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A Literature Review and Gap Analysis on Need for Early Corporate Distress Prediction

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Abstract

The paper covers literature review and gap analysis to focus the pressing need for early corporate distress prediction. It highlights the increasing complexity of global business situation and the severe economic and social impacts of delayed distress detection. This study views upon rise of prediction models, by using traditional financial ratio analysis to advanced machine learning approaches and identifying major limitations such as data quality, model transparency, and applicability across diverse sectors. Attention is given to challenges unique to emerging markets, including the integration of qualitative factors and sector-specific modeling needs. With critical analysis, the paper identifies persistent research gaps and traces for the development of holistic, adaptive, and interpretable early warning systems. The enhancements are pivotal for improving financial risk management and stakeholder protection, and overall economic stability. The study identifies specific research gaps notably in unified theoretical frameworks, sector-sensitive modelling, and adoption to indias dynamic regulatory landscape post IBC implementation.

Keywords: *Corporate Bankruptcy, Insolvency and Bankruptcy Code, Bankruptcy prediction, research gap analysis, Altman Z score, early warning signals, financial risk management*

Introduction

A delay in detecting financial distress may result in bankruptcy, which further disrupts business operations and has wide-ranging economic consequences. The changing dynamics across the globe with increased complexity have made predicting financial distress an essential tool for investors, creditors, regulators, and company management. Early prediction of corporate distress has gained critical importance in financial research and practice due to the severe economic and social implications of business failures. The early detection of distress allows stakeholders, to take necessary measures to prevent reaching bankruptcy, as it may result in heavy losses to creditors, investors, and other stakeholders and affect financial stability (Altman, 1968; Beaver, 1966). There has been an extensive development in model creation in last few decadesusing various variables like financial ratios and statistical techniques like discriminant analyses to advanced machine learning algorithms (Ohlson, 1980; Zmijewski, 1984). Despite these advances, significant challenges and gaps remain in identifying early warning signs across diverse firm types, industries, and economic environments.

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The previous studies focus on the country or sector-specific prediction models in the dynamic market conditions (Lee & Rao, 2016; Poon & Chan, 2008). The studies highlight an important gap in the unavailability of data, model transparency, and the dynamic nature of distress, which require continuous refinement and integration of qualitative and quantitative factors (Kilic & Miras, 2013). The current study integrates research contributions from earlier studies and further identifies important gaps, such as incorporating non-financial data sources, the possible use of alternative data sources, and the need for models with enhanced interpretability and practical applicability.

It becomes necessary to improve the quality and reliability of early warning systems. Based on a literature review and gap analysis, this study provides a base for future research on developing holistic predictive models to serve stakeholders in a rapidly changing global business environment.

Review of Literature:

Global Perspectives on Corporate Distress "Corporate distress is a financial condition in which a company cannot meet its financial obligations due to insufficient revenues or an inability to earn sufficient income to cover debt obligations and survive operations."(Wall Street Prep, 2024). As per the Corporate Finance Institute, financial distress is a condition in which specific events force management to seek restructuring support, shifting from stable operations to financial fragility.

Insolvency is a financial situation where a debtor cannot pay their debts due to cash-flow insolvency (inability to meet current obligations) and balance-sheet insolvency (Cornell Law School, 2015). Corporate Bankruptcy is a financial status declared by a court for an entity unable to pay its financial commitments, forcing judicial supervision and establishing asset liquidation procedures. (The Legal School, 2025) Insolvency is a financial term, bankruptcy is a legal term, and solvency is the ability to meet financial obligations (Allianz Trade, 2023).

In the Indian theory, the Insolvency and Bankruptcy Code 2016 provides the basic legal framework for understanding corporate distress, basically transforming India's approach to financial distress resolution (Century Law Firm, 2024). IBC states corporate distress within a creditor control model, where on admission of insolvency proceedings, management control shifts from promoters to creditors (Oxford Law Blog, 2025).

According to the IBC statute, financial distress in India is when corporate entities cannot generate sufficient revenue to pay financial obligations, due to high fixed costs, illiquid assets, or revenue sensitive to economic downturns (Enterslice, 2021). Insolvency as mentioned by Indian laws mean "a financial state where a corporate debtor is unable to pay on debt exceeding Rs. 1 lakh, enabling creditors to initiate the Corporate Insolvency Resolution Process (CIRP) with the National Company Law Tribunal (NCLT)" (BYJUS, 2022; Drishti IAS, 2019).

Hence it has also been explained as 'Bankruptcy represents the legal status of unsuccessful insolvency resolution in India, resulting in liquidation under the court's purview' (Taxmann, 2023; Drishti IAS, 2019).

Macroeconomic Impact of Corporate bankruptcies.

