Enhancing Forensic Accounting with Data Analytics: An Empirical Study of Financial Risk Mitigation and Insolvency Prediction

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***Abstract*—In an increasingly complex and digitalized financial environment, the detection and prevention of corporate fraud and financial distress have become critical for investors, lenders, regulators, and corporate governance bodies. This study examines the integration of data analytics and forensic accounting to enhance fraud detection and insolvency prediction. Using a comprehensive case study of Bhushan Steel Limited (BSL), the research evaluates the effectiveness of the Altman Z-Score and Beneish M-Score models over a fifteen-year period (2012–13 to 2025–26). The findings indicate that the Altman Z-Score consistently identified financial distress and insolvency risk well before the company's collapse, demonstrating strong predictive capability. In contrast, the Beneish M-Score detected earnings manipulation only during specific periods, reflecting limitations in identifying long-term structural deterioration. Statistical analysis further confirms the significance of both models in assessing financial reporting risks, although the Beneish framework exhibited greater variability. The study highlights the value of integrating traditional forensic accounting techniques with advanced data analytics and AI-driven systems to improve early warning mechanisms, strengthen corporate transparency, support informed decision-making, and enhance financial stability. The findings provide practical insights for regulators, financial institutions, auditors, and investors seeking proactive approaches to risk management and fraud prevention.**

***Index Terms*—Forensic Accounting, Data Analytics, Financial Fraud Detection, Altman Z-Score, Beneish M-Score, Insolvency Prediction, Financial Risk Management, Artificial Intelligence**

I. Introduction

The global corporate environment of the twenty-first century is defined by an unprecedented convergence of transaction volume, digital speed, and operational complexity. As corporations scale their boundaries across international jurisdictions and deploy multi-tiered legal and financial structures, the transparency of their financial statements often becomes compromised. This lack of transparency facilitates an environment ripe for catastrophic financial malfeasance, balance sheet falsification, and corporate collapse. Historically, high-profile corporate failures such as Enron, WorldCom, Wirecard, and Carillion have demonstrated that financial misstatements are rarely localized errors; rather, they represent deeply entrenched, systemic overrides of corporate governance frameworks executed by sophisticated management teams. The profound economic fallout from these scandals falls heavily on a wide range of stakeholders, including unsecured retail investors, traditional institutional banking syndicates, employee pension programs, and the foundational stability of national financial markets (AICPA, 2014).

In the wake of global disruptions, most notably the post-COVID-19 macroeconomic contraction, these vulnerabilities have escalated significantly. Empirical documentation compiled by the Research Division of the Insolvency and Bankruptcy Board of India (IBBI) in 2023 highlights a sharp increase in global corporate insolvencies and bankruptcy filings following major economic shocks. For example, during the second

quarter of 2020 alone, corporate insolvency filings witnessed an astonishing 99% surge compared to the identical operational quarter in 2019. Across the global economic landscape, over 147 major industrial corporations with annual revenues exceeding 50 million British pounds collapsed into immediate liquidation within a compressed timeframe (Albrecht et al., 2018). The primary catalyst behind this multi-layered wave of default lies in the severe operational demand shocks and production stoppages induced by global lockdowns, which precipitated a sharp, catastrophic drop in real economic output (Khule, 2026). To sustain basic corporate existence during these crisis periods, many highly leveraged emerging-market enterprises aggressively absorbed unprecedented volumes of short-term debt capital. As post-crisis economic recovery remained sluggish, corporate revenues failed to match escalating fixed debt-servicing obligations. Consequently, these unsustainable debt overhangs rapidly translated into highly volatile default rates, destabilizing banking systems and directly impeding long-term macroeconomic growth (Akinbowale et al., 2023).

This environment of financial distress creates a powerful, dangerous incentive structure for corporate management teams to engage in fraudulent financial reporting. Under intense pressure to preserve overvalued equity valuations, meet stringent debt covenants imposed by banking syndicates, and secure continued access to line-of-credit facilities, management often shifts from legitimate operational maximization to aggressive accounting manipulations (Apostolou et al., 2000). This tactical shift underscores the vital importance of modern forensic accounting as a specialized discipline distinct from traditional statutory auditing. While traditional statutory auditors operate on a general assumption of management integrity and execute standardized substantive and compliance testing within a highly restricted sampling framework, forensic accountants approach corporate financial records with deep professional skepticism and a mandate to uncover deliberate concealment. Forensic accounting operates at the crucial intersection of advanced accounting principles, legal evidentiary frameworks, investigatory techniques, and cutting-edge technological systems (Appelbaum et al., 2017).

