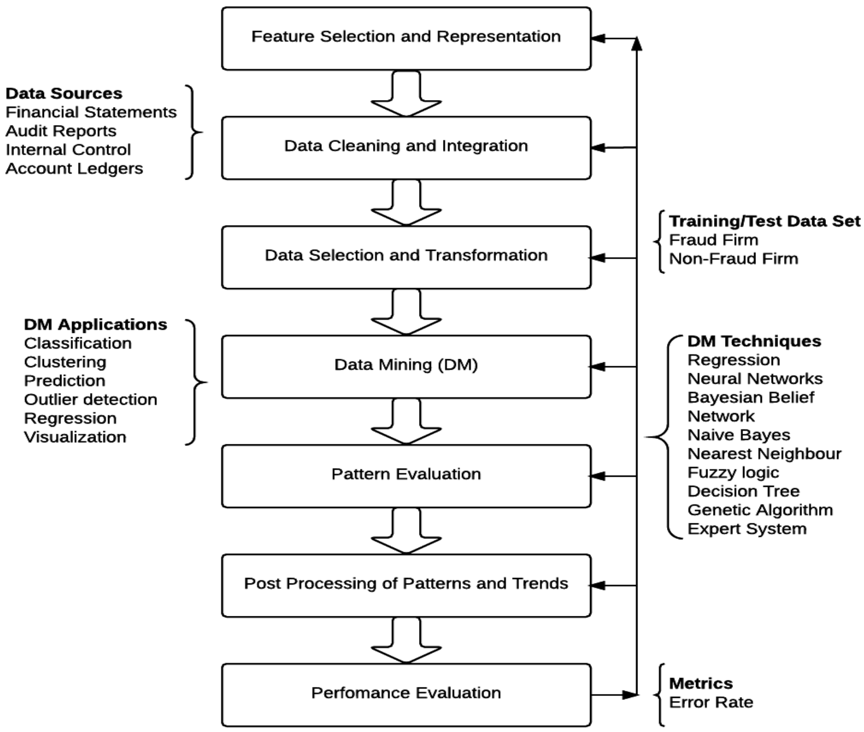

Figure no.4 The Data Mining Based Framework for Financial Accounting Fraud Detection (remade)

(*Source*: Sharma and Panigrahi, 2012, pp. 38-41)

Business intelligence analysis. Taking a step forward from the presented analysis techniques, there were developed more and more complex systems of fraud detection that integrate the traditional fraud detection approaches with the more modern ones. An integrated forensic accounting framework using business intelligence was created by Wong and Venkatraman, the three-phase model depicted in Figure no.5, for performing the financial trend analysis for fraudulent financial reporting.

