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Research paper

Evaluating The Fraud Triangle Perspective in India's Pharmaceutical Sector

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Abstract

The research paper examines the usefulness of the Fraud Triangle Theory (FTT) in describing financial statement fraud in the context of the Indian pharmaceutical industry, where empirical research at a large scale is scarce. The analysis is done using a panel dataset of 135 listed pharmaceutical firms on NSE and BSE in the period 2014-2022, where the indicators of pressure, opportunity, and rationalization are taken (liquidity, solvency, asset turnover, firm size, and profitability ratios) to predict the occurrence of fraudulent financial reporting with the fraud proxy (qualified opinion, emphasis of matter content). The findings demonstrate that solvency risk (debt-to-equity ratio) is a huge determinant and more likely to generate fraud, and asset-based firms are less likely to declare fraudulent statements. Other pressure, opportunity, and rationalization proxies have weak explanatory power, implying that FTT has a minor role in explaining the levels of fraud in this industry. The results are informative to the auditors, regulators, and managers as they draw attention to the red flags associated with leverage, and the necessity to monitor financially strained pharmaceutical companies more closely, as well as to the shortcomings of using FTT and audit-opinion-based proxies in high-R&D industries. It is one of the first large-scale empirical estimates of the Fraud Triangle Theory in the pharmaceutical industry in India that provides industry-specific results and helps to fill the gaps in the research on fraud detection and regulation in the emerging economy.

Keywords: *Financial Statement Fraud; Pharmaceutical Companies; Fraud Triangle Theory; Audit Opinion; India.*

1. Introduction

Even though financial statement fraud constitutes 5 percent of the cases of global fraud, it leads to the largest median losses of USD 766,000 per case (ACFE, 2024). Fraud caused financial and social damage in both the government and corporate sectors, which reduced investor trust and weakened the control systems (Rezaee, 2005; Wells, 2005). The well-known failures, like Enron in the United States, indicate how the manipulation of the financial reporting may result in enormous losses and long-term destabilization of the institution (Spathis, 2002; Dechow et al., 2011). In India, also, there have also been recurrent cases of corporate fraud, and this has brought up the issue of transparency and effectiveness of regulation. The Ranbaxy case in 2013 exemplified systematic governance failures in the pharmaceutical industry, in which falsified data, lack of adherence to regulations, and fraudulent disclosures resulted in significant fines and reputational damage (Sharma and Dev, 2021; Gupta and Gupta, 2015).

Financial statement fraud is hard to detect due to fraudulent manipulation, which in most cases is covered by the legitimate accounting procedures and needs the expertise of specialized analytical knowledge (Kassem and Higson, 2012; Ravisankar et al., 2011). In order to comprehend the cause of fraud, various theoretical models have been established, and the FTT by Cressey (1953), which is composed of the forces of pressure, opportunity, and rationalization, is one of the most common theories (Cressey, 1953; Dorminey et al., 2010). FTT is now built into international auditing standards, including International Standard on Auditing (ISA) 240, and it emphasizes its importance in terms of fraud-risk assessment (AICPA, 2019). Although various studies have been conducted on FTT in various countries, there is a limited amount of evidence on it in Indian settings, especially in high-risk sectors like the pharmaceutical industry (Lokanan, 2014; Omar et al., 2017). Indian companies do not function in as homogenous a disclosure environment as those in global environments, which have more transparent capital markets and stricter regulatory enforcement (compared to settings), and it is not clear that traditional FTT proxies would also perform well in those settings (Nasir and Hashim, n.d.; Sandhu and Saluja, 2023).

The available literature on accounting fraud in India is based more on case studies, descriptive analysis, or governance-based discussion as opposed to large-sample empirical studies with existing theories of fraud (Gupta and Gupta, 2015; Rezaee, 2005). This gap is essential because modern fraud detection studies are becoming more and more involved in implementing high-order analytical methods like machine learning, forensic data mining, textual analysis, and ESG-risk calculations (Shahana et al., 2023; Hajek and Henriques, 2017). Such new methods point to the fact that the old theory-based measures, like the ones in FTT, may no longer be applicable in understanding the phenomenon of fraud behaviour in the industry, which is not only complicated but also highly focused on research and development. Consequently, the applicability of FTT to financial statement fraud in the Indian pharmaceutical industry, where the intensity of research and development, strict government regulation, and intense reporting regulations, as well as confrontation with operational risks, are the main features of the industry, is still under-explored empirically (Spathis, 2002; Shahana et al., 2023). This study fills this gap by quantitatively testing the Fraud Triangle Theory in a large sample of Indian pharmaceutical companies. Financial ratios are used to operationalize pressure, opportunity, and rationalizations based on the ISA 240 indicators of liquidity and solvency (pressure), asset turnover and firm size (opportunity), and profitability-based indicators (rationalization): (Dechow et al., 2011; Ravisankar et al., 2011). This research will shed some sector-specific light on the predictive ability and the weakness of FTT in an emerging market by analyzing the relationship between these indicators and fraudulent financial reporting. By this, the research has a theoretical contribution in the sense that it evaluates the fact that FTT explanatory mechanisms are not applied differently in an R&D-intensive, highly regulated sector and detects context-specific deviations of the traditional expectations of fraud risks (Hajek and Henriques, 2017; Shahana et al., 2023). In addition to the theoretical contribution, the findings are practical to the auditors, regulators, and investors. They emphasize that financial indicators have a higher likelihood of predicting a risk of fraud within pharmaceutical companies and that the conventional triangles of fraud indicators may not be effective because of the peculiarities of the industry (Lokanan, 2014; Omar et al., 2017). This evidence needs to be strengthened to enhance a better system of assessment of fraud-risk, improvement in the mechanism of governance, and dialogue with the healthy growth of the capital markets in India (Rezaee, 2005; Shahana et al., 2023).

