









Revitalizing the Forensic Accounting: An Exploratory Study on Mitigating the Financial Risk Using Data Analytics



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Abstract: Risk mitigation and fraud prevention in the present times have more focus on digital metadata, wherein forensic accountants are required to make use of robust IT techniques and tools. Data Analytics has huge implications for forensic accounting. With the ever-increasing electronic element of fraud in the present age of digitalization and the complexity of financial transactions and instruments, the challenges are growing exponentially for the forensic accounting profession. The use of data analytics techniques, which enables the processing of large data in almost no time, simplifies the task of forensic accountants to a large extent. It enables the identification of patterns and anomalies with the use of machine learning, deep learning, natural language processing, data mining, and other statistical techniques. Beneish M-score and the Altman Z-score models have proven to be effective forensic accounting tools in fraud detection and insolvency prediction. This study has been undertaken to test the effectiveness and efficiency of these forensic tools in fraud detection and insolvency prediction with the case study of Bhushan Steel Ltd. Based upon the findings of the study. It is suggested that these models should be integrated with data analytics, as these are highly effective and efficient in the detection of financial statement frauds and this integration would equip the naïve investor in the selection of financially sound company(s) to invest in. Since, there is increased funding by many international funding agencies, including the World Bank, for empowering forensic accountants and increasing awareness towards this profession, especially in developing countries, this study provides valuable insights about the significance of this integration and consequential benefits lying at the intersection of data analytics and forensic accounting.

Introduction

According to the Research Division, IBBI (2021), the post-Covid scenario has witnessed a sharp increase in insolvency filings. The second quarter of 2020 saw a 99% increase over the same quarter in 2019. Around 147 companies with turnover of 50 million pounds and more became insolvent across the world. The COVID-19 crisis caused a sharp decline in output, especially in emerging markets and led to increased debt levels. Given the slow recovery of income, the rising debt eventually translates

into higher default rates, having a direct effect on overall growth of the economy. Thus, it becomes pertinent to keep the insolvencies at bay. The recent trend of increased frauds and increased insolvency filings in the corporate sector calls for forensic accounting for early detection of such frauds and mitigation of financial risk (Apostolou et al., 2000; Bellovary et al., 2007). According to a survey conducted by AICPA (American Institute of Certified Public Accountants) in 2014, big data emerged as the top issue for forensic and valuation



professionals. The use of data analytics has thus become inevitable in view of voluminous data requiring effective handling in a time-bound manner (Ashok et al., 2022; Richey et al., 2022). Data analytics enables the identification of patterns and anomalies with the use of machine learning, deep learning, natural language processing, data mining, and other statistical techniques (Kilic, 2020; Herath and Joshi, 2023).

Beneish M-score and the Altman Z-score models are proven effective forensic accounting tools in fraud detection and insolvency prediction (MacCarthy, 2017; Kukreja et al., 2020; Drábková, 2016). The present study has been undertaken to test the effectiveness and efficiency of these forensic tools in fraud detection and insolvency prediction, using the case study of Bhushan Steel Ltd. Based upon this, it is explored that if these models are integrated with the data analytics, this can empower the naïve investor in the selection of financially sound company(s) to invest in. In the auto-grade steel industry, Bhushan Steel Limited (BSL) is considered to be the largest manufacturer in India. In July 2017, the company went into liquidation and was acquired by Tata Steel BSL Limited in November 2018. The company was amongst the twelve companies who were the top defaulters of banking loans and constituted 25 percent of NPAs in 2017, where it had a loan default of Rs 44,478 crores. The consortium of lenders, wherein the State Bank of India (SBI) was the lead bank, approached the National Company Law Tribunal (NCLT) for the recovery. In 2022, PNB reported the fraud of Rs. 3805 crores at the company as part of the requirements of regulation no. 30 of the SEBI (LODR), regulations 2015. The fraud was detected through the forensic investigation findings, and various charges of falsification of documents, obtaining the funds fraudulently and misappropriation of funds were levied against the company's former CFO and director, who was arrested consequently. The fraud had a combined overseas exposure of around 600 crores at Dubai and Hong Kong branches. The remaining exposure was at its Chandigarh branch.

Review of Literature

It is just not possible to completely rule out the possibility of any fraud from happening in any organization, but taking the services of forensic accountants/auditors can surely reduce the probabilities of fraud, and the risk of fraud can be managed to a great extent. The scope of forensic accounting services in a business set up is immense. "The world of forensic accounting, in the past decade, has expanded in scope and

has become more specialized in skills" (Rechtman, 2020). Besides their main function of auditing and fraud detection, they can play a bigger role in organizations by resolving many critical challenges faced by them (Alshurafat, 2021). Usually, the big public accounting firms like Deloitte, PwC, Ernst and Young and KPMG have a separate department dealing with forensic investigation assignments, wherein they absorb forensic accountants. They can help to strengthen the various information systems of the company and their mere presence can improve management accountability, corporate governance, the statutory audit function and the financial reporting system of the organization (Blythe, 2020). "They can prove to be catalysts in strengthening auditors' independence and in securing additional assurance for audit committees of the organization" (Odeyemi, 2021). Forensic accountants have the expertise in fraud detection and prevention as well as within the area of alternative dispute resolution, and they can also render arbitration and mediation services for the business organizations (Madumere, 2013). The corporate can use the services of forensic accountants to unravel cases regarding contract dispute, construction claims, product liability claims, patents and trademark etc. Insurance firms can use their services to assess claims accurately and settle them. Policyholders seek their help to question the claim sanctioned by the insurance company (Ozili, 2020).

Role of Data Analytics in Forensic Accounting

Many studies have proved that weakness in the internal control systems of organizations results in fraud in the majority of cases, and thus, the role of forensic accounting and the use of data analytics has assumed a prominent place in the field of fraud protection. An increasing number of organizations are using these for their risk management (Mittal, 2020). As compared to the traditional approach, where the forensic auditor has to employ sampling methodology, now, with the help of data analytics techniques, it becomes a lot easier to analyze the financial data of multiple years to identify the high-risk transactions which need to be reviewed, and that too within a significantly reduced timeline and the increased efficiency (Albrecht et al., 2018).

Combinatorial Explosion

Handling the massive data volumes and complexities of financial data are big challenges for forensic accounting, and thus, the use of data analytics techniques has become inevitable. To start with, very few organizations were using data analytics and machine learning to detect and deter fraud, but quite a sizeable number of organizations are gradually planning to adopt

such technologies soon (Rezaee and Wang, 2019). While a larger part of the time by the forensic accountant was spent in sifting through large volumes of data, searching for evidence and trying to get a clue as to where to head to further in the investigation, now data analytics helps save that time and let him focus on the case itself by getting him to reach where he needs to be quick. Thus, data analytics complements his services (Fanning et al., 1995). With the passage of time, the initial simple algorithms used earlier started proving to be slower and ineffective in dealing with bigger reasoning problems in face of "combinatorial explosion", as the advancements in the field and refinements in the technology were made, resulting in fast solving of problems (Hariri et al., 2019).

