

INTERNATIONAL JOURNAL OF LAW  
MANAGEMENT & HUMANITIES  
[ISSN 2581-5369]

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Volume 8 | Issue 3  
2025

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# Predictive Modelling based Financial Distress Estimation System to better Deal with Insolvency Situation

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PIHU MISHRA<sup>1</sup> AND DR. AMIT DHALL<sup>2</sup>

## ABSTRACT

*Financial distress happens when a company consistently experiences significant losses or when it becomes bankrupt, meaning its debts outweigh its assets. However, there are various factors related to methods and practices which contribute to the significant number of bankruptcy and other financially troubled situations that company encounter. The study aims to construct an accurate prediction model of financial distress of the firms and improve insolvency control with the help of diverse financial signals. Conducting the research within the descriptive and exploratory research framework, the study includes both the qualitative and quantitative data and primarily uses the financial reports and industry analysis data. The study also underscores the importance of identification of the financial disorders especially at initial- stages in view of newly evolved environment of insolvency reform and India's Insolvency and Bankruptcy Code, 2016. The rationale of this legislation is to modernise insolvency procedures and restore public credibility to insolvent businesses' creditors. The proposed model moves such financial indicators as insolvency filings, the financial distress scores and differentiates them from other financial indicators which include profitability and liquidity for the evaluation of the financial position of a company. The conclusions' purpose is to help the commercial undertakers and policymakers who need this fundamental data to balance and reduce the risks involved in the expenditure of resources and the timely planning of the future.*

**Keywords:** *Financial distress, predictive modelling, insolvency, financial indicators, risk management, economic stability.*

## I. INTRODUCTION

Insolvency refers to the state of being unable to repay debts in the normal course of business or to meet financial obligations as they arise, regardless of whether or not an act of insolvency has been performed (Goel, 2017). Nevertheless, if a debtor engages in specific actions that aim to hinder or postpone the rights of their creditors, they might be declared bankrupt and

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<sup>1</sup> Author is a Research Scholar at Amity Law School, Amity University Noida, India.

<sup>2</sup> Author is an Assistant Professor at Amity Law School, Amity University, Noida, India.

become subject to the regulations of bankruptcy laws. In the past, in India, there was a lack of comprehensive legislation that specifically regulated bankruptcy and insolvency proceedings.

Before the enactment of the Insolvency and Bankruptcy code, 2016 (IBC/Code), the Indian system for dealing with debt default did not align with global expectations. Creditors' efforts to collect debts, as specified in the Indian Contract Act, 1872 and other statutes like the Recovery of Debts Due to Banks and Financial Institutions Act, 1993 and the Securitization and Reconstruction of Financial Assets and Enforcement of Security Interest Act, 2002, were unsuccessful. The winding up provisions of the Companies Act, 1956 and the Sick Industrial Companies (Special Provisions) Act, 1985 did not prove effective in terms of loan collection or company restructuring (Ravi, 2015).

The creditor's trust was undermined (Shukla, 2020). Borrowers' ability to borrow money was limited due to lenders' lack of faith. This fact is clearly illustrated by the state of India's lending markets. The majority of India's lending sector is comprised of secured loans provided by banks. The corporate bond markets remained underdeveloped. Given these circumstances, the Code was introduced to streamline the insolvency process and restore confidence in the lending market. This new legislation aimed to provide a more efficient and transparent mechanism for resolving insolvency cases, ultimately benefiting both creditors and debtors.

The Code's objective is as follows: *“A Code to consolidate and amend the laws relating to reorganisation and insolvency resolution of corporate persons, partnership firms and individuals in a time bound manner, for maximization of the value of assets of such persons, to promote entrepreneurship, availability of credit and balancing the interest of stakeholders including alteration in the order of priority of payment of Government dues and to establish an Insolvency and Bankruptcy Board of India, and for matters connected therewith or incidental thereto.”*

The IBC offers