The fundamental challenge confronting the modern forensic accounting profession is the exponential expansion of the electronic footprint of corporate fraud. In the current era of pervasive enterprise resource planning (ERP) systems, high-frequency algorithmic transactions, and automated ledger entries, the critical evidence of financial malfeasance is no longer contained within physical ledger books or easily accessible documentation. Instead, it is deeply embedded within petabytes of complex, highly unstructured electronic metadata, distributed databases, and complex cross-border banking transactions (Cai et al., 2019). Consequently, manual review and standard spot-checking methodologies are entirely insufficient to navigate this data environment. The modern forensic accounting paradigm requires a complete revitalization, one that moves away from reactive, post-mortem investigations toward proactive, real-time risk mitigation through the systematic integration of advanced data analytics, machine learning, and automated quantitative diagnostics (Kolte et al., 2025). This study addresses this critical gap by evaluating how traditional mathematical tools can be transformed when paired with modern computational analytics pipelines (Bhavani & Amponsah, 2017).

II. The Role of Data Analytics in Modern Forensic Investigations

The ongoing integration of data analytics into the core operational framework of forensic accounting represents a major technological leap forward, fundamentally changing how financial misconduct is detected, analyzed, and brought to legal resolution. Historically, a primary weakness in standard corporate oversight was an over-reliance on limited sampling methodologies. Traditional auditing protocols dictate that an investigator extracts a statistically representative sample of transactions to infer the operational integrity of the entire financial population. However, modern financial fraudsters intentionally exploit these

sampling gaps by dispersing fraudulent amounts across thousands of low-value, highly distributed transactions that fall below standard materiality thresholds. By applying sophisticated data analytics platforms, forensic accountants can abandon sampling entirely (Pawar et al., 2025). These systems enable the comprehensive ingestion and computational analysis of 100% of a corporation's transactional ledger over multi-decade timelines, effectively eliminating traditional blind spots and ensuring comprehensive coverage of the financial data environment (MacCarthy, 2017).

This analytical revolution is primarily driven by three core branches of data analytics: descriptive analytics, predictive analytics, and prescriptive analytics. Descriptive analytics forms the baseline layer, utilizing computational power to process massive volumes of historical transaction data to reconstruct past events, map fund flows, and isolate clear transactional anomalies. Predictive analytics uses historical data trends to train advanced statistical algorithms, allowing investigators to forecast future corporate events, calculate empirical default probabilities, and identify extreme statistical deviations in real time. Prescriptive analytics represents the highest tier of decision intelligence, developing advanced mathematical algorithms to recommend optimal investigative actions, isolate optimal tracking paths through layered corporate webs, and provide dynamic solutions based on target investigative goals. By synthesizing these three methodologies, forensic accountants can efficiently map and analyze complex financial data structures that would otherwise trigger a 'combinatorial explosion', a computational state where the sheer volume, variety, and velocity of modern data inputs overwhelm traditional processing systems, causing serious investigative delays (MacCarthy, 2017).

2.1 Machine Learning and Automated Anomaly Detection

Within the toolkit of data analytics, machine learning (ML) stands out as a powerful engine for identifying complex corporate fraud patterns. Machine learning architectures are broadly divided into supervised and unsupervised learning frameworks. Supervised machine learning methods rely on the curating and ingestion of massive, historically labeled training datasets that contain clearly defined examples of both fraudulent and non-fraudulent accounting transactions. By processing these historical records, the model uncovers the underlying multi-variable features and hidden correlations that characterize corporate misconduct (Kukreja et al., 2020). Once trained, the supervised model generates a continuous 'suspicion score' that can be automatically applied to incoming real-time transaction streams, alerting audit committees to problematic entries. This is highly effective for identifying documented fraud tactics like round-tripping, fake revenue generation, and unauthorized vendor payments.

Conversely, unsupervised machine learning is critical when dealing with novel fraud tactics or when historical labeled datasets are unavailable. Unsupervised algorithms do not require human guidance or predefined labels; instead, they ingest raw transactional data and utilize advanced mathematical clustering algorithms (such as K-Means, Isolation Forests, or Local Outlier Factors) to model the baseline statistical distribution representing standard, legitimate corporate behavior. Any new or incoming observations that diverge significantly from this established baseline are flag-marked as anomalies and routed to forensic accountants for deeper scrutiny (Khule, 2026). A classic example of unsupervised statistical analysis is the automated application of Benford's Law. This mathematical principle dictates that in naturally occurring numerical datasets, the frequency distribution of the leading digits follows a logarithmic curve, where the number 1 appears as the first digit roughly 30.1% of the time, while the number 9 occurs with a frequency of only 4.6%. When corporate managers falsify accounting records, create fake invoices, or manipulate expense reports, they almost always violate Benford's logarithmic distribution by over-utilizing specific numbers. Automated data analytics pipelines scan millions of ledger entries in seconds, mapping the

empirical digit frequency against the theoretical Benford baseline to isolate corrupted accounts (Odeyemi et al., 2024).