Data Analytics Techniques for Forensic Accounting

The three types of data analytics techniques are- Descriptive Analytics techniques, Prescriptive Analytics techniques and Predictive Analytics techniques. As the name suggests, descriptive analytics techniques help identify trends and anomalies in historical data. The focus of Prescriptive Analytics techniques is to invent efficient algorithms to find the most appropriate course of action in view of the desired outcome, while the Predictive Analytics techniques are meant for predicting future events (Tang and Karim, 2019). Out of the various techniques, three are discussed below, along with their applications in forensic accounting.

Machine Learning

Machine learning (ML) consists of algorithms that have the ability to learn from their experience and thereby, improve their functioning. It has two types-unsupervised learning and supervised learning, where the former does not require the human labelling of inputs for generating the patterns in a stream of input (Sadgali et al., 2019). The supervised learning methods of fraud detection make use of existing fraudulent and non-fraudulent cases to build a model that provides a suspicion score to apply in new cases (Pal et al., 2023). In unsupervised learning, existing observations are not available, instead a baseline distribution representing normal behaviour is modelled and the observations detected departing from the baseline are considered outliers and are more closely observed to check whether they are fraudulent or not, as in the case of Benford's Law (Bolton and Hand, 2002). With the use of ML, a company's expense policy may be read and a scrutiny of receipts and expenses claims can be done at a faster speed to ensure the forensic accountant can review compliance and then the questionable claims to check for any discrepancies, which can guide for further cause of

action. Thus, a lot of time and effort is saved through the use of ML (Ali et al., 2022).

Another prominent area in the field of forensic accounting is risk assessment, wherein information is required to be pulled from previous projects and analysed to do a comprehensive assessment of the proposed project. With the limited available time in hand and given the large scale of the project, the task can be quite tedious (Jain et al., 2023). ML can ensure the completion of such tasks at a relatively much faster speed with more accuracy. It has been found that ML algorithms many times outperform forensic experts at picking up pervasive but subtle patterns (Cai et al., 2019). In many cases, the data to be processed may be highly unstructured, which may make it very difficult to process. Analysing this unstructured data in the form of text documents, contract papers, returns filed, legal documents, press releases, e-mails etc. becomes easier with ML. The recent developments in ML have expanded to the areas of analysing the financial statements, identification of red flags and predicting default by customers and bankruptcy of organizations (Raghavan and Gayar, 2019).

Natural Language Processing

According to a survey conducted by AICPA (American Institute of Certified Public Accountants) in 2014, big data emerged as the top issue for forensic and valuation professionals. Natural Language Processing (NLP) provides solution to this issue. NLP refers to the ability of machines to read and understand human language and allows for applications like- information retrieval and text-mining. The application of information retrieval, 'Metadata' is of particular significance. It literally means "data about data" and can be used to extract basic information about data to help track the means of creation of the data, its purpose, its creator, the process used and the location of the computer network where it was created (Pollitt, 2013). It can also help in searching for the times, origins and destinations of all kinds of telecommunications viz. telephone calls, e-mails, electronic messages etc. Another application, called 'Data virtualization' which emerged in 2000s helps in stacking metadata in servers as a permanent persistent repository, which can easily facilitate the recovery of data whenever required. Similar technology is the 'Data warehousing', wherein correct, "cleaned" and timely data is stored in a standardized, structured, consistent and integrated manner, which is extracted from various operational systems in an organization and helps in providing an enterprise-wide perspective on the problem in hand (Odeyemi et al., 2024).

Deep Learning

The deeper a fraud gets into the system of an organization, the more difficult it is to identify its origin. 'Deep learning' can spot and recognize relationships and similarities between the data from the organization as well as from the unstructured data on social media (Akinbowale, 2023). Events that do not conform to an expected pattern in a data set can be detected and worked upon further for anomaly detection. This system is also equipped to improve the range of detection by uncovering new patterns. It is also possible with this technology to prioritize the cases where the anomaly is detected in the new patterns and, thereby, reducing the probability of a similar case, which allows to speed up the whole process of fraud detection at an early stage (Schreyer et al., 2018). This application would be particularly helpful in conducting of forensic audits of banks, as it has been seen in many cases that the fraud perpetrators engage in deploying similar fraud tactics in conning different banks at the same time. Deep learning provides an innovative solution to problems of corrupted data, where the criminal may change the file format and may also add the malicious content, which can destroy the evidence (Neaimi et al., 2020).

Early detection of fraud and prevention

Early detection of fraud and prevention are always desirable in order to take timely actions and minimize the brunt of losses (Skrzypek, 2018). There should be some mechanism to analyze the reliability of financial statements and to identify the risk points so that a detailed assessment can be done to check the level of manipulations, if any (Drabkova, 2016). Beneish and Nichols (2007) suggested that investors do not make use of publicly available information to detect fraud. Amongst the various forensic accounting tools available, Beneish M-Score model is used to detect the manipulation of financial statements and Altman Z-Score predicts bankruptcy based on financial data in the financial statements of the firm and computation of various ratios in the process (Kukreja et al., 2020). One of the oldest types of research on predicting insolvency through the use of financial ratios was conducted by Beaver (1966). He mentioned about the 'trend effect' which means the signs of failure are indicated in ratio analysis as early as before five years of failure; and become increasingly apparent each succeeding year. Financial ratios models help investors distinguish good firms from bad (Bhavani and Amponsah, 2017). Bellovary et al. (2007) opined that the focus should be on using the existing models by bankers, auditors, investors, lenders, analysts etc. and not on the development of new models.

Materials and Methods

For the purpose of the study, two forensic accounting tools, viz., Altman Z Score model and Beneish M Score, were applied to the financial data of Bhushan Steel Ltd. For the computation of Z-Scores and M-Scores, the financial figures for fifteen years (from 2003-04 to 2017-

18) were extracted from the CMIE (Centre for Monitoring Indian Economy) database. With this data, Z-Scores for various years are computed to assess whether the information contained in the financial statements already indicated the likely insolvency and bankruptcy of the company. M-scores are also calculated to hint at any possibilities of earnings manipulation in the financial statements. The computed M scores were benchmarked with the standard Beneish M- scores. Effectiveness of the models in predicting bankruptcy and establish earnings manipulation was tested using T-test.