The remainder of this paper is organized as follows. Section 2 presents a comprehensive literature review and develops the study's hypotheses. Section 3 describes the data, variables, and methodology used for analysing FSF in Indian pharmaceutical firms. Section 4 reports the empirical results, while Section 5 provides robustness checks and additional analyses. Section 6 offers an expanded discussion, integrating global comparisons and clarifying the relevance and limitations of FTT in the Indian pharmaceutical context. Finally, Section 7 summarizes the key findings, highlights the study's theoretical and practical implications, acknowledges its limitations, and outlines directions for future research.

2. Literature Review

The initial research on financial statement fraud involved mostly trying to detect red flags in financial data. Romney et al. (1980) created the first list of fraud warning signs. Later, Albrecht et al. (1986) expanded this work and identified 87 signs of manipulation after interviewing convicted fraudsters. These initial findings encouraged researchers to investigate whether financial ratios would help to identify fraudulent and non-fraudulent companies. This concept was proved by empirical data: Summers and Sweeney (1998) demonstrated that several accounting ratios could help to identify the patterns of fraud, in particular, the fraud involving revenue, receivables, and the manipulation of expenses.

Based on this, Spathis (2000) employed logistic regression to determine the most predictive ratios of fraudulent reporting in Greek companies. When the most correlated variables were eliminated, ten ratios based on profitability, liquidity, solvency, and efficiency generated a classification accuracy greater than 84 per cent, proving that standard financial statement data could be effectively employed to identify anomalies. These measures were still used in subsequent studies based on the assumption that abnormal ratio patterns are indicative of aggressive reporting behaviour.

With the evolution of the field, scholars began to stop using the numerical indicators and began to examine the reasons behind fraud. This brought about more theoretical models, which was the FTT introduced by Cressey (1953). According to FTT, the three conditions that lead to fraud are pressure, opportunity, and rationalization. Skousen et al. (2009) used the three elements of the Fraud Triangle, measured through accounting and governance variables, and provided evidence that these factors help identify material misstatements. Later research has found that the variables of FTT are still applicable to predicting fraud in various countries and sectors (Zainudin and Hashim, 2016; Kagias et al., 2021).

To illustrate this, Omar et al. (2017) followed Spathis and used the ratio method and again obtained the predictive accuracy of 94.87, which demonstrates the usefulness of ratio-based analysis. As shown by Rahman et al. (2024), leverage and liquidity pressures contribute positively to the risk of fraud in China, whereas the independence of the board and the size of the audit committee are the characteristics of the governance that contribute to the minimization of fraud risk. These studies indicate that FTT is empirically well-grounded on the global level.

2.1. Global experience and developing trends

FTT predictors have similar trends in most global contexts, like the United States, Europe, and East Asia. Research studies have continually discovered that high leverage, weakening liquidity, and opportunity driven by assets (ex, receivables and inventory misstatements) are related to fraud (Dechow et al., 1995; Kagias et al., 2021). High disclosure norms and strict enforcement of regulations are contributing factors to these trends, as they affect the behavior of firms in the face of financial strain.

Nonetheless, the shortcomings of FTT are also noted in studies across the globe. In other contexts, only one or two aspects of the triangle are significantly predictive. This discrepancy implies that the level of FTT explanatory power differs within industries, regimes, and organizational cultures. It implies that the applicability of FTT should be experimented with in any case, although it provides a valuable background.

Moreover, the studies of fraud detection have also recently outgrown the traditional ratio-based methods. More sophisticated ones are machine learning models, forensic analytics, sentiment analysis in annual reports, and ESG-related risk indicators (Hajek and Henriques, 2017; Shahana et al., 2023). These new methods tend to be better than the classical ratio models since they are able to capture the pattern of complexities, behaviour-based signals, and unstructured information that cannot be seen in financial statements only. Consequently, researchers are beginning to doubt the efficacy of FTT-based proxies in fraud detection, particularly in sectors that contain complicated transactions or in ones with non-physical assets.

2.2. Indian context and the requirement of sector-specific evidence

The empirical fraud research in India, compared to other nations, is limited and tends to be qualitative in nature, with case studies or stories of corruption, but not based on theory and statistical results (Ashtaina and Martin, 2021). Even though there are studies that analyze failures in governance and the manipulation of accounting, there are few empirical tests of FTT in large samples. This leaves a huge gap in the research since India has a more heterogeneous governance environment with different internal controls, disclosure, and enforcement practices (Lokanan, 2014; Omar et al., 2017).

This is particularly the case in the pharmaceutical industry. It is highly regulated, intensive in research and development, and reliant on multifaceted deals, like clinical testing, intellectual property assessment, quality production, and exportation records (Gupta and Gupta, 2015; Sharma and Dev, 2021). Such features may provide the chance of smoothing incomes, shifting costs, or inaccuracy in classifying R&D and manufacturing costs. Simultaneously, the level of regulatory control implies that a company is frequently under pressure to show stability, compliance, and competitive results. This creates a special vulnerability of pharmaceutical firms to regulatory oversight as well as to earnings management.

That being the case, whether or not the traditional FTT indicators, which have been developed primarily in the Western and manufacturing-driven environment, are reliable predictors of fraud in the Indian pharmaceutical industry is unclear. These differences support the fact that a context-specific and comparative evaluation is necessary. Taking the tendencies of the world and the increasing use of artificial intelligence (AI)-based fraud detection, as well as the specifics of the institutional environment in India, it is necessary to re-evaluate the applicability of FTT in a specialized and the most highly regulated sector of the pharmaceutical industry. The research is thus conducted in accordance with the provisions of the ISA 240 and aligns the three FTT elements of pressure, opportunity, and rationalization in financial metrics that are commonly applied in the existing literature. The following hypothetical statements mirror these existing theoretical connections and enable us to assess the fact of whether FTT is predictive in the context of the Indian pharmaceutical environment or not.