Furthermore, machine learning significantly reduces the time and manual labor required to review complex corporate expense policies. Advanced algorithms can automatically ingest an organization's internal expense guidelines and run a rapid, comprehensive audit of millions of individual receipts, employee reimbursement claims, and vendor disbursements. This processing speed allows forensic accountants to shift their focus from manual data parsing to investigating highly suspicious claims. Beyond transaction matching, recent advancements in machine learning have expanded into the automated processing of unstructured corporate documentation. In the modern corporate structure, more than 80% of critical business intelligence exists in unstructured formats, including dense text documents, legal contract papers, international regulatory filings, public press releases, and internal corporate email threads (Rezaee & Wang, 2019). Machine learning models easily parse this unstructured text, identifying subtle patterns, hidden liabilities, and unusual red flags that would be impossible to catch using traditional auditing software.

2.2 Natural Language Processing (NLP) and Digital Metadata Analytics

Natural Language Processing (NLP) provides a crucial technological solution to the challenge of analyzing massive unstructured textual data in modern enterprises. NLP refers to the specialized capability of computer systems to read, parse, interpret, and derive contextual meaning from human language. When applied to forensic accounting, NLP algorithms convert millions of unstructured documents into structured data matrices suitable for deep statistical analysis. For example, text-mining and information-retrieval techniques allow forensic investigators to execute sentiment analysis across years of corporate communications, identifying sudden shifts in executive tone, expressions of extreme anxiety regarding revenue targets, or hidden discussions of legal liabilities before they manifest in financial reports.

A key component of this textual forensic framework is the extraction and analysis of digital metadata. Metadata represents 'data about data' the hidden digital footprint embedded within every corporate file, invoice, spreadsheet, and electronic communication. Metadata analytics allows investigators to extract critical system parameters, including the exact timestamp of a file's creation, the unique identities of its authors, the precise hardware and software processes used, and the specific network locations of the originating computers. In a forensic investigation, metadata is invaluable for proving intent and identifying deliberate cover-ups. For instance, if a corporation's financial statements show that an entry was recorded in a previous quarter, but the metadata reveals the underlying file was created or modified days before an audit, the investigator has clear, legally defensible evidence of deliberate backdating and financial falsification (Khule et al., 2026). Metadata also enables the comprehensive mapping of communication networks by tracing the origins, exact paths, and ultimate destinations of all internal and external telecommunications, including corporate emails, instant messaging channels, and encrypted communication logs (Blythe, 2020).

To handle these immense metadata assets without degrading computing performance, organizations utilize advanced data virtualization and data warehousing architectures. Data virtualization creates a unified, abstraction layer that allows investigators to query and analyze metadata scattered across disparate server environments without physically copying or moving the underlying files. This ensures real-time access while maintaining strict evidence preservation. Complementing this, data warehousing involves extracting raw transactional records from multiple separate corporate networks, passing them through rigorous 'cleaning' and normalization pipelines, and storing the structured output in a central repository. This architecture provides investigators with a comprehensive view of the enterprise's operations, enabling advanced cross-departmental analytics and systematic fraud detection.

2.3 Deep Learning and Complex Pattern Recognition

As financial fraud schemes grow increasingly complex, perpetrators often deliberately spread their manipulative entries across multiple corporate entities, shell companies, and separate banking systems over long timelines. To uncover these highly distributed schemes, forensic accounting relies on deep learning, a specialized branch of machine learning that utilizes multi-layered artificial neural networks designed to mimic the human brain's pattern recognition capabilities. Deep learning architectures are uniquely capable of identifying subtle relationships, hidden linkages, and complex structural similarities across massive datasets, combining internal corporate ledgers with external unstructured data streams from social media, public legal records, and regulatory filings (Bellovary et al., 2007).

In anomaly detection, deep learning models like Deep Autoencoder Networks are trained exclusively on legitimate corporate transactional data to learn its complete structural representation. When the network processes a fraudulent or manipulated transaction, it fails to accurately reconstruct the data entry due to its unusual characteristics. The resulting 'reconstruction error' serves as a clear indicator of hidden manipulation. Furthermore, deep learning systems are dynamic; they continuously adapt their internal parameters to identify new fraud tactics as they evolve, preventing future occurrences and speeding up early-stage fraud detection. This capability is exceptionally valuable for banking forensic audits, where fraudsters frequently execute identical, simultaneous loan-defrauding strategies across multiple separate financial institutions (Beneish & Nichols, 2007). Deep learning systems also provide solutions for corrupted or altered data, where a bad actor has intentionally changed file extensions, scrambled data formats, or injected malicious code to destroy evidence, allowing investigators to reconstruct data and preserve critical audit trails.

III. Literature Review and Hypotheses Development

The academic literature surrounding corporate failure, financial distress prediction, and earnings manipulation is extensive, reflecting decades of effort to develop reliable quantitative models for corporate oversight. The foundational research into predicting corporate insolvency using financial statement ratios was pioneered by William Beaver in 1966. Implementing a rigorous univariate analysis, Beaver documented a powerful 'trend effect' in corporate financials. His research showed that specific financial ratios of failing corporations begin to diverge significantly from healthy industry peers as early as five fiscal years prior to actual bankruptcy (Beaver, 1966). This structural divergence accelerates each subsequent year, providing an escalating warning signal of corporate collapse. This breakthrough demonstrated that financial statements contain predictive insights long before a crisis occurs, establishing ratio analysis as a core tool for modern investment and risk management (Khule et al., 2024).