Altman Z-Score Model: An Overview

This simple forensic accounting tool is used to evaluate the financial position of an organization using ratio analysis. Professor Edward Altman gave this model in 1968 for the first time to test for manufacturing companies (Altman, 1968). This was the time of Great Depression, when there were many instances of default by the companies. His contention was that a financially distressed company will exhibit quite different profitability, liquidity, solvency and other ratios measurements than their counterparts. There are five ratios included in the model and they are assigned weights based on the statistical analysis conducted by Altman, as presented in Table 1.

Table 1. Altman Z-Score Model.

Variables and Measurement	Computation of Z-Score	
$X_1 = (\text{Working Capital i.e. Current Assets minus Current Liabilities}) \text{ divided by Total Assets}$	<i>For Manufacturing Companies</i>	<i>For Non-Manufacturing Companies</i>
$X_2 = \text{Retained Earnings divided by Total Assets}$	$Z \text{ Score} = 1.2 X_1 + 1.4 X_2 + 3.3 X_3 + 0.6 X_4 + 0.999 X_5$	$Z \text{ Score} = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$
$X_3 = \text{Earnings before Interest and Taxes (EBIT) divided by Total Assets}$	<i>Interpretation</i>	<i>Interpretation</i>
$X_4 = \text{Market value (MV) of equity divided by Total liabilities}$	$Z \text{ Score less than } 1.81 \text{ means 'Distress Zone'}$	$Z \text{ Score less than } 1.1 \text{ means 'Distress Zone'}$
$X_5 = \text{Revenue divided by Total Assets}$	$Z \text{ Score equal to or more than } 1.81, \text{ but less than or equal to } 2.99 \text{ means 'Grey Zone'}$	$Z \text{ Score equal to or more than } 1.1 \text{ but less than or equal to } 2.6 \text{ means 'Grey Zone'}$
	$Z \text{ Score more than } 2.99 \text{ means 'Safe Zone'}$	$Z \text{ Score more than } 2.6 \text{ means 'Safe Zone'}$
	<ul style="list-style-type: none"> • <i>Distress Zone indicates high probability of bankruptcy</i> • <i>Grey Zone indicates a warning signal to work for financials improvement</i> • <i>Safe Zone indicates very low probability of bankruptcy</i> 	

The rationale of the five ratios is given below-

Table 2. Beneish M-Score Model

Measurement	Variables	Rationale
Current year (CY) Ratio of net receivables to sales/ previous year (PY) ratio	Days Sales of Receivables Index (DSRI)	A high index reflects the possibility of inflated revenues.
PY Gross Margin ratio i.e., (Sales-COGS/Sales) divided by CY ratio	Gross Margin Index (GMI)	Indicates the financial and growth prospects of the firm, as lower profitability may provoke the tendency to manipulate earnings.
CY ratio of non-current assets to total assets divided by PY ratio, here, plant, property and equipment (PPE) are to be excluded from non-current assets.	Asset Quality Index (AQI)	The proportion of intangible assets in total assets is considered. This reflects any tendency to defer costs in the form of Intangible assets.
CY Sales divided by PY Sales	Sales Growth Index (SGI)	The increase in sales is not indicative of manipulation <i>per se</i> , but this may mean that the firm is growing and may want to show higher potential to lure investors.
The PY depreciation rate is divided by the CY rate, where the depreciation amount divided by gross PPE gives a rate.	Depreciation Index (DEPI)	If DEPI is larger than 1, then assets are depreciating more slowly. It could reflect the company's adjustment of depreciation methods and rates to temporarily inflate earnings.
CY SGA expenses to Sales ratio divided by PY ratio	Sales, General and Administrative Expenses Index (SGAI)	A growing ratio may mean providing more SGA expenses through hefty remuneration to management and inflating expenses.
Ratio of Total Accruals to Total Assets, where Total accruals are given by the difference between Income and cash flows from continuing operations	Total accruals to Total assets (TATA)	High number of accruals indicate the likelihood of earnings manipulation because the management might have used discretionary accounting policies and methods to inflate the earnings.
CY ratio of total debts to total assets divided by PY ratio	Leverage Index (LVGI)	If LVGI exceeds the value of 1, this implies an increase in leverage. This endangers the solvency of the firm and also hints that the firm might have raised more debt to finance the existing debt servicing obligations.

1. *Working Capital/Total Assets*: This ratio is given by how much of a company's assets are financed by its working capital. A lower ratio indicates higher financial risk.
 2. *Retained Earnings/Total Assets*: This variable tells about the accumulation of a company's profits that have been retained for future growth. A higher ratio indicates better financial stability.
 3. *Earnings Before Interest and Taxes (EBIT)/Total Assets*: This is an indicator of the operating profitability in relation to total assets. A higher ratio indicates higher profitability.
 4. *MV of Equity/ Total Liabilities*: This variable tells how much the market value of equity is relative to total liabilities. A higher ratio indicates greater market confidence.
 5. *Sales/Total Assets*: The efficiency of the company in generating sales from its assets is reflected by this ratio. A higher ratio indicates better asset utilization.
- Based on the above discussion, the proposed null hypothesis is as follows.

$H_0(1)$. The five factored Z- Score does not detect the bankruptcy risk of Bhushan Steel Ltd effectively.

Beneish M-Score Model: An Overview

This model is a simple forensic accounting tool, given by Professor Messod Beneish in 1999 and is similar to Altman Z score model, though it uses eight ratios instead of five and indicates earnings manipulation instead of bankruptcy. It is claimed that the students of Cornell University could identify 'Enron' manipulating its earnings using the M score. There are eight ratios included in the model, and they are weighted as below (Beneish and Nichols, 2007). The description and rationale are presented in Table 2.

$$\text{"M-Score} = -4.84 + 0.92 \text{ DSRI} + 0.528 \text{ GMI} + 0.404 \text{ AQI} + 0.892 \text{ SGI} + 0.115 \text{ DEPI} - 0.172 \text{ SGAI} + 4.679 \text{ TATA} - 0.327 \text{ LVGI}"$$

Beneish and Nichols, 2005 gave a trimmed form of the M-score model, which is based on five variables-

$$\text{"M- Score} = -6.065 + 0.823 \text{ DSRI} + 0.906 \text{ GMI} + 0.593 \text{ AQI} + 0.717 \text{ SGI} + 0.107 \text{ DEPI}"$$

The M-score of a value less than -2.22 indicates lesser likelihood of manipulation. However, any value higher

than -2.22, suggests towards high possibility of manipulation. There are two limitations attached with the M-score, first is that it cannot be used for detecting every type of financial statements manipulation, and secondly, it cannot be used for financial firms.