2.2.1. Pressure

Pressure can be defined as the financial or operational pressure that compels the managers to distort the reported performance (Cressey, 1953). Liquidity shortages and solvency risks are some of the red flags that are brought to the fore in ISA 240. Companies experiencing decreasing liquidity will have difficulties in paying off short-term debts, and this motivates managers to give off a facade of being stable. Persons (1995) believes that poor solvency and increased likelihood of fraud are portended by low current ratios. In line with the previous research (Zainudin and Hashim, 2016), the research paper measures pressure based on liquidity.

H1: Low current assets in comparison to current liabilities enhance the chances of committing fraudulent financial reports.

Solvency issues can also cause pressure. Firms that have significant leverage exposure are exposed to more debt covenant risk, investor discontent, and bankruptcy. According to Wells (1997), as cited in Spathis (2002), companies that are faced with solvency pressure tend to misreport their financial information. Debt-to-equity ratio, therefore, reflects this aspect.

H2: The greater the debt-to-equity ratios, the greater the probability of fraudulent financial reporting.

2.2.2. Opportunity

Opportunity presents itself when the weak internal controls, complex transactions, or unverifiable accounts permit the manipulation to be carried out without detection. ISA 240 observes that fraud is common in judgmental accounts like receivables and inventories. Omar et al. (2017) remark that the accounts of turnover are often targeted due to their easy manipulation, which cannot be easily traced. A high ratio of receivables to sales can be an indicator of aggressive recognition of revenue or slow collection, which can also be an indicator of manipulations (Dechow et al., 1995).

H3: An increase in the accounts receivable to sales ratios will increase the chances of fraudulent financial reporting.

On the same note, too many inventories can be an indicator of overproduction, obsolescence, and manipulation of valuations (Jones, 1991; Dechow et al., 1995).

H4: The higher the inventory-to-sales ratios, the more probable that the financial reporting is subject to fraud.

Opportunity may also be dependent on firm size. Smaller companies might not have good internal controls or streamlined reporting systems, hence can be easily manipulated. According to Dechow et al. (1995), smaller firms would be tempted to control the outcomes so that investor confidence could be kept.

H5: The lower the total assets of the firm, the higher the chances of reporting fraudulent financial reports.

2.2.3. Rationalization

Rationalization can be described as an internal justification for committing fraud by the managers. Although it is not easily noticed, the ISA 240 points out that abnormally high profitability or inconsistent earnings trends may be indicators of aggressive reporting. It has been shown in the previous literature that decreasing earnings provides a reason for managers to manipulate outcomes in order to live up to expectations (Persons, 1995; Kaminski et al., 2004). There are chances that a low sales-to-total assets ratio can indicate the underutilization of assets, so that managers will inflate revenues in the short run (Dechow and Skinner, 2000).

H6: Companies that have lower sales-to-total asset ratios have a higher probability of having fraudulent financial reporting.

The decrease in the profit margins also heightens the incentives to manipulate. Jones (1991) discovered that the more a firm declines in terms of profitability, the more it is driven to overreport income.

H7: Lower net-profit-to-sales ratios of firms increase the likelihood of firms reporting fraudulent financial statements.

On the same note, low returns on assets can lead to managers manipulating accounting estimates or capitalizing on expenses (Beneish, 1999).

H8: The lower the net-profit-to-total-assets ratios, the higher the likelihood of committing fraud by the firms.

Deficits in working capital suggest liquidity and operational issues and can be employed to misreport in the external environment. According to Spathis (2002), companies that have a small working capital tend to commit fraud.

H9: Lower working-capital-to-total-assets ratios increase the likelihood of fraudulent reporting.

3. Research Methodology

Previous studies on fraud, such as Omukaga (2020), used a descriptive research design. This approach is also suitable for examining how the three components of the Fraud Triangle Theory—pressure, opportunity, and rationalization—affect the likelihood of reporting fraudulent financial statements among India's listed pharmaceutical firms. A descriptive–explanatory design is particularly appropriate here because it enables the study to (i) describe observable patterns in firms' financial characteristics and (ii) explain their theoretical relationship with fraud risk, consistent with ISA 240 and prior fraud-risk modelling research.

India has 182 publicly traded pharmaceutical companies. Based on the firms' classification as pharmaceutical companies, the availability of complete financial information, and the requirement that the firm be publicly listed throughout the study period, the final sample consists of 135 companies (135/182 = 74%) over the nine years 2014–2022. This sample size is comparable to prior fraud-detection studies and provides adequate statistical power for hypothesis testing. Table 1 summarizes the sample selection procedure.

Table 1: Study Sample Summary

Summary	Firms
The target population of the study	178
Excluded due to inadequate data.	43
Sample used for the study	135
Source: Compiled by the author, 2024	

3.1. Data and sample

This research employed secondary data that was collected in the annual financial statements of the selected firms between the year 2014 and 2022. The data were obtained by using CMIE ProwessIQ, which is a popular Indian corporate database comprising audited Indian financial data on NSE- and BSE-listed companies. The last dataset comprises 135 companies and 1,333 company-year observations, including 254 that were reported to have been fraudulent according to the audit report. The nine-year panel data will help the study gain year-to-year variation in reporting behaviour and the patterns of persistent fraud.