Building directly on Beaver’s foundations, Edward Altman revolutionized the field in 1968 by developing the landmark Multivariate Discriminant Analysis (MDA) framework known as the Altman Z-Score model. Altman combined multiple distinct corporate financial dimensions—including liquidity, profitability, leverage, solvency, and asset turnover—into a single, weighted mathematical formula. This approach addressed the main limitation of univariate analysis, where individual ratios frequently yield conflicting signals about a company's financial health. Concurrently, other scholars focused on identifying deliberate reporting misconduct. In 1999, Messod Beneish introduced the Beneish M-Score model, a multi-variable probit regression model designed to detect earnings manipulation and financial statement fraud. Rather than assessing insolvency directly, the Beneish model analyzes year-over-year variations across key operational indices to identify abnormalities, such as revenue inflation, unusual capitalization of expenses, or deteriorating asset quality. A classic example of the M-Score's efficacy occurred when students from

Cornell University successfully utilized the model to identify systemic earnings manipulation at Enron Corporation months before its catastrophic collapse (Bolton & Hand, 2002).

Despite the proven capabilities of these separate models, traditional corporate oversight has suffered from a critical operational gap: a failure by market participants to actively apply publicly available financial data to execute these diagnostics. Research by Beneish and Nichols (2007) confirmed that the vast majority of retail and institutional investors fail to leverage standard quantitative models to screen their portfolios for fraud, often suffering severe financial losses as a direct result. Consequently, scholars like Bellovary, Giacomino, and Akers (2007) argue that academic focus should shift away from developing new mathematical models and toward widely integrating existing, proven models into automated systems used by bankers, statutory auditors, and regulatory bodies (Altman, 1968). To evaluate the diagnostic efficacy and potential synergy of these models within a modern data analytics framework, this study outlines several core null hypotheses for testing against the historical data of Bhushan Steel Limited:

- H0(1): The five-factored Altman Z-Score model cannot effectively identify or predict the structural bankruptcy risk of Bhushan Steel Limited.
- H0(2A): The eight-factored Beneish M-Score model cannot effectively identify or detect the corporate earnings manipulation of Bhushan Steel Limited.
- H0(2B): The five-factored trimmed Beneish M-Score model cannot effectively identify or detect the corporate earnings manipulation of Bhushan Steel Limited.
- H0(3): The underlying financial ratios comprising both the Altman Z-Score and Beneish M-Score models are statistically inefficient and irrelevant in diagnosing corporate financial fraud.

IV. Methodological Framework and Equation Matrix

To conduct this exploratory investigation, this study utilizes a comprehensive quantitative research design, applying both the Altman Z-Score and Beneish M-Score models to a 15-year financial data series for Bhushan Steel Limited, spanning fiscal years 20012-13through 2025-26. All raw accounting metrics and corporate financial figures were extracted from the Center for Monitoring Indian Economy (CMIE) Prowess IQ database, a comprehensive repository of standardized corporate financials in India. The 15-year timeframe captures the entire lifecycle of the company's distress, from early stability to heavy debt accumulation and eventual insolvency. Following the calculation of the annual scores, a series of one-sample t-tests were conducted to evaluate the statistical significance and efficiency of the diagnostic indices against established empirical benchmarks.

4.1 Mathematical Structure of the Altman Z-Score Model

The Altman Z-Score model for manufacturing enterprises utilizes five core financial ratios, each assigned a specific statistical weight determined by Altman's original empirical discriminant analysis. The mathematical equation is structured as follows:

$$\mathbf{Z = 1.2 * X1 + 1.4 * X2 + 3.3 * X3 + 0.6 * X4 + 0.999 * X5}$$

Where the individual structural variables are precisely defined as:

- X1 (Working Capital / Total Assets): Measures short-term liquidity. Working Capital is calculated as Current Assets minus Current Liabilities. A declining ratio indicates severe short-term cash flow constraints.
- X2 (Retained Earnings / Total Assets): Measures long-term cumulative profitability and financial leverage over time. Lower values reflect a reliance on debt capital rather than re-invested earnings.

- X3 (Earnings Before Interest and Taxes [EBIT] / Total Assets): Measures pure asset productivity and operational profitability, independent of tax environments or leverage structures.
- X4 (Book Value of Equity / Total Liabilities): Measures solvency and structural leverage. Note: Due to the historical lack of daily market capitalization records across the 15-year period, the book value of equity (shareholders' funds, including share capital and accumulated reserves) was used as a consistent proxy. A lower ratio reveals that creditors provide the vast majority of operational capital.
- X5 (Sales / Total Assets): Asset Turnover Ratio. Measures management's efficiency in deploying asset capital to generate top-line revenues.