From the above discussion, the proposed null hypotheses for the study are as below:

$H_0(1)$: The five factored Altman Z- Score does not detect the bankruptcy risk of Bhushan Steel Ltd.

$H_0(2A)$: The eight factored Beneish M- Score does not effectively detect the earnings manipulation of Bhushan Steel Ltd.

$H_0(2B)$: The five factored Beneish M- Score does not effectively detect the earnings manipulation of Bhushan Steel Ltd.

In addition to the testing of the above hypotheses, the efficiency of the various ratios comprising the two models to detect financial fraud was also evaluated. Thus, the proposed null hypothesis for this is as below:

$H_0(3)$: The ratios used in Altman Z-Score & Beneish M-Score models are not efficient in detecting the financial fraud of Bhushan Steel Ltd.

Results and Discussion

Altman Z-Score of Bhushan Steel Ltd.- Results and Discussion:

The results of the application of Altman Z-Score model for Bhushan Steel Ltd. are depicted in Table 3.

Table 3. Altman Z-Score for Bhushan Steel Ltd. from 2004-2018.

Years	Variables					Z-Score
	X ₁	X ₂	X ₃	X ₄	X ₅	
2004	0.2457	0.0443	0.1429	0.1938	0.9028	1.8477
2005	0.2390	0.0562	0.1633	0.4874	1.1364	2.3332
2006	0.1618	0.0403	0.1164	0.2951	0.8679	1.6797
2007	0.1552	0.0557	0.1317	0.5370	0.7778	1.7987
2008	0.0981	0.0467	0.1036	0.4030	0.5305	1.2974
2009	0.0788	0.0336	0.0921	0.1787	0.4452	0.9979
2010	0.0971	0.0480	0.0913	0.5481	0.3462	1.1601
2011	-0.104	0.0391	0.0839	0.4799	0.2998	0.7935
2012	-0.053	0.0296	0.0945	0.3436	0.3225	0.8175
2013	0.0066	0.0205	0.0774	0.3031	0.2726	0.7465
2014	-0.050	0.0007	0.0542	0.2449	0.2075	0.4732
2015	-0.010	-0.023	0.0418	0.0331	0.2217	0.3335
2016	-0.242	-0.054	0.0355	0.0143	0.2135	-0.027
2017	-0.294	-0.052	0.0450	0.0198	0.2235	-0.042
2018	-1.241	-0.550	-0.430	0.0133	0.3858	-3.284

Source: 'The Authors'

The findings and analysis of the five individual ratios of the model applied to the financial data of Bhushan Steel Ltd. for various years are as below:

X₁: As shown in table 3, the working capital to total assets ratio has largely remained less than one for all years of study, from 2004 to 2018 and is on constant decline. It is even negative for the years onwards 2011.

This indicates the persistent liquidity issues faced by the company, which ultimately led to bankruptcy.

X₂: The results for this ratio are even lesser for all the years, as low as 0.0443 for the first year of study (2004). The ratio saw marginal ups and downs during the initial years of study and dropped to the lowest level of 0.0072 in the year 2014 and became negative for all the remaining years, from 2015 to 2018. Clearly, it is because the EBIT to total assets ratio itself is so low for all these years and negative for the last year.

X₃: As discussed above, the results for this ratio for all the years are not on the promising side and for the last year, the ratio is even negative. Thus, the profitability of the company was poor.

X₄: Due to the non-availability of market capitalization figures, the book value of the equity is taken to compute the fourth ratio required for the computation of Z score. Shareholders' funds, which is the sum total of total capital and reserves and surplus, are included in the equity. This ratio is less than one for all the years and ranges between 0.2 to 0.5 for all the years up to 2013-14. Thereafter, it fell to 0.03 and declined further through the years and reached all all-time low 0.013 in the last year 2017-18. This indicates the usage of more borrowed funds in comparison to owned funds.

X₅: The results of sales to total assets ratio were also not good. This ratio was close to 2 up to the year 2007 and then started declining, largely remained less than one, and finally negative for the last three years. This indicates the inefficient use of assets to generate the revenue.

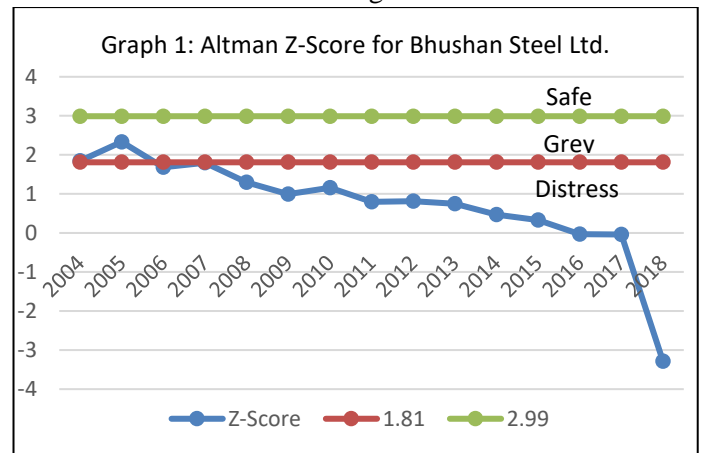


Figure 1. The results of the Z-Score model applied to the financial data of Bhushan Steel Ltd.

Z- Score for all the years under study except the first two years is less than the benchmark score of 1.81 (distress zone), hinting that the company was facing financial difficulties for a very long time. Even for the first two years, it was in the grey zone. It clearly indicates that the bankruptcy of the company was already in sight. The findings are supported by Bhavani and Amponsah (2017) and Kukreja et al. (2020). So, we can reject the

first null hypothesis $H_0(1)$. It can be concluded that the five factors of the Altman Z- Score could detect the bankruptcy risk of Bhushan Steel Ltd. effectively. *Beneish M-Score of Bhushan Steel Ltd.- Results and Discussion:*

The results for Beneish M-Score model for Bhushan Steel Ltd. are presented in Table 4.

Table 4. Beneish M-Score for Bhushan Steel Ltd. from 2005-2018.