3.2. Dependent and independent variables measurement

3.2.1. Dependent variable

The study's dependent variable is fraudulent financial statements (FRAUD). The auditor's report (Kirkos et al., 2007; Patel et al., 2019a) classifies the financial statements into fraud and non-fraud categories as follows, as per the Indian Comptroller and Auditor General's (Auditing, 2023):

- Unmodified or unqualified audit opinion: The financial statements are devoid of material errors. This does not necessarily imply that no fraud occurred.
- Qualified audit opinion: The financial statements contain substantial inaccuracies in specific values, or there is insufficient evidence to conclude that the quantities are not significantly erroneous.
- Adverse audit opinion: The financial accounts contain major errors. However, conclusive evidence of fraud is not available.
- Disclaimer: The firm did not provide sufficient records to provide an audit opinion.

In addition to the opinions stated above, auditors' reports may include an "Emphasis on the Matter" paragraph. The auditor includes this "Emphasis of Matter" subsection in the audited financial statements when they believe there is an important matter in the financial statements that users should be aware of, and there is sufficient evidence to demonstrate that it is not significantly incorrect.

In this study, we categorized the statements of healthcare companies as non-fraudulent if they possess a clean or unqualified audit opinion, which aligns with previous research work (Moepya et al., 2016; Patel et al., 2019b; Kirkos et al., 2007). Meanwhile, we consider the financial statements of healthcare companies to be fraudulent if the auditor mentions a qualified, adverse, disclaimer audit opinion or emphasizes a particular matter in the annual report. The dependent variable (FRAUD), which is qualitative and depicts the presence or absence of financial fraud in the organization, serves as a dummy variable. We assign a value of 1 if the company's financial statement contains fraudulent activity and 0 otherwise (Rahman and Jie, 2024).

3.2.2. Independent variables

The three elements of the fraud triangle theory entirely relate to the independent variables: pressure, represented by the liquidity ratios (CA/CL) and solvency ratios (DE/EQ), opportunity, indicated by asset turnover ratios (AR/SAL, INV/SAL), and business size (TA). Finally, the utilization of profitability ratios (SAL/TA, NP/SAL, NP/TA, and WC/TA) leads to rationalization (Omar et al., 2017). Table 2 shows the measurements for the independent variables.

Table 2: Fraud Triangle, Fraud Risk Indicators, Proxies, and Variables

Elements of the Fraud Triangle	Indicators of fraud (ISA 240)	Independent variables	Measurements	References
Pressure	Threat of bankruptcy due to operational losses	Liquidity ratio	Current assets/current liabilities (CA/CL)	(Rahman and Jie, 2024) (Spathis, 2002) (Zainudin and Hashim, 2016)
		Solvency ratio	Debt/equity (DE/EQ)	(Omar et al., 2017)
Opportunity	1. Accounts that are challenging to verify 2. Inefficient stakeholder monitoring	Asset turnover ratios	Account receivables/sales (AR/SAL)	(Omar et al., 2017)
			Inventories/sales (INV/SAL)	(Omar et al., 2017)
		Firm size	Total assets (TA)	(Omar et al., 2017)
Rationalization	Aggressive profit trend	Profitability ratios	Sales/total assets (SAL/TA)	(Omar et al., 2017)
			Net profit/sales (NP/SAL)	(Omar et al., 2017)
			Net profit/Total assets (NP/TA)	(Omar et al., 2017)
			Working capital/Total assets (WC/TA)	(Omar et al., 2017)

3.3. Data analysis method

Since the dependent variable will be discrete (fraudulent 1, non-fraudulent 0), the hypotheses will be tested by logistic regression. The reason why logistic regression will be suitable is that it does not assume the independent variables to have a normal distribution. It is an effective estimate of the likelihood of the categorical outcomes (Ghozali, 2011; Khamainy et al., 2022). It has been extensively used in studies of fraud detection because it is interpretable and it can deal with non-linear associations between financial predictors and the probability of fraud.

The logistic regression model used to test the hypotheses is specified as follows:

$$FRAUD = \alpha + \beta_1 CA/CL + \beta_2\, DE/EQ + \beta_3\, AR/SAL + \beta_4\, INV/SAL + \beta_5\, TA + \beta_6\, SAL/TA + \beta_7\, NP/SAL + \beta_8\, NP/TA + \beta_9\, WC/TA$$

Logistic regression estimates the likelihood that a firm issues a fraudulent financial statement based on its pressure, opportunity, and rationalization indicators.

4. Results and Analysis

4.1. Descriptive analysis

Table 3 shows the descriptive statistics of 1,333 firm-years observations consisting of 254 fraudulent and 947 non-fraudulent financial statements. The standard deviation, mean, minimum, and maximum values give an overview of the differences between the nine proxy variables of the two groups. Early insights into the characteristics of fraudulent firms indicate that they are more leveraged and less asset-based, but other ratios exhibit less significant variations. These trends provide some initial information about the behaviour of pharmaceutical companies and point to the fact that not all FTT-based indicators might change significantly across fraud types in the industry. Nevertheless, descriptive patterns are not enough to establish predictive relationships, and, hence, formal multicollinearity and regression analysis are the next procedures.