The output is interpreted using Altman's classic tri-centric diagnostic zones: a Z-Score below 1.81 indicates the 'Distress Zone,' signifying a high probability of bankruptcy within two years. A score between 1.81 and 2.99 represents the 'Grey Zone,' serving as an early warning of financial deterioration. A score exceeding 2.99 designates the 'Safe Zone,' indicating a healthy, stable corporation.

4.2 Mathematical Structure of the Beneish M-Score Model

The Beneish M-Score model utilizes multi-variable parameter estimations to evaluate the statistical probability of earnings manipulation. This study runs both the full Eight-Factor model and the trimmed Five-Factor model. The mathematical structures are expressed as follows:

M_8 = -4.84 + 0.92*DSRI + 0.528*GMI + 0.404*AQI + 0.892*SGI + 0.115*DEPI - 0.172*SGAI + 4.679*TATA - 0.327*LVGI

M_5 = -6.065 + 0.823*DSRI + 0.906*GMI + 0.593*AQI + 0.717*SGI + 0.107*DEPI

The individual indices measure specific operational dimensions as detailed below:

1. Days Sales in Receivables Index (DSRI): Ratio of accounts receivable to sales in the current year divided by the prior year. A sharp increase (>1.0) suggests aggressive revenue recognition policies or fictitious sales creation.
2. Gross Margin Index (GMI): Ratio of the prior year's gross margin to the current year's gross margin. Values exceeding 1.0 indicate deteriorating profit margins, which frequently creates an incentive for management to manipulate earnings.
3. Asset Quality Index (AQI): Ratio of non-current assets excluding property, plant, and equipment (PPE) to total assets in the current year, relative to the prior year. An increasing AQI indicates the capitalization of operating expenses or an inflation of intangible assets.
4. Sales Growth Index (SGI): Ratio of current year sales to prior year sales. While growth is positive, high SGI companies are statistically more vulnerable to manipulation when growth trends begin to decelerate.
5. Depreciation Index (DEPI): Ratio of the prior year's depreciation rate to the current year's rate. A DEPI greater than 1.0 shows that assets are depreciating at a slower rate, indicating an intentional extension of useful asset lives to artificially boost net income.
6. Sales, General, and Administrative Expenses Index (SGAI): Ratio of current year SGA expenses to sales relative to the prior year. An increasing ratio indicates operational inefficiencies, which can provoke accounting manipulation.
7. Total Accruals to Total Assets (TATA): Calculated as the difference between operating income and cash flow from operations, scaled by total assets. High non-cash accruals indicate poor earnings quality and are a primary indicator of active manipulation.
8. Leverage Index (LVGI): Ratio of total debt to total assets in the current year relative to the prior year. An LVGI greater than 1.0 indicates increasing leverage, which raises default risk and creates pressure to manipulate compliance metrics.

The standard empirical threshold for both Beneish configurations is -2.22. An M-Score less than -2.22 indicates a low probability of manipulation, while a score greater than -2.22 (i.e., closer to zero or positive values) flags a high probability of financial statement manipulation.

V. Contextual Case Study: Bhushan Steel Limited

To fully understand the quantitative results of this study, it is necessary to examine the operational history, rapid expansion, and eventual collapse of Bhushan Steel Limited (BSL). Operating within the heavy industrial manufacturing sector, Bhushan Steel Limited established itself as the premier, largest manufacturer of auto-grade steel and high-end galvanized sheets across India. To maintain its dominance and meet growing demand from the automotive and infrastructure sectors, BSL's management embarked on an aggressive, highly ambitious capacity expansion program. This expansion was heavily financed through debt capital, secured from a large consortium of commercial banks led by the State Bank of India (SBI). The company absorbed vast amounts of credit to build massive, capital-intensive manufacturing facilities.

However, this debt-fueled expansion model was highly vulnerable to global macroeconomic shifts. As international commodity markets experienced a severe downturn, characterized by a flood of cheap steel imports and a drop in domestic steel prices, BSL's operational revenues fell sharply. The company's specialized manufacturing plants failed to generate the cash flows required to cover its massive fixed debt-servicing obligations. By mid-2017, the corporation collapsed into a severe liquidity crisis, accumulating an unmanageable loan default of INR 44,478 crores. This default represented a massive portion of the non-performing assets (NPAs) plaguing the Indian banking sector, placing BSL among the top twelve corporate defaulters identified by the Reserve Bank of India (RBI) for immediate resolution. Consequently, the SBI-led lender consortium approached the National Company Law Tribunal (NCLT) to initiate corporate insolvency resolution proceedings. This process culminated in July 2017 with the formal liquidation of the enterprise and its subsequent acquisition by Tata Steel BSL Limited in November 2018.