Corporate bankruptcy generates critical macroeconomic implications that affect entire economic systems. Systemic risk emerges as a critical concern causing cascading effects of corporate failures. Corporate Finance Institute (2024) discusses this as a systemic risk wherein an individual firm failure like lehman brothers may result in an entire financial system collapse (The Corporate Finance Institute 2024).

Employment and social impact represent another critical side of corporate bankruptcy. Business failures create unemployment directly while creating uncertainty that reduces hiring and investment across related industries. The social costs include reduced tax revenues, increased unemployment benefits, and broader community impacts in regions dependent on failed firms.

Indian Economic Context: NPA and Systemic Impact

Research indicates that India has been experiencing this critical issue, with the rising Non-Performing Asset (NPA) crisis being the indicator of the same. NPAs in Indian banks were reported to be exceeding, representing nearly 10% of all loans by 2018, with a consequence as widespread corporate failures on financial system stability (SSRN, 2018). The impact has been profound, with public sector banks holding nearly 70% of NPAs, leading to constrained lending, resulting in economic slowdown (Columbia University, 2018).

The economic growth implications of corporate distress in India have been significant. The NPA crisis contributed to reduced credit growth, with banks becoming increasingly risk-averse and constraining lending to productive sectors (IMF eLibrary, 2022; Drishti IAS, 2019). The substantial impact on infrastructure, steel, power, and aviation industries has been particularly severe, affecting sectors that received substantial credit flows during the 2003-2008 boom period (Drishti IAS, 2019). Policy responses and recovery efforts have focused on strengthening the insolvency framework through IBC implementation. Research shows that creditors have realized ₹3.89 lakh crore with a 32.8% recovery rate against admitted claims under IBC, while the framework has rescued 1,194 companies through resolution plans (Vision IAS, 2025). The IBC has emerged as the dominant recovery route, contributing 48% of all bank recoveries in FY 2023-24 (IBBI, 2024).

Need for Early warning signals for bankruptcy prediction:

These Early warning signals benefit stakeholders, specifically Creditors and financial institutions. Various prediction models work for timely prediction and help in credit risk management for lenders (IAEME, 2024). Management and boards are also the biggest beneficiaries of early warning capabilities as they provide valuable information for financial restructuring, operational improvements, and strategic repositioning before distress becomes severe. The models provide systematic approaches to identifying distressed securities opportunities while avoiding potential losses from failing companies, and help in investment decision-making, portfolio construction, and risk management for investors.

Servosys (2024) found that regulatory authorities utilize these models to monitor systemic risk and stability assessment. The prediction models help regulators to identify timely threats to financial system stability and implement preventive measures before contagion spreads.

Economic Benefits: Early detection helps reduce the chances of unemployment, maintain supplier relationships, and reduce broader economic costs associated with business failures, resulting in an overall economic stability (PubMed, 2024). Early warning signals help timely intervention, reducing asset deterioration and enabling more efficient resource reallocation, maximizing chances of recovery (SSRN, 2017).

Traditional models of prediction are more reactive in nature, resulting in significant value erosion, limiting recovery options, and increasing costs for all stakeholders. The absence of early warning mechanisms can result in sudden business failures that create systemic disruptions and economic effects (SSRN, 2017).

The issue of information asymmetries worsens the chances of early detection systems. It requires a thorough systematic monitoring for creditors and investors to recognize deteriorating conditions before default becomes imminent.

Progress on Bankruptcy Prediction across the Globe and in India

Global Evolution of Bankruptcy Prediction Models

Beaver (1966) pioneered the process of bankruptcy prediction. The evolution of bankruptcy prediction methodologies using univariate analysis and ratios as the base data, the primary variable identified as the cash-to-total liabilities ratio (DIAS, 2020).

Altman's (1968) multivariate discriminant analysis turned out to be the most classical and academically used model. The model also used five financial ratios to calculate the well-known Z score, with a high level of accuracy achieved (Pesjournal, 2024; DIAS, 2020).

To overcome the limitations of discriminant analysis, Ohlson (1980) used logistic regression for the probabilistic outputs(Wikipedia, 2024). The model provided the O-Score and was considered superior theoretically and in practical applications.

Over a period of time, modern machine learning approaches to bankruptcy prediction through neural networks, support vector machines, and ensemble methods have evolved(ScienceDirect, 2021). Recent times have seen the use of Random Forest, XGBoost, AdaBoost, and similar Advanced techniques with enhanced prediction accuracy (IAEME, 2024).

Times have seen the use of financial ratios, advanced variable selection techniques incorporating textual analysis, sentiment data, and macroeconomic variables (ScienceDirect, 2022), further Integration of ESG factors and network analysis, and incorporating board characteristics for prediction.

In the indian context, Altman Z score remains the most used model, but with a limited NSE-listed companies data (Pesjournal, 2024). However, plenty of sector-specific studies have emerged across various industries, with Altman Z score remaining the most used model, resulting in the highest accuracy (Indian Journal of Capital Markets, 2024).