Table 3: Descriptive Analysis of Variables

	Fraud				Non-Fraud			
Variables	Mean	Std	Min	Max	Mean	Std	Min	Max
CA/CL	2.70	12.41	0.02	182.67	4.01	32.74	0.02	902.00
DE/EQ	3.64	9.05	0.00	44.90	0.92	2.95	0.00	39.67
AR/SAL	0.40	1.46	0.00	23.07	0.36	0.99	0.00	26.82
INV/SAL	0.63	3.55	0.00	45.00	0.46	3.30	0.00	54.17
TA	1249.15	3686.53	0.07	38971.01	2180.69	5347.63	0.01	46334.23
SAL/TA	0.79	1.86	-0.10	29.42	1.37	14.54	-0.03	444.78
NP/SAL	-1.76	17.32	-257.33	43.56	-0.90	17.93	-468.00	115.00
NP/TA	0.01	0.38	-3.04	3.94	0.08	1.05	-5.50	27.60
WC/TA	-0.14	1.36	-16.71	0.99	-0.05	2.46	-47.00	0.95

4.2. Multicollinearity problem detection

Before the estimation of the logistic regression model, multicollinearity has been evaluated as high interrelationships among the independent variables might increase the variance and decrease the reliability of the coefficient estimates (Gujarati et al., 2003). All predictors were calculated to give Pearson correlation coefficients, tolerance values, and variance inflation factors (VIF) to provide stable parameter estimates. Such diagnostics are also necessary due to the fact that the financial ratios tend to be mechanically related to each other. According to Kennedy (1985), the value of tolerance that is below 0.25 and VIF more than 10 indicates possible multicollinearity. Table 4 demonstrates that all tolerance values are greater than 0.25 and all VIFs are near to 1, which demonstrates that multicollinearity between the variables does not exist. Thus, in the regression model, all predictors were kept. The findings are again summarised in Table 5 and bear out the fact that the variables can be simultaneously incorporated without distorting model estimation.

Table 4: Multicollinearity Statistics: Tolerance and VIF Value

Feature	VIF	Tolerance
CA/CL	1.01	0.99
DE/EQ	1.01	0.99
AR/SAL	1.28	0.78
INV/SAL	1.26	0.79
TA	1.02	0.99
SAL/TA	1.03	0.97
NP/SAL	1.02	0.98
NP/TA	1.35	0.74
WC/TA	1.32	0.76

Table 5: Correlation Analysis

Variables	CA/CL	DE/EQ	AR/SAL	INV/SAL	TA	SAL/TA	NP/SAL	NP/TA	WC/TA	FRAUD
CA/CL	1.00	-0.03	0.02	0.03	-0.02	-0.01	-0.02	0.00	0.03	-0.02
DE/EQ	-0.03	1.00	0.01	0.03	-0.07	-0.01	0.01	-0.04	-0.01	0.22
AR/SAL	0.02	0.01	1.00	0.43	-0.02	-0.02	-0.02	-0.02	-0.02	0.02
INV/SAL	0.03	0.03	0.43	1.00	-0.03	-0.01	0.00	-0.01	0.01	0.02
TA	-0.02	-0.07	-0.02	-0.03	1.00	-0.02	0.03	0.00	0.04	-0.08
SAL/TA	-0.01	-0.01	-0.02	-0.01	-0.02	1.00	0.01	-0.10	-0.08	-0.02
NP/SAL	-0.02	0.01	-0.02	0.00	0.03	0.01	1.00	0.14	0	-0.02
NP/TA	0.00	-0.04	-0.02	-0.01	0.00	-0.10	0.14	1.00	-0.47	-0.03
WC/TA	0.03	-0.01	-0.02	0.01	0.04	-0.08	0.00	-0.47	1	-0.02
FRAUD	-0.02	0.22	0.02	0.02	-0.08	-0.02	-0.02	-0.03	-0.02	1

4.3. Logistic regression analysis

4.3.1. Model evaluation

The model viability was evaluated using the Hosmer-Lemeshow goodness-of-fit test. The chi-square is 13.625 with the significance level of 0.0921, and the value is greater than 0.05, which shows that the model fits the data appropriately (Khamainy et al., 2022), illustrated in Table 6. The statistics of likelihood also support this conclusion. Log-likelihood is lower in the null model (-619.63) than in the full model (-590.91), which suggests that the predictors explain the data better.

Table 6: Hosmer-Lemeshow Test

Hosmer-Lemeshow test statistic	13.625
Degree of freedom	8
P-value	0.0921
The model fits the data well (p-value > 0.05)	

Table 7: Result of Likelihood Ratio Test

Null Model Log-Likelihood	-619.63
Full Model Log-Likelihood	-590.91
G-squared	57.43
Degrees of Freedom	9
P-value	0.00
Note: The full model fits the data significantly better than the null model.	

Table 7 indicates that the G-squared value of 57.43 ($p < 0.01$) indicates that the overall model is indeed a significant improvement in the explanatory power. There are two pseudo-R^2 measures that give an insight into explanatory strength. The R^2 of 0.0463 by McFadden and Nagelkerke, R^2 of 0.0305 represent a small portion of the variance in fraudulent reporting that is explained by the model, as depicted in Table 8. These low values are typical of fraud studies because the occurrence of fraud is difficult and infrequent, and may only be partially reflected in financial ratios, indicating that there are industry-dependent qualitative aspects to fraud-risk behaviour.

Table 8: pseudo-R-Square Values

McFadden's R^2	0.0463
Nagelkerke's R^2	0.0305

The next step is to examine the hypothesis and analyze the impact of independent variables on the dependent variable, as shown in Table 9. We analyze the logistic regression results, which serve as an empirical basis for assessing and interpreting research hypotheses, ultimately leading to the acceptance or rejection of each hypothesis. According to Bland and Altman (1995), a hypothesis is considered significant if the significance level is less than 0.05. Therefore, we accept hypotheses when the value falls below 5% and reject them when it surpasses 5%.