While the company's collapse was initially viewed as a consequence of market forces and aggressive leverage, subsequent forensic investigations revealed a deeply entrenched system of corporate fraud and financial manipulation. In 2022, Punjab National Bank (PNB) formally reported a massive fraud of INR 3,805 crores at Bhushan Steel Limited, in compliance with Regulation 30 of the SEBI (Listing Obligations and Disclosure Requirements) Regulations, 2015. Deep forensic examinations uncovered widespread falsification of commercial documents, the fraudulent acquisition of banking funds through fake letters of credit, and the extensive misappropriation of corporate resources through unmapped shell networks. These fraudulent activities had international dimensions, including a combined overseas financial exposure of approximately INR 600 crores diverted through illicit corporate branches in Dubai and Hong Kong, with the remaining exposure concentrated at its domestic branch in Chandigarh. These findings led to severe criminal charges, the arrest of the former Chief Financial Officer (CFO), and the detention of the Managing Director, highlighting a total breakdown of internal controls and executive integrity.

VI. Empirical Results and Systemic Breakdown

This section presents the annual quantitative scores generated by applying the Altman Z-Score and Beneish M-Score models to the fifteen-year financial records of Bhushan Steel Limited, providing a detailed year-by-year analysis of the data.

6.1 Altman Z-Score Analysis

Table 3 displays the annual trends for the individual variables (X1 through X5) alongside the final compiled Altman Z-Scores for Bhushan Steel Limited from 2012 to 2025.

Source: Compiled primary data from empirical analysis of CMIE database records.

An analysis of the data in Table 3 reveals a clear, structural decline in the financial health of Bhushan Steel Limited. The variable X1, which evaluates short-term liquidity via the Working Capital to Total Assets ratio, begins at a modest positive value of 0.2457 in 2012 but experiences a continuous decline. By 2018, X1 drops into negative territory (-0.1040), reflecting severe, structural liquidity issues. This negative trend worsens significantly over time, reaching a critical low of -1.2410 in 2025. This persistent negative liquidity confirms that BSL was systematically utilizing short-term commercial liabilities to fund long-term fixed assets, a highly risky capital structure policy that ultimately led to bankruptcy.

Similarly, the cumulative profitability ratio, X2 (Retained Earnings / Total Assets), shows extremely low values across the entire period, starting at just 0.0443 in 2012. This ratio fluctuates weakly before dropping to 0.0072 in 2021, and turns negative from 2022 through 2025, bottoming out at -0.5500. This indicates that the company was completely exhausting its reserves and running severe net operational losses. This decline is directly linked to the performance of X3 (EBIT / Total Assets), which reflects a highly inefficient capital allocation process, with operating profitability falling significantly short of the company's massive asset expansion. Concurrently, the solvency proxy X4 (Book Value of Equity / Total Liabilities) demonstrates a heavy reliance on debt capital. X4 remains below 1.0 for all fifteen years; it stays between 0.2 and 0.5 until 2021, then plummets to 0.03, and reaches an all-time low of 0.0133 in 2018. This confirms that outside lenders provided nearly 99% of the long-term capital structure, leaving the company highly vulnerable to insolvency. Finally, the asset turnover ratio X5 drops from close to 2.0 down to a sustained level below 1.0, indicating highly inefficient asset utilization. As a result, the final Altman Z-Score placed BSL in the Grey Zone (between 1.81 and 2.99) for only the first two years, followed by a continuous decline deep into the Distress Zone (<1.81) from 2013 onward, eventually reaching an extreme low of -3.2840 in 2025. This confirms that the model successfully provided a warning of bankruptcy twelve full years prior to liquidation, allowing us to confidently reject the first null hypothesis H0(1).

6.2 Beneish M-Score Analysis

Table 4 provides the multi-variable index breakdowns along with the final configurations for both the Eight-Factor and Five-Factor Beneish M-Scores.

Year	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	TATA	M-8 F	M-5 F
2012	0.5893	1.2792	0.9461	1.6432	0.7735	0.8021	1.0377	-0.0366	-2.3340	-2.5991
2013	1.1064	0.9389	0.7790	1.0706	1.0748	1.2355	1.0709	-0.0881	-2.9080	-2.9592
2014	0.9754	0.8842	0.9782	1.3686	1.1814	1.1414	1.0322	-0.0149	-2.3275	-2.7733
2015	1.0315	0.8534	0.7174	1.1120	1.0631	0.9751	1.0544	-0.0089	-2.5904	-3.1065
2016	0.8696	0.9634	0.8145	1.1577	1.0057	1.3242	0.9826	-0.0133	-2.6652	-3.0558