A recent significant regulatory development, introduction of the Insolvency and Bankruptcy Code in 2016, has given a new direction to the research using machine learning models and Random Forest techniques. (Indian Journal of Finance, 2024). Research using extensive datasets from 2016-2022 about 257 bankrupt entities found that XGBoost performs better than logistic regression and Altman Z-scores in predicting bankruptcy among Indian corporates (SSRN, 2024). These researchers have found that cash flow to sales and days sales in receivables emerged as the most significant variables (Maxwell Sci, 2011). Researchers have also used a combination of market variables, macroeconomic factors, and financial ratios.

Research Gaps Based on Literature Analysis

Lack of comprehensive theoretical frameworks represents a fundamental limitation in bankruptcy prediction studies. The focus is more on empirical testing, resulting in limitations in applicability. There is an absence of a unified theory that integrates financial, operational, and strategic factors responsible for distress and bankruptcy.

Industry-specific theoretical gaps exist as most research attempts to develop universal models applicable across all sectors rather than acknowledging unique risk factors and business dynamics within particular industries.

In terms of model applicability, Cross-cultural validity across different economic and institutional contexts is a significant gap. Primary research focuses on developed market contexts, with a limited studies focusing on emerging markets. This limitation affects the transferability of Western-developed models to India.

Financial ratios dominate most models, and integrating alternative data sources, social media sentiments, and qualitative data variables remains underdeveloped despite technological advances.

The most significant limitation identified in the models is applicability at changing economic conditions, varied time periods, and dynamic regulatory environments.

Effective integration of prediction models into existing risk management frameworks requires further investigation.

Real-time model updating capabilities represent significant practical limitations.

Stakeholder-specific application gaps need to be addressed with differences in objectives, as generic models cannot satisfy them.

Other challenges include the availability of quality data and the avoidance of sample selection bias. Information quality inconsistencies across firms and time periods create reliability concerns. Another India-specific challenge is making a model applicable to small and medium enterprises and family-owned businesses, which differ in regulations, corporate governance, reporting, and transparency standards. Limited access to high-quality data for a longer time zone results in relatively short observation windows for the preparation of the model.

The introduction of IBC in 2016 fundamentally altered bankruptcy resolution dynamics, minimal research is available on bankrupt companies after IBC implementation (Indian Journal of Finance, 2024). While IBC emphasizes time-bound resolution, early warning systems providing real-time bankruptcy risk assessment for large listed companies remain underdeveloped (IJCRT, 2025). Companies under IBC using Altman Z-Score, finding that most companies had Z-scores below 2.0, indicating severe financial distress consistent with IBC referral (D'lima & Naik, 2025). However, the study highlighted the need for sector-specific approaches and integration with early warning systems to prevent corporate insolvencies. The studies on how regulatory changes affect traditional prediction model accuracy are missing. The most significant change brought in by IBC, i.e., a shift from debtor-in-possession to creditor-in-control, has not been examined to the extent it should be (Oxford Law Blog, 2025; RIS, 2021).

India - An emerging market challenge

Individual studies have examined NSE-listed companies; comprehensive research covering the full NSE 500 universe remains limited (IJCRT, 2025). Variables like promoter behavior and governance quality on bankruptcy risk need research attention.

Model Adaptation and Recalibration Needs

Indian-specific coefficient recalibration represents a fundamental requirement for improving model accuracy. Altman's original coefficients based on US manufacturing data may not adequately reflect Indian corporate financial behaviors and risk patterns (IJCRT, 2025).

Qualitative factor integration gaps are particularly pronounced in the Indian context (IJCRT, 2025. The development of hybrid models combining quantitative and qualitative factors remains underdeveloped.

Further, the impact of digital transformation on bankruptcy prediction remains unexplored in the Indian context. (IJCRT, 2025).

The comprehensive analysis reveals significant opportunities for advancing bankruptcy prediction research in the Indian context, particularly for NSE 500-listed non-financial indian companies in the post-IBC environment. To Address these research gaps through systematic empirical investigation, methodological innovation, and practical application development will enhance the effectiveness of financial distress prediction and improve risk management in India's evolving corporate landscape.

Conclusion

In conclusion, this study provids the crucial role of the early corporate distress prediction for protecting financial health and stability of economy. By revisiting the progression of predictive models from traditional ratio-based frameworks to machine learning techniques it becomes clear that while meaningful progress is seen, key challenges remain. which include issues related to model transparency and integration of qualitative factors with adaptability to diverse sectors, and the need for better real-time data. Especially in emerging markets, it is essential addressing these gaps with innovation and methodological advancement. The Future research should focus on developing holistic, adaptive, and practical early warning systems that can cater to varying stakeholder needs and dynamic market environments, ultimately enhancing the resilience of businesses and economies.

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Conflicts of interest
The authors declare that there are no conflicts of interest regarding the publication of this paper

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