Table 9: Logistic Regression Result

Variable	Coefficient	Standard Error	Wald Value	P-Value
Const	-1.3383	0.1053	-12.7042	0.0000
CA/CL	-0.0020	0.0042	-0.4673	0.6403
DE/EQ	0.0875	0.0166	5.2540	0.0000
AR/SAL	0.0014	0.0672	0.0206	0.9836
INV/SAL	0.0070	0.0219	0.3225	0.7471
TA	0.0000	0.0000	-2.1236	0.0337
SAL/TA	-0.0644	0.0666	-0.9673	0.3334
NP/SAL	-0.0017	0.0036	-0.4636	0.6429
NP/TA	-0.1504	0.2096	-0.7178	0.4729
WC/TA	-0.0468	0.0446	-1.0494	0.2940
Nagelkerke R^2	0.0725			

H1: Effect of CA/CL on Financial Statement Fraud.
The liquidity ratio (CA/CL) has a negative but not significant impact on financial statement fraud (coefficient =0.0020; p = 0.6403). Consequently, H1 is rejected. The insignificance can be explained by the presence of industries where it is expected that pharmaceutical companies have the ability to retain constant liquidity statuses owing to the predictable working-capital cycles and good operational cash flows. The homogeneity of the values of liquidity between fraudulent and non-fraudulent companies (1.4014 vs. 1.1217) is evidence that liquidity is not an informative pressure factor in this industry. This is in line with Wesa and Otinga (2018) but opposite to other research findings that liquidity pressure amplifies the risk of fraud (Zainudin and Hashim, 2016). On the whole, the given finding means that the pressure component of FTT might not be as applicable to industries with consistent cash-flow dynamics.
H2: Effect of DE/EQ on Financial Statement Fraud
A positive but extremely significant impact on fraud is the solvency ratio (DE/EQ) (coefficient = 0.0875; p = 0.0000). Thus, H2 is accepted. Fraudulent firms have greater leverage (mean = 3.6417) than non-fraudulent firms (mean = 0.9183) by a significant margin, which means that financial distress and debt-related pressure enhance motivation towards misreporting. This finding is in line with other existing research works (Chow and Rice, 1982; Spathis, 2002; Summers and Sweeney, 1998), which found that solvency stress is a very good predictor of fraud. This also validates the applicability of the pressure element of FTT with solvency only, but not liquidity, in the pharmaceutical industry.
H3: Effect of AR/SAL on Financial Statement Fraud
The relationship between fraud and accounts receivable-to-sales ratio (AR/SAL) is positive but insignificant (coefficient = 0.0014; p = 0.9836). Therefore, H3 is rejected. The pharmaceutical industry has long sales cycles, multi-stage distribution channels, and accrual variability that is caused by R&D, which has an effect on revenue recognition (Wong and Venkatraman, 2015). These operational variables compromise receivables data in fraud detection. Though it is implied in the previous studies that receivables manipulation is possible (Sihombing, 2016), this ratio does not substantially distinguish between fraudulent and non-fraudulent companies in this sample.

H4: Effect of INV/SAL on Financial Statement Fraud
The inventory-to-sales ratio (INV/SAL) demonstrates some positive but insignificant effect (coefficient = 0.0070; p = 0.7471) that leads to the rejection of H4. The elevated inventory rates of pharmaceutical companies may be the result of the lengthy production cycle, quality standards, and regulatory stocks, as opposed to the fraudulent accounting (Bhattacharya et al., 2013; Bolineni, 2016). These aspects of the industry reduce the predictive use of inventory ratios to identify fraud, in line with Khamainy et al. (2022). This implies that opportunity indicators in FTT do not work in highly regulated and long production cycle industries.
H5: Effect of TA on Financial Statement Fraud
Total assets (TA) hurt fraud, which is statistically significant (coefficient ≈ -0.0000; p = 0.0337). Thus, H5 is accepted. Companies that have less substantial asset bases seem more susceptible to manipulation, which may be explained by the lack of strong internal controls, their greater operational vulnerability, and their lesser monitoring ability. This is in agreement with Spathis (2002), and this proves that the size of the firm is among the most consistent opportunity-related predictors of fraud.
H6: Effect of SAL/TA on Financial Statement Fraud
The outcome of the sales-to-total-assets ratio (SAL/TA) is negative but insignificant (coefficient = -0.0644; p = 0.3334), which results in the rejection of H6. This ratio is a weak indicator of rationalization used to detect fraud, as high R&D investments and a protracted process of developing a product inflate total assets without a corresponding rise in sales. This fact points out that the conventional profitability indicators are not well-suited to the industry structure.
H7: Effect of NP/SAL on Financial Statement Fraud
Net profit-to-sales (NP/SAL) exerts a negative (-0.0017), although not significant (p = 0.6429) influence on fraud and leads to the rejection of H7. The money spent on R&D, meeting requirements, and litigation threats lowers the profit margin in the industry, making it less effective in fraudulent behaviour detection. Therefore, rationalization indicators can be obscured in the pressure of systems in pharmaceuticals.
H8: Effect of NP/TA on Financial Statement Fraud
The insignificant negative impact is also reflected in net profit-to-total-assets (NP/TA) (coefficient = -0.1504; p = 0.4729), which results in the rejection of H8. Assets of pharmaceutical companies have patents, production plants, and capital related to research and development and which dilute profitability ratios. In that regard, NP/TA fails to significantly reflect the motivations of manipulation in this industry.
H9: Effect of WC/TA on Financial Statement Fraud
Working capital-to-total-assets (WC/TA) has a negative, albeit insignificant, coefficient (coefficient = -0.0468; p =0.2940), which leads to the rejection of H9. The fact that seasonal changes in production, inventory cycles, and strategic working-capital management make the ratio less sensitive to fraud. This supports the observation that a majority of the rationalization proxies are not industry effective.

5. Testing of Robustness

The robustness checks were done to assess the stability of the model in case of substituting the variables or eliminating them. As it was done by Lu and White (2014), the model was re-estimated after excluding AR/SAL and WC/TA and including Return on Total Assets (ROTA) and Operating Profit Margin (OPM). Multicollinearity diagnostics were satisfactory, and all the VIF values were less than 10, as shown in Table 10. The patterns in the logistic regression in Table 11 are similar to the main model. The positive and significant relationship between solvency (DE/EQ) and fraud still exists, and the total assets are still showing a significant negative relationship. There are no significant liquidity, turnover, and profitability measurements. Such congruent findings are very strong indicators of the soundness of the results, and they can support the idea that solvency pressure and firm size are the sole significant predictors of financial statement fraud in the Indian pharmaceutical industry, which are industry-specific weaknesses of the Fraud Triangle Theory.