Year	DSRI	GMI	AQI	SGI	DEPI	SGAI	LVGI	TATA	M-8 F	M-5 F
2017	1.0696	0.9265	0.8963	1.1097	1.2362	1.3374	0.9633	0.0151	-2.3469	-2.8859
2018	0.8205	0.8041	1.7802	1.2621	2.8734	1.1007	1.2466	-0.0109	-2.1333	-2.3932
2019	1.3090	1.0341	0.9632	1.4245	0.5815	0.9067	0.9319	-0.0629	-2.1180	-2.3960
2020	1.7753	1.0121	0.9908	1.0933	0.9042	0.9324	0.9953	0.0207	-1.5818	-2.2188
2021	1.1330	1.1147	1.0039	0.8983	1.0455	1.1043	1.0836	-0.0456	-2.6394	-2.7713
2022	1.0527	1.0836	1.4058	1.1070	1.6355	1.1418	1.0371	-0.0648	-2.3944	-2.4145
2023	0.3323	1.1683	0.9247	1.1153	0.7044	1.4420	1.1096	-0.0695	-3.4038	-3.3096
2024	1.1314	0.7814	0.9658	1.1481	1.0649	0.9910	0.9774	-0.0633	-2.6361	-2.9161
2025	0.7937	1.7016	1.4974	1.1582	0.9285	1.0371	2.5923	-0.5898	-5.2523	-2.0524

(Source: Primary computational derivations mapping year-over-year operational index transformations)

The analysis of the Beneish metrics in Table 4 reveals complex behavior across individual indices. The Days Sales in Receivables Index (DSRI) fluctuates significantly, starting at 0.5893 in 2012, rising to 1.1064 in 2013, and peaking at 1.7753 in 2020, though it never consistently surpasses the standard manipulator threshold of 2.0. The Gross Margin Index (GMI) remains below 1.0 until 2011, indicating steady or improving historical margins during the early years, before rising above 1.0 in subsequent years and peaking at 1.7016 in 2025, which reflects a severe late-stage collapse in profitability.

Crucially, the Asset Quality Index (AQI) captures a major structural abnormality in 2018, jumping to 1.7802 and significantly exceeding the manipulator baseline mean of 1.254. A similar spike occurs in 2022 (1.4058) and 2018 (1.4974). These spikes indicate specific fiscal periods where management was aggressively reclassifying operational expenses or capitalizing costs as intangible assets on the balance sheet. This interpretation is reinforced by the Depreciation Index (DEPI), which exceeds 1.0 in eight out of fourteen years (peaking at 2.8734 in 2018 and 1.6355 in 2022). This confirms that the company slowed its depreciation rates during these periods to temporarily inflate reported earnings. Concurrently, the SGAI index consistently exceeds 1.0, highlighting severe operational inefficiencies where administrative costs grew faster than top-line revenues. The Leverage Index (LVGI) also shows a severe structural breakdown, exploding to 2.5923 in 2025, which confirms that the company was taking on unsustainable debt volumes to service existing credit lines.

The final compiled M-Scores demonstrate that the full Eight-Factor framework successfully flagged active manipulation by generating values greater than -2.22 across three consecutive years: 2018 (-2.1333), 2019 (-2.1180), and 2020 (-1.5818). This aligns with the period when the company was aggressively masking its operational downturn. For the remaining years, however, the score stayed below -2.22, indicating non-manipulation. The trimmed Five-Factor model yielded similar results, staying below -2.22 for the majority of the timeline but rising to -2.0524 in 2025, thereby flagging late-stage balance sheet distortions.

These successful detections allow us to reject the null hypotheses H0(2A) and H0(2B), confirming that both Beneish models successfully captured specific phases of financial statement manipulation.

VII. Inferential Statistical Evaluation

To validate the diagnostic efficacy of the accounting ratios and determine if the results were statistically significant or merely accidental, we executed rigorous one-sample t-tests at a 5% significance level. Table 6 provides a comprehensive breakdown of the results, comparing the mean values, standard deviations, t-statistics, and two-tailed p-values for both models across the entire 2012–2025 timeline.

M-Idx	Mean	SD	t-stat	p-val	Z-Idx	Mean	SD	t-stat	p-val
DSRI	0.9993	0.3349	11.991	0.0000	X1	-0.0611	0.3625	-0.652	0.5250
GMI	1.0389	0.2370	17.619	0.0000	X2	-0.0177	0.1518	-0.452	0.6590
AQI	1.0474	0.3006	14.002	0.0000	X3	0.0562	0.1396	1.560	0.1410
SGI	1.1906	0.1829	26.162	0.0000	X4	0.2730	0.1945	5.437	0.0001
DEPI	1.1480	0.5574	8.278	0.0000	X5	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: Inferential statistical t-test calculations using primary ratio data series)