Years	Variables									
	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	TATA	M-Score 8 Factors	M-Score 5 Factors
2005	0.5893	1.2792	0.9461	1.6432	0.7735	0.8021	1.0377	-0.0366	-2.3340	-2.5991
2006	1.1064	0.9389	0.7790	1.0706	1.0748	1.2355	1.0709	-0.0881	-2.9080	-2.9592
2007	0.9754	0.8842	0.9782	1.3686	1.1814	1.1414	1.0322	-0.0149	-2.3275	-2.7733
2008	1.0315	0.8534	0.7174	1.1120	1.0631	0.9751	1.0544	-0.0089	-2.5904	-3.1065
2009	0.8696	0.9634	0.8145	1.1577	1.0057	1.3242	0.9826	-0.0133	-2.6652	-3.0558
2010	1.0696	0.9265	0.8963	1.1097	1.2362	1.3374	0.9633	0.0151	-2.3469	-2.8859
2011	0.8205	0.8041	1.7802	1.2621	2.8734	1.1007	1.2466	-0.0109	-2.1333	-2.3932
2012	1.3090	1.0341	0.9632	1.4245	0.5815	0.9067	0.9319	-0.0629	-2.1180	-2.3960
2013	1.7753	1.0121	0.9908	1.0933	0.9042	0.9324	0.9953	0.0207	-1.5818	-2.2188
2014	1.1330	1.1147	1.0039	0.8983	1.0455	1.1043	1.0836	-0.0456	-2.6394	-2.7713
2015	1.0527	1.0836	1.4058	1.1070	1.6355	1.1418	1.0371	-0.0648	-2.3944	-2.4145
2016	0.3323	1.1683	0.9247	1.1153	0.7044	1.4420	1.1096	-0.0695	-3.4038	-3.3096
2017	1.1314	0.7814	0.9658	1.1481	1.0649	0.9910	0.9774	-0.0633	-2.6361	-2.9161
2018	0.7937	1.7016	1.4974	1.1582	0.9285	1.0371	2.5923	-0.5898	-5.2523	-2.0524

Source: 'The Authors'

The findings and analysis of the eight indices of the model applied to the financial data of Bhushan Steel Ltd. for various years are as below:

DSRI scores for various years do not show any increasing or decreasing trend. It was 0.589 in the year 2005, rose to 1.106 in the next year and then dropped again to less than one in the succeeding year. It is behaving in the same manner for the rest of the years and never was equal to 2 or more.

GMI index was 1.279 in 2005 and declined to less than one and remained so till the year 2011. Then, it increased marginally and crossed the figure of one and continued so for all the remaining years except for the year 2017, when it was again less than one. It was at its highest 1.701 in the last year 2018. However, it never exceeded the manipulator's mean of 1.193.

AQI index remained less than one for all the years up to 2009-10, but it touched the value of 1.780 in the year 2011, which even exceeded the manipulator's mean of 1.254. It then fell to less than zero and remained so for the next two years, increasing marginally, exceeding one, and then in 2014-15, it became 1.405, exceeding the

manipulator's mean of 1.254 again. Then, it dropped again for two years and crossed the manipulator's mean again, reaching at 1.497 in 2017-18.

SGI index has remained in the range of 1 to 1.5 for all the years, except the year 2013-14, when it was 0.898. It was highest at 1.643 for the first year of study, 2005. After that, it has declined and increased on and off.

DEPI index is greater than one for 8 years out of a total of 14 years of study. DEPI index of more than one could mean that the assets are subject to a lower rate of depreciation by the adjustment of depreciation methods and rates. This could mean that the company is trying to temporarily inflate earnings.

The SGAI index has crossed the benchmark of 1 of Beneish model for almost all the years except a few. Even for these years of exception, the value is quite close to 1. This reflects that the selling, general and administrative expenses have increased. If this information is combined with SGI, as discussed above, these increases are without a corresponding increase in revenue, which is quite alarming. Either the management is deliberately manipulating the figures or the possible explanation could be administrative inefficiencies.

LVGI is greater than 1 or close to one for all the years and has even touched the figure of 2.592 for the last year of study, 2018. It indicates an increase in leverage. This endangers the solvency of the firm and also hints that the firm might have raised more debt to finance the existing

debt servicing obligations. This might indicate that the possibility of manipulation is higher.

Table 5. Standardizing with Beneish Model.

Variables	Mean Values of Bhushan Ltd.	Standard Mean values of Manipulators
DSRI	0.9993	1.465
GMI	1.0389	1.193
AQI	1.0474	1.254
SGI	1.1906	1.607
DEPI	1.1480	1.077
SGAI	1.1051	1.041
TATA	-0.0738	1.111
LVGI	1.1511	0.031

Source: 'The Authors'

The TATA index was negative for all the years of study except for the years 2010 and 2013. The figures are very small and well below the manipulators mean of 1.111. This means that other than the primary source of income for the business, there are no other sources, and due to this, the income and cash flows from the continuing operations are not very different.

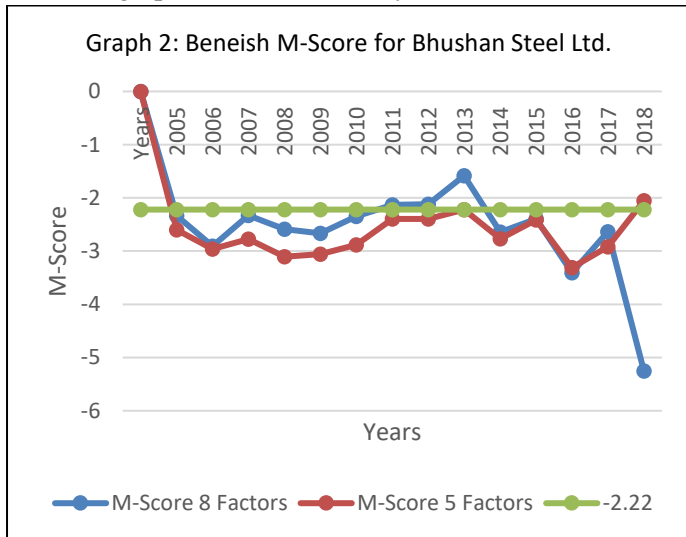


Figure 2. The results of the application of Beneish Model to the financial data of Bhushan Steel Ltd.

The eight variable M-Score is less than -2.22 for all the years under study, except for three years between 2011 to 2013, indicating non-manipulation. For the said three years, the score is greater than 2.22, hinting manipulation. So, we reject the null hypothesis $H_0(IA)$ and conclude that the eight factored Beneish M-Score could detect the earnings manipulation of Bhushan Steel Ltd.

Similar results were obtained through the five variable M-Score model. M-Score is less than -2.22 for all the years under study from 2005 to 2017, indicating non-manipulation for all these years. However, for the last year under study, 2018, the score is greater than -2.22,

hinting manipulation. So, we reject the null hypothesis $H_0(IB)$ and conclude that the five factored Beneish M-Score could detect the earnings manipulation of Bhushan Steel Ltd. Similar results were obtained by Kukreja et al. (2020) and MacCarthy (2017).

Benchmarking with the Beneish Model

The Beneish model divides the companies into two categories based on the average values on each index of the M score: non-manipulators and manipulators and offers the benchmark mean values of each category for all the said variables involved in the calculation of M score. For the purpose of the study, the mean values of each variable of the company under study are compared with these benchmark values to draw inferences (Table 5).