Table 10: Multicollinearity Statistics: Tolerance and VIF Value

Feature	VIF	Tolerance
CA/CL	1.01	0.99
DE/EQ	1.06	0.95
INV/SAL	1.01	0.99
TA	1.02	0.98
SAL/TA	1.01	0.99
NP/SAL	1.02	0.98
NP/TA	1.04	0.97
ROTA	1.05	0.95
OPM	1.07	0.94

Table 11: Logistic Regression Result

Variable	Coefficient	Standard Error	Wald Value	P-Value
Const	-1.3397	0.0977	-13.7166	0.0000
CA/CL	-0.0021	0.0044	-0.4714	0.6374
DE/EQ	0.0778	0.0164	4.7324	0.0000
INV/SAL	0.0069	0.0197	0.3514	0.7253
TA	-0.0000	0.0000	-2.0640	0.0390
SAL/TA	-0.0290	0.0530	-0.5474	0.5841
NP/SAL	-0.0020	0.0036	-0.5637	0.5730
NP/TA	-0.0578	0.1495	-0.3869	0.6988
ROTA	-0.0033	0.0031	-1.0545	0.2917
OPM	0.0000	0.0000	-1.6448	0.1000
Nagelkerke R^2	0.0770			

6. Discussion

This paper tested the hypothesis that the FTT can be successful in explaining financial statement fraud in the pharmaceutical industry of India. The findings demonstrate that it is only two variables, namely solvency pressure (DE/EQ) and the firm size (TA), which are statistically significant predictors of fraud; the other seven conventional FTT-based financial indicators are not. Such a trend implies that fraud in the pharmaceutical industry does not act as in most international settings, as well as in other Indian industries, which makes it necessary to interpret FTT in specific relations to the sector.

6.1. Significant and insignificant variables interpretation

There is a very high positive correlation between the debt-to-equity ratio and fraud, meaning that the most effective force that causes manipulations in this industry is solvency pressure. Pharmaceutical companies are relying excessively on long-term borrowings to finance research and development, clinical trials, approval, and distribution around the world. In case of high leverage, the managers are under pressure to exhibit financial stability to the lenders and investors. This behaviour is in line with the previous studies that indicate that financial stress predisposes individuals to misreporting (Chow and Rice, 1982; Summers and Sweeney, 1998; Spathis, 2002). In India, however, this pressure is even more intense because of the price-control policies, strict compliance requirements, and frequent inspections by the authorities like the US FDA (Bose and Malhotra, 2021). Such an institutional environment increases managerial pressures to sanitize profits or conceal business flaws, and solvency is a highly effective trigger of fraud in the Indian pharmaceutical environment.

The firm size is also negatively related to fraud. The bigger the pharmaceutical, the greater the internal controls, the specialized audit committee, and the broader the watchfulness of the local and international regulators. Institutional investors and analysts also scrutinize them, diminishing the opportunities for manipulation. Smaller firms, conversely, tend to have less governance, fewer resources in compliance, and more uncertainty in their operations. These attributes offer more room to misstate, which coincides with the opportunity aspect of FTT (Beasley, 1996; Roychowdhury and Srinivasan, 2019). The regulatory attention in India is usually centered on bigger companies that have international approvals, meaning that the smaller companies are left relatively unchecked and susceptible to fraud.

This can be attributed to several peculiarities of the pharmaceutical sector. Liquidity: Pharmaceutical companies tend to have stable liquidity as there is a reliable production cycle and demand for the necessary drugs on a long-term basis (Persons, 1995). Fluctuations in liquidity are thus unreliable indicators of stress or manipulation; Receivables and Inventories: Long credit terms, sales of drugs to exports, clinical trial timelines, and high inventory standards do not predict these ratios regardless of fraud (Wong and Venkatraman, 2015; Bhattacharya et al., 2013); Profitability Ratios: Profit margins in pharma are inherently volatile due to R&D, patent expiries, delays in regulatory approvals, and legal suits (Beneish, These differences are operational facts not fraud motives; and Sales Efficiency: Intangible assets, R&D cycles and manufacturing shifts may distort asset utilisation ratios and that these are unreliable measures of fraud. Such industry-dependent dynamics undermine the rationalization and opportunity proxies that have been employed in FTT, demonstrating that traditional fractional predictors are unable to fully explain the risk of fraud in complex and innovation-intensive industries.

6.2. Pseudo-R^2 2 is low, and the inconvenience of ratio-based models

The poor pseudo-R^2 (approximately 3-4 percent) is consistent with the previous studies that show that fraud is infrequent, hidden, and driven by governance, incentives, and behavioural factors rather than by pure numerical measurements (Dechow et al., 2011; Perols, 2011). Ratio-based models only identify symptoms, but not the underlying managerial intents and off-book transactions that result in fraud. These results confirm the emerging trend in the world literature that traditional FTT proxies require being supplemented by: governance variables, behavioural indicators, text analysis of annual reports, and machine learning-based anomaly detection. Therefore, the limited explanatory force presented in this article confirms that FTT is only a partial explanation of the phenomenon of fraud in contemporary industries, importantly, those that are characterized by a high level of R&D, an uncertain regulatory environment, and opaque reporting conditions.