The inferential results in Table 6 show that for the Beneish M-Score framework, nearly all primary indices (DSRI, GMI, AQI, SGI, DEPI, SGAI, and LVGI) achieved extremely high t-statistics alongside two-tailed p-values of 0.0000. This confirms that these metrics are highly significant and possess substantial power to differentiate between normal reporting and active manipulation. The lone exception within the Beneish framework is the TATA accruals index, which generated a p-value of 0.0720, failing to clear the 5% alpha threshold due to the company's structural lack of secondary non-operational cash channels. For the Altman Z-Score model, the financial structure variables X4 (Solvency Proxy, p-value = 0.0001) and X5 (Asset Efficiency, p-value = 0.0000) demonstrated overwhelming statistical significance. However, variables X1 (p-value = 0.5250), X2 (p-value = 0.6590), and X3 (p-value = 0.1410) exceeded the 5% threshold, reflecting the persistent, unvarying nature of the company’s severe distress across the multi-year study period. Overall, because the p-values for both frameworks are deeply related to the identification of structural reporting anomalies, we reject the null hypothesis H0(3), confirming that these accounting ratios are efficient and relevant tools for modern fraud diagnosis.

VIII. Discussion and Strategic Accounting Synergy

The comparative analysis between these two established models reveals an important operational insight regarding their real-world application. The empirical findings demonstrate that the Altman Z-Score model was more effective and consistent than the Beneish M-Score framework in providing an early warning of corporate failure at Bhushan Steel Limited. The Altman model identified severe distress as early as 2013, placing the company in the Distress Zone for over a decade prior to its formal liquidation. This high level of efficacy stems from the model's structural focus on absolute financial health, directly capturing the continuous erosion of liquidity, capital reserves, and asset efficiency that characterized BSL's debt-heavy operations.

In contrast, the Beneish M-Score framework operates on a relative basis, evaluating year-over-year variations across indices rather than absolute structural health. Consequently, if a corporation systematically manipulates its financial statements at a stable rate or experiences continuous balance sheet deterioration over time, the year-over-year index changes may remain minimal. This mathematical characteristic explains why the Beneish model categorized BSL as a non-manipulator during several critical operational periods, only triggering active manipulation alerts when management aggressively increased its manipulative practices (such as the asset quality and depreciation distortions between 2018 and 2020). This confirms that utilizing either model in isolation creates systemic blind spots for investors and risk managers.

Therefore, this study strongly suggests a strategic integration of both frameworks within a modern data analytics pipeline, as illustrated in the operational blueprint below:

Pipeline Stage	Core Technologies Ingested	Target Risk Mitigation Output
1. Comprehensive Ingestion	Data Warehousing architectures, ERP integration pipelines, automated metadata harvesters.	Ingests 100% of historical ledger data, eliminating blind spots from traditional sampling.
2. Quantitative Diagnostics	Automated Altman Z-Score calculators, dynamic Beneish M-Score indices.	Simultaneously tracks long-term solvency trends alongside sudden year-over-year reporting anomalies.
3. Advanced AI Core	Unsupervised machine learning, Natural Language Processing, Benford's Law distribution mapping.	Isolates subtle fraud patterns, capitalization anomalies, and suspicious executive communications.

By deploying this integrated framework, stakeholders can convert traditional, reactive auditing processes into a proactive defense mechanism. Retail investors can automatically screen prospective investments for both insolvency risk and reporting irregularities, protecting their capital. Banking syndicates and institutional lenders can continuously monitor corporate borrowers' compliance metrics, reducing loan default exposures. Finally, corporate audit committees and regulatory bodies can leverage these real-time

dashboards to identify management misconduct early, enforcing accountability and safeguarding broader macroeconomic stability.

IX. Conclusion

This exploratory investigation highlights the value of combining traditional quantitative models with modern data analytics techniques to improve corporate oversight and forensic accounting. The empirical case study of Bhushan Steel Limited demonstrates that both the Altman Z-Score and Beneish M-Score frameworks provide valuable, distinct diagnostic insights. The Altman Z-Score model successfully flagged severe, structural insolvency risks twelve years prior to liquidation, while the Beneish M-Score model identified specific periods of intense earnings manipulation, validating their mathematical relevance. Crucially, the study shows that these models are most effective when integrated into an automated, comprehensive analytics framework rather than used in isolation. However, implementing this integrated technological framework presents certain operational challenges that organizations must address. First, data analytics systems are not entirely foolproof; they are vulnerable to data quality issues and can generate false alarms or miss hidden fraud if the underlying algorithms are poorly calibrated. Furthermore, developing and deploying customized machine learning models requires a significant investment of time, capital, and specialized talent, creating a cost structure that may initially outweigh the short-term benefits for smaller organizations. Despite these limitations, the long-term advantages of early fraud detection, automated compliance, and minimized capital losses make this integration a critical investment for modern enterprises. The future research should address the limitations of this study by expanding the empirical scope beyond a single-company analysis. Comparative studies across different industries and longer timelines will provide deeper insights into sector-specific fraud patterns. Additionally, future models should integrate qualitative indicators alongside traditional quantitative metrics, tracking parameters such as the composition of the Board of Directors, executive rotation frequencies, and auditor remuneration structures to build a more comprehensive and robust corporate governance diagnostic tool.

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