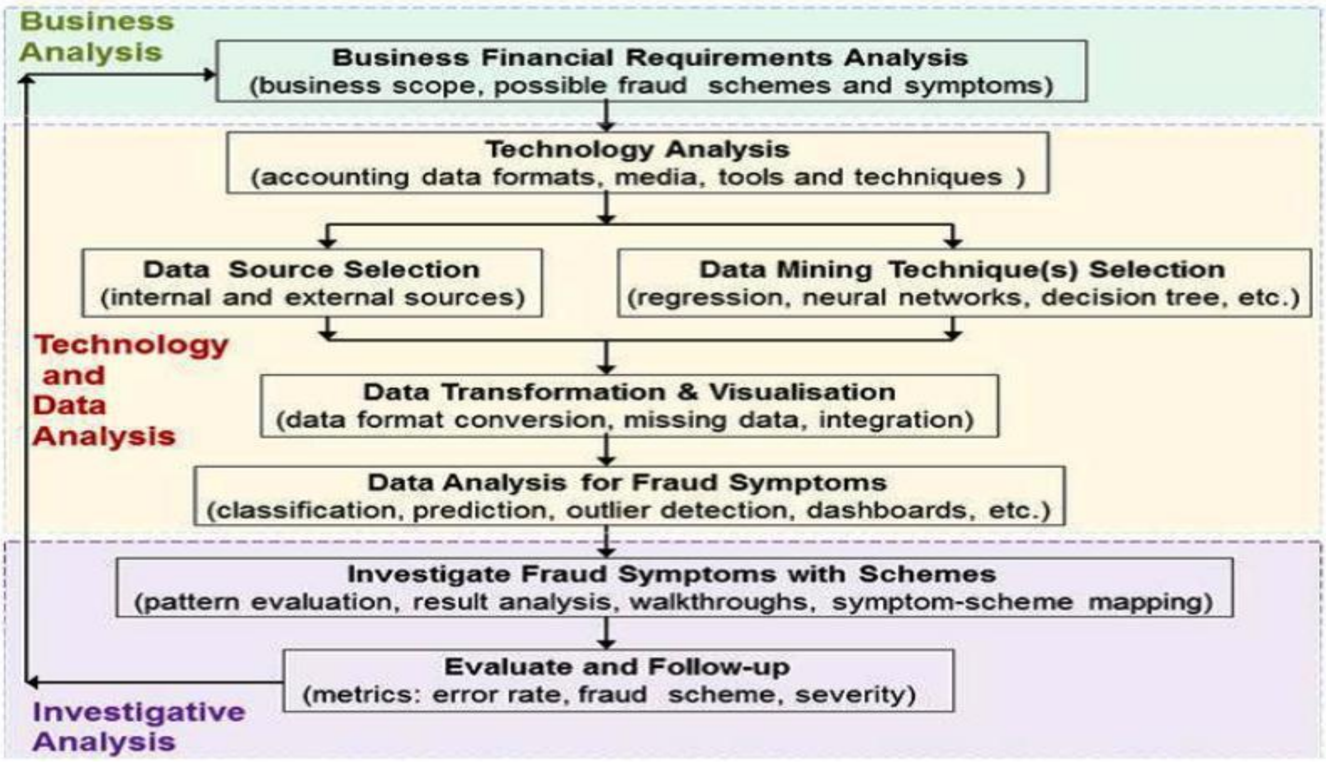

Figure no.5 Forensic Accounting Framework Using Business Intelligence

(*Source*: Wong and Venkatraman, 2015, pp. 1192)

The three phases considered in this framework are presented below:

- phase 1: Business Analysis – it is a step that considers the understanding of the specific business, its purpose, its operations and industry experiences in financial fraud, including the corporate policies and procedures, various financial statements, possible fraud symptoms and schemes specific to the industry.
- phase 2: Technology and Data Analysis – it considers diverse technologies, various data sources from inside or outside the business entity and data mining techniques.
- phase 3: Investigative Analysis – based on the outputs of the first two phases, this step involves the evaluation of the patterns, validation of the results, mapping the fraud symptoms and schemes and it allows a feedback loop through the three phases as part of continuous improvement (Wong and Venkatraman, 2015).

The researchers tested this Forensic Accounting Framework based on business intelligence on a company from the telecommunication industry and the results show that this tool had successfully identify the fraud areas within the entity's financial reports (Wong and Venkatraman, 2015).

There are many tools that a forensic accountant can use in his investigation, from simple ones to others very complex. However, it is important to keep in mind that none of these techniques detect fraud all by themselves and the investigator has to apply or to work with several at once. It is the forensic accountant's role to choose among them, to decide which of them are more appropriate for the investigation. He may combine them as he likes as long as they serve his purpose.

Conclusions

This paper aims to review a specialized branch of accounting which is known as forensic accounting, is presented as a mix of resources of several professional fields, like accounting, auditing, criminology, statistics, psychology etc. and it had an important development in the last twenty years, expansion that appeared due to the numerous cases of fraud that were revealed in the last years and the need to counteract them.

There is a wide-range of technical instruments available for a forensic accounting investigation that goes from financial analyses to business intelligence. It is the forensic accountant prerogative to choose the appropriate methods and tools according to the nature of the investigation, its complexity and its purpose, as some of them proved to be more useful than others. It is important to keep in mind that on their own they might rise questions, but none of the methods or techniques prove or disprove fraud alone. There has to be used several methods which can validate each other's results and together lead to a final conclusion on the occurrence or dimension of fraud.

The review wouldn't have been relevant without an exploration of fraud and the findings showed that fraud is a wide-spread phenomenon, which created important financial losses, led companies to bankruptcy and it is still spreading, constantly finding new ways to manifest itself. It can be defined in many ways and the existing literature on the subject offers a lot of information about it, from categories of existing fraud, to indicators and motivational context.

The paper could be considered useful by those which are interested in the fraud fighting subject, as they could relate to it as to a minimal guide. However, there are limitations to it. The subject is considered only from the accounting point of view, although forensic accounting is, as said, an integrative professional field. Moreover, another limitation is given even by the extensive existing literature on the matter.

The subject is large enough to offer many directions for further inquiries, such as researches on the other perspectives of forensic accounting, the other professional areas which complete it, or on more analysis tools in order to be determined if and to what extent they are useful in a forensic accounting investigation. As long as fraud keeps expanding, forensic accounting has to find new ways to keep up.

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