Only three indices DEPI, SGAI and LVGI, out of total of eight indices are, exceed the manipulator mean (Graph 3), which does not confirm the presence of red flags of manipulation on the part of the company.

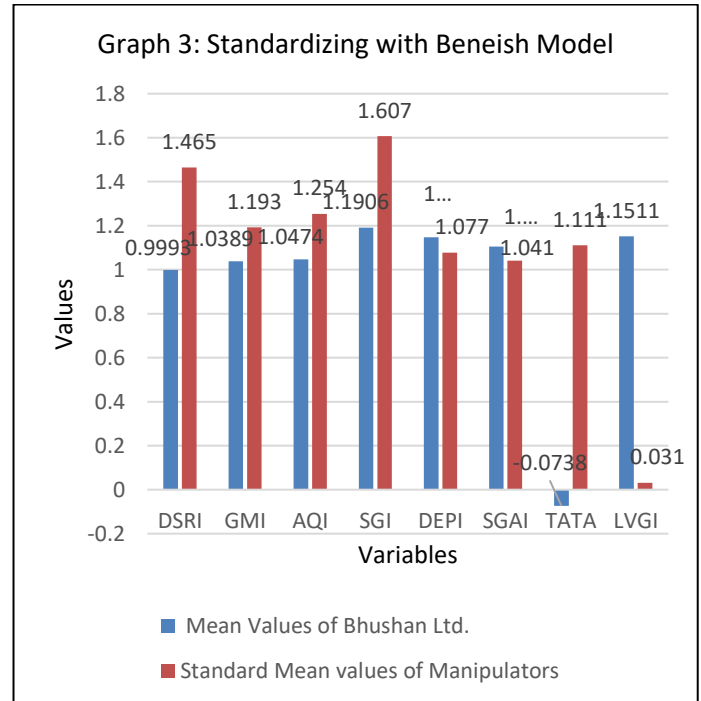


Figure 3. Standardizing with Beneish Model.

M-Score and Z-Score Models: Inferential Statistics Results

T-test was employed to evaluate the efficiency of the ratios of the two models used in the study. Table 6 shows the results of the T-test- the mean values, standard deviations, one sample t-stat and p-values for 2004-2018 ratios of Bhushan Steel Ltd. On the basis of these, it can be said that the Beneish model ratios appeared to vary between groups more significantly than the Z-score model ratios. In comparison to the Altman model, the Beneish model had a larger mean difference between the independent ratios.

Table 6. M-Score and Z-Score Models Statistical Analysis.

M-Score Model					Z-Score Model				
Variable	Mean	SD	t-stat	p-value	Variable	Mean	SD	t-stat	p-value
DSRI	0.9993	0.3349	11.991	0.0000	X ₁	-0.0611	0.3625	-0.652	0.5250
GMI	1.0389	0.2370	17.619	0.0000	X ₂	-0.0177	0.1518	-0.452	0.6590
AQI	1.0474	0.3006	14.002	0.0000	X ₃	0.0562	0.1396	1.560	0.1410
SGI	1.1906	0.1829	26.162	0.0000	X ₄	0.2730	0.1945	5.437	0.0001
DEPI	1.1480	0.5574	8.278	0.0000	X ₅	0.4769	0.2997	6.164	0.0000
SGAI	1.1051	0.1820	24.402	0.0000					
TATA	-0.0738	0.1522	-1.948	0.0720					
LVGI	1.1511	0.4219	10.965	0.0000					

Source: 'The Authors'

The p-values at 5% significance level are found to be less than 0.05 for both the models. As a result, it can be concluded that the ratios of both the models were related and found to be effective in identifying the fraud in Bhushan Steel Ltd financial statements. Therefore, at the 5% significance level, there was strong evidence to reject H₀(3).

Conclusion

Risk mitigation and fraud prevention in the present times have more focus on digital metadata, wherein forensic accountants are required to make use of robust IT techniques and tools (Liodorova and Fursova, 2018). Data analytics is thus indispensable in the field of forensic accounting in the present era (Rezaee and Wang, 2019). Data analytics techniques are still gaining ground in accounting and auditing, and thus, it will take time for forensic accounting as well (Raguseo, 2018). Since, there is increased funding by many international funding agencies, including the World Bank, for empowering the forensic accountants and increasing awareness towards this profession, especially in developing countries (Ozili, 2020). It can be hoped that the integration of data analytics with forensic accounting will gain momentum soon.

It was found that the five factors of the Altman Z-Score could detect the bankruptcy risk of Bhushan Steel Ltd. effectively. The Z-Score results indicate the distress zone for almost all the years of study, which means that the company has been facing financial difficulties for a very long time. It clearly indicates that the bankruptcy of the company was already in sight. However, the results of both the eight factored and five factored M-Scores indicated the lower possibility of manipulation on the part of the company for the majority of the years of the study. The Altman Z score is proven to be more effective as compared to Beneish M-Score in this study as well, and this is similar to the findings of earlier studies done in

this respect, like by Kukreja et al. (2020); Bhavani & Amponsah (2017); Mehta et al. (2012) and MacCarthy (2017). Many previous studies (Gnyana, 2015; Charalambos, 2002; Hawariah et al., 2014) find that Altman Z score alone in itself is enough for unearthing of fraudulent representation of statements by a company. Many new models are there in the market, like the "Pustylnick P-score" model, "Dechow F-score" model, "Montier C_Score" model, "J-Score" which can help in the differentiation of financially sound firms from financially distressed ones (Parikh and Shah, 2022). It is thus suggested that the investors in the market should be equipped with some data analytics tools integrated with these simple and effective models, which they can make use of in selection of financially sound and properly governed firms and safeguard their interests. In fact, all the stakeholders in the organization can make use of these tools for their benefit. The industry needs to recognize the importance of the integration of data analytics in forensic accounting to make better business decisions and ensure better risk management and compliance (Banarescu, 2015).

It is but natural that the data analytics techniques are not foolproof and are susceptible to some new forms of errors and fraud (Chiu et al., 2020). It has been observed that there are hardly any cases of fraud that are identical to each other. The basic elements could be the same in every case, but a newer approach is called for success. False alarms, missed frauds and technical risks are some of the limitations attached to the use of these techniques in forensic accounting. It is not possible to design any technique with a hundred percent accuracy, and only the suspicious cases that are highlighted by the techniques need to be probed further to classify them as fraudulent (Appelbaum et al., 2017). Also, developing a technology takes a whole lot of time, energy and effort, the cost of which may actually outweigh the benefits associated with it. However, the advantages associated with such

integration make it worth the effort certainly in the longer run. Thus, it is highly suggested that the business, along with forensic accounting practitioners should actively work on developing such integrated models, which can detect financial statement frauds at an early stage in the time-bound manner. These tools should be used of to detect the destructive self-dealing activities on the part of promoters and management at an early stage (Seifzadeh et al., 2022). The fraud committees of the organizations can make regular use of these integrated models to rule out any possibility of manipulation in its financial statements, and at the same time, the business can devise appropriate strategies to maneuver its leverage capacity to maximize the returns to the shareholders and prevent the risk of bankruptcy.