In general, the findings suggest that FTT has not lost its significance in pressure and opportunity explanation, but its rationalization measures and various classical financial variables remain less significant in the Indian pharmaceutical industry. This implies that fraud control systems within this sector rely more on financial strains and internal control loopholes than on normal performance and turnover ratios. It also emphasizes the usefulness of a combination of FTT with extended theories and sector-deliberate proxies to determine better fraud-risk measurement.

6.3. Theoretical contributions

This research provides some of the theoretical contributions to the literature on fraud. To start with, it shows that not all industries use the three pillars of FTT, which include pressure, opportunity, and rationalization. The most notable attributes of the Indian pharmaceutical market are that only pressure (measured by solvency) and an opportunity (captured by firm size) have a significant impact on fraud, whilst the traditional rationalization proxies of profitability ratios are insignificant predictors (Beneish, 1999; Persons, 1995; Kumar and Rout, 2020). This underscores the fact that FTT needs to be applied in a particular industry and regulatory setting, instead of being universal (Sharma and Dev, 2021; Bose and Malhotra, 2021). Second, the findings indicate that there are critical drawbacks to the ratio-based fraud indicators. The breakdown of seven popular FTT proxies implies that financial ratios may not be effective enough to spell out the motive or behavioural facets of fraud (Dechow et al., 2011; Perols, 2011). It confirms the theoretical change to the multi-dimensional fraud models that include the quality of governance, managerial motivation, behavioural indicators, regulatory pressure, and textual indicators (Hajek and Henriques, 2017; Shahana et al., 2023). Third, the paper lends credence to the importance of combining FTT with new systems, including Fraud Diamond, Fraud Hexagon, Beneish M-score, and AI-based analytics. These broadened theories incorporate other aspects such as capability, collusion, arrogance, and digital anomalies- aspects that are becoming more powerful in sophisticated industries such as pharmaceuticals. The study has demonstrated the inadequacy of the classical FTT proxies and so encourages future studies to embrace theoretically hybrid approaches that integrate behavioural, operational, regulatory, and data-driven indicators.

6.4. Practical contributions

These findings produce some valuable practical implications on the part of the auditors, regulators, and investors. The first point is that the study has definite high-risk profiles: more vulnerable to fraud are highly leveraged and smaller pharmaceutical companies. It allows conducting the audit planning and enforcement on a risk basis and prioritizing those firms that need more attention (Beasley, 1996; Roychowdhury and Srinivasan, 2019). Second, the results highlight the limitations of generic financial indicators—such as liquidity, profitability, receivables, and inventory ratios—because these metrics are heavily influenced by long R&D cycles, government price controls, regulatory testing requirements, and complex distribution channels (Wong and Venkatraman, 2015; Bhattacharya et al., 2013). Regulators and auditors should therefore rely on sector-specific risk factors, such as R&D capitalization practices, regulatory observations, product pipeline risks, and compliance history. Third, the study emphasizes the need to incorporate governance, behavioural, and regulatory indicators into fraud-risk assessment. These include board oversight quality, internal control effectiveness, managerial incentives, history of regulatory sanctions, and behavioural red flags in disclosures (Lokanan, 2014; Omar et al., 2017). Such indicators can significantly strengthen early-warning systems and support proactive fraud detection. Together, these contributions provide a more realistic and context-sensitive understanding of fraud risk in the Indian pharmaceutical sector and guide the development of more effective audit and regulatory strategies.

7. Conclusion

The paper evaluated the relevance of the FTT in the explanation of financial statement fraud in the pharmaceutical sector in India. The results show that there are only two indicators that are significant in the fraud risk, these are the solvency (debt-to-equity ratio) and the firm size. Fraud is not well forecasted by other financial parameters, including liquidity, profitability, receivables, and inventory ratios, in large part because of the intensive operations of the sector in terms of research and development, long production and credit cycle, and the high regulatory standards (Bose and Malhotra, 2021; Kumar and Rout, 2020; Wong and Venkatraman, 2015). All these traits undermine the conventional financial red flags and show that frauds appear in the highly controlled knowledge-intensive sectors differently (Dechow et al., 2011; Spathis, 2002). The research adds to the theory, as it emphasizes the fact that the pressure and opportunity elements of FTT are influenced by the industry context in a strong manner (Cressey, 1953; Skousen et al., 2009). Meanwhile, it suffers a number of limitations. Audit opinions are used to proxy financial statement fraud and help identify reporting anomalies, but not to verify the existence of intentional fraud (Perols, 2011). It is also based on financial ratios (only) and neglects the inclusion of governance, behavioural, and regulatory indicators that are usually at the center of fraud (Hajek et al., 2017; Shahana et al., 2023). In addition, the results are only applicable to the pharmaceutical industry but not necessarily to other industries. Logistic regression model also has a small explanatory power, which is consistent with the concealed and complicated nature of fraud (Dechow et al., 2011; Beneish, 1999). Such restrictions provide a research option in the future. Research ought to embrace multidimensional frameworks that consider the governance schemes, board features, managerial incentives, behavioural indicators, and regulatory enforcement information (Lokanan, 2014; Omar et al., 2017). High-end machine-learning algorithms would be able to learn non-linear associations neglected by the current models (Ravisankar et al., 2010; Rahman et al., 2024). Lastly, creating industry-specific fraud-risk models would assist in understanding more effectively how fraud arises in industries with high R&D and heavy regulation, better predicting and intervening in practice.

CRediT Authorship Contribution Statement

Himanshoo - conception or design of the work, including acquisition of data, analysis, and interpretation of data; prepared all tables and figures. Sunitha- revised the work critically and approved the version to be published. All authors reviewed the manuscript.

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Data Availability

Data is available with the corresponding author.

Declarations

Competing interests

The authors have no competing interests to declare that are relevant to the content of this article.

Ethical Approval

The authors confirm that they followed the ethical guidelines of the journal and respect the ethical responsibilities of authors.

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