Limitations and Scope for further research

The present study is limited to the case of Bhushan Steel Ltd., and thus, the results cannot be generalized for all kinds of businesses and markets. In order to draw more useful insights, comparative studies of corporates across various industries and different intervals of time should be undertaken. The models used in the study are merely the indicators of probable manipulations and fraudulent activities. The future works should focus on developing comprehensive and customised models including more quantitative factors and should also make use of various qualitative signals, like the strength of Board of Directors (BOD), the membership of BOD, meetings held during the year, the remuneration paid to the directors and to the auditors etc., in order to draw conclusive results from the application of the models.

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Conflict of Interest

The authors declare no conflict of interest.

References

AICPA. (2014). Survey on International Trends in Forensic and Valuation Service. 2014-fvs-trend-survey-results.pdf (aicpa.org) (Accessed on 25 Feb, 2023)

Akinbowale, O.E., Mashigo, P., & Zerihun, M.F. (2023). The integration of forensic accounting and big data technology frameworks for internal fraud

mitigation in the banking industry. *Cogent Business & Management*, 10(1).
<https://doi.org/10.1080/23311975.2022.2163560>

Albrecht, W.S., Albrecht, C.O., Albrecht, C.C., & Zimbelman, M.F. (2018). *Fraud Examination*. Cengage Learning.

Ali, A., Abd Razak, S., Othman, S. H., Eisa, T.A.E., Al-Dhaqm, A., Nasser, M., & Saif, A. (2022). Financial Fraud detection based on machine learning: A systematic literature review. *Applied Sciences*, 12(19), 9637

Alshurafat, H. (2021). Is Forensic accounting a profession in Australia? A sociological perspective. *Meditari Accountancy Research*, 30(2), 395-423.
<https://doi.org/10.1108/MEDAR-04-2020-0865>

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589-609.
<https://doi.org/10.1111/j.1540-6261.1968.tb00843.x>

Apostolou, B., Hassell, J. M., & Webber, S. A. (2000). Forensic expert classification of management fraud risk factors. *Journal of Forensic Accounting*, 1, 181-192.
<https://maaw.info/JournalOfForensicAccounting.htm>

Appelbaum, D., Kogan, A. & Vasarhelyi, M.A. (2017). Big data analytics in the modern audit engagement: Research Needs. *Auditing: A journal of practice and Theory*, 36(4), 1-27.
<https://doi.org/10.2308/ajpt-51684>

Ashok, M., Madan, R., Joha, A. and Sivarajah, U. (2022). Ethical framework for Artificial Intelligence and Digital technologies. *International Journal of Information Management*, 62.
<https://doi.org/10.1016/j.ijinfomgt.2021.102433>

Banarescu, A. (2015). Detecting and Preventing fraud with data analytics. *Procedia economics and finance*, 32, 1827-1836.
[https://doi.org/10.1016/s2212-5671\(15\)01485-9](https://doi.org/10.1016/s2212-5671(15)01485-9)

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 4, 71-111.
<https://doi.org/10.2307/2490171>

Bellovary, J. L., Giacomino, D. E., & Akers, M. D. (2007). A Review of Bankruptcy Prediction Studies: 1930 to Present. *Journal of Financial Education*, 33, 1-42.
<http://www.jstor.org/stable/41948574>

Beneish, M. D., & Nichols, D. C. (2007). The predictable cost of earnings manipulation. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.1006840>

Bhavani, G., & Amponsah, C.T. (2017). M-Score and Z-Score for Detection of Accounting Fraud. *Accountancy Business and The Public Interest* 2017.
<https://www.researchgate.net/publication/318489930>

- Blythe, S.E. (2020). Financial Statement Fraud: Lessons learned from selected U.S. legal cases in the past twenty years. *Journal of Modern Accounting and Auditing*, 16(1). <https://doi.org/10.17265/1548-6583/2020.01.001>
- Bolton, Richard J., & Hand, D. J. (2002). Statistical Fraud Detection: A Review. *Statistical Science*, 17(3), 235–255. <https://www.jstor.org/stable/3182781>
- Cai, C.W., Linnenluecke, M.K., Marrone, M., & Singh, A.K. (2019). Machine learning and expert judgement: Analyzing emerging topics in accounting and finance research in the Asia-Pacific Abacus, 55(4), 709-733
- Charalambos, T. S. (2002). Detecting false financial statements using published data: Some evidence from Greece'. *Managerial Auditing Journal*, 17(4), 179-191.
- Chiu, T., Wang, Y. & Vasarhelyi, M.A. (2020). The automation of financial statement fraud detection: A framework using process mining. *Journal of Forensic and Investigative Accounting*, 12(1), 86-108
- Drábková, Z. (2016). Models of Detection of Manipulated Financial Statements as part of the Internal Control System of the Entity. *Oxford Journal of Finance and Risk Perspectives*, 5, 230-234. <http://www.acrn-journals.eu/resources/jofrp05011.pdf>
- Fanning, K., Cogger, K. O., & Srivastava, R. (1995). Detection of management fraud: A Neural Network approach. *Intelligent Systems in Accounting, Finance and Management*, 4(2), 113-126. <https://doi.org/10.1002/j.1099-1174.1995.tb00084.x>
- Gnyana, R. B. (2015). Prediction of financial distress using Altman Z- score: A study of select FMCG companies'. *Indian Journal of Applied Research*, 5(9). <https://doi.org/10.36106/ijar>
- Hariri, R. H., Fredericks, E.M., & bowers, K.M. (2019). Uncertainty in big data analytics: survey, opportunities, and challenges. *Journal of Big Data*, 6(1), 1-16
- Hawariah, D., Amrizah, K., Zuraidah, Mohd. S., & Khairun, S. K. (2014). Accountability in financial reporting: detecting fraudulent firms. *Science Direct Procedia - Social and Behavioral Sciences Elsevier Ltd*, 145, 61 – 69
- Herath, S.K., & Joshi, P.L. (2023). Audit data analytics: A game changer for audit firms. *International Journal of Auditing and Accounting studies. Special Issue on Auditing in the Digital Age.*, 5(1), 29-48. <https://doi.org/10.47509/IJAAS.2023.v05i01.02>
- Jain, R., Kaur, A., & Mittal, P. (2023). A Co-occurrence Network analysis of research work in supply chain finance and corporate sustainability strategy in Industrial sector. *International Journal of Experimental Research and Review*, 32, 378-386. <https://doi.org/10.52756/ijerr.2023.v32.033>
- Kilic, B. I. (2020). The Effects of big data on forensic accounting practices and education. Emerald Publishing Limited. *Contemporary Issues in audit Management and Forensic Accounting* pp. 11-26.
- Kukreja, G., Gupta, S.M., Kumaraswamy, S., & Sarea, A.M. (2020). Beneish M-score and Altman Z-score as a catalyst for corporate fraud detection. *Journal of Investment Compliance*, 21(4), 231-241. <http://dx.doi.org/10.1108/JOIC-09-2020-0022>
- Liodorova, J., & Fursova, V. (2018). Forensic accounting in the world: Past and present. *Journal of Economics and Management Research*, 7, 84-99. <https://doi.org/10.22364/jemr.7.06>
- MacCarthy, J. (2017). Using Altman Z-score and Beneish M-score Models to Detect Financial Fraud and Corporate Failure: A Case Study of Enron Corporation. *International Journal of Finance and Accounting*, 6(6), 159-166. <https://doi.org/10.5923/j.ijfa.20170606.01>
- Madumere, I. (2013). Forensic Accounting: A relief to corporate fraud. *Research Journal of Finance and Accounting*, 4(14).
- Mehta, U., Patel, A., Patel, H and Purohit, R. (2012). Detection of Fraudulent Financial Statement in India: An Exploratory Study. *Proceedings of the 2nd International Conference on Enterprise Systems & Accounting (ICESA 2005)*, GFMJR, January – June Vol.No.4.
- Mittal P. (2020). Big Data and Analytics: A Data management perspective in public administration. *International Journal of Big Data Management*, 1(2), 152. <https://doi.org/10.1504/ijbdm.2020.112415>
- Neaimi, M., Al Hamadi, H., Yeun, C., & Zemerly, J. (2020). Digital Forensic Analysis of Files Using Deep Learning. *3rd International Conference on Signal Processing and Information Security*. <https://doi.org/10.1109/ICSPIS51252.2020.9340141>
- Odeyemi, S. O. (2021). The Role of Forensic Audit on Management Frauds in Nigerian Deposit Money Banks. *International Journal of Accounting, Finance and Risk Management*, 6(3), 69-75. <https://doi.org/10.11648/j.ijafmr.20210603>
- Odeyemi, O., Ibeh, C.V., Mhlongo, N. Z., Asuzu, O. F., Awonuga, K.F., & Olatoye, F. O. (2024). Forensic accounting and fraud detection: A review of techniques in the digital age. *Finance & Accounting Journal*, 6(2), 202-214. <https://doi.org/10.51594/farj.v6i2.788>
- Ozili, P.K. (2020). Advances and issues in fraud research: A commentary. *Journal of Financial Crime*, 27(1), 92-103. <https://doi.org/10.1108/JF-01-2019-0012>
- Pal, R., Pandey, M., Pal, S., & Yadav, D. (2023). Phishing Detection: A hybrid model with feature selection and machine learning techniques. *International Journal of Experimental Research and Review*, 36,

- 99-108.
<https://doi.org/10.52756/ijerr.2023.v36.009>
- Parikh, Y., & Shah, K. (2022). 'Financial Statement Fraud Detection Models: An Exploratory Study'. *A Global Gyan Journal of Social Sciences*, 5(3), 21-26. <https://www.gapgyan.org/>
- Pollitt, M. (2013). The Hermeneutics of the hard drive: Using narratology, Natural language processing and knowledge management to improve the effectiveness of the digital forensic process. *Electronic Theses and dissertations*, 2994. <https://stars.library.ucf.edu/etd/2994>
- Raghavan, P. & Gayar, N.E., (2019). Fraud detection using Machine learning and deep learning. *International Conference on Computational Intelligence and Knowledge Economy*, Dubai, UAE.
<https://doi.org/11.1109/ICCIKE47802.2019.9004231>
- Raguseo, E. (2018). Big data technologies: An Empirical investigation into their adoption, benefits and risks for companies. *International Journal of Information Management*, 38(1), 187-195. <https://doi.org/10.1016/j.ijinfomgt.2017.07.008>
- Rechtman, Y. (2020). The past, present and future of forensic accounting. The CPA Journal- The voice of profession. 2020 March. <https://www.cpajournal.com/2020/04/10/the-past-present-and-future-of-forensic-accounting/>
- Research Division, IBBI. (2021). Financial stress in corporate sector: A study on India, 2021, IBBI working paper series WP 01/2021
- Rezaee, Z., & Wang, J. (2019). Relevance of big data to forensic accounting practice and education. *Managerial Auditing Journal*, 34(3), 268-288. <https://doi.org/10.1108/MAJ-08-2017-1633>
- Richey, M., Morgan, J., & Li, S. (2022). Ethical artificial intelligence for fraud prevention in finance and accounting. *Ethics in Information Technology*, 22(2), 175-193
- Sadgali, I., Sael, N., & Benabbou, F. (2019). Performance of machine learning techniques in the detection of financial frauds. *Procedia Computer Science*, 148, 148-154. <https://doi.org/10.1016/j.procs.2019.01.007>
- Schreyer, M., Sattarov, T., Borth, D., Dengel, A., & Reimer, B. (2018). Detection of anomalies in large-scale accounting data using deep autoencoder networks. <https://doi.org/10.48550/arXiv.1709.05254>
- Seifzadeh, M., Rajaei, R., & Allahbakhsh, A. (2022). The relationship between management entrenchment and financial statement fraud'. *Journal of Facilities Management*, 20(1), 102-119.
- Skrzypek, A. (2018). The importance of financial liquidity analysis in an enterprise. *International Journal of Experimental Research and Review*. 17, 17-19. <https://doi.org/10.52756/ijerr.2018.v17.004>
- Tang, J., & Karim, K.E. (2019). Financial fraud detection and big data analytics- Implications on auditors' use of fraud brainstorming session. *Managerial Auditing Journal*, 34(3), 324-337. <https://doi.org/10.1108/MAJ-01-2018-1767>
- Tiwari, H. (2023). Promoter's Shareholding, Financial Distress and Capital Structure Decisions: An Empirical Study of Indian Firms. *Journal of Business Management and Information Systems*, 10(2), 43-49. <https://doi.org/10.48001/jbmis.2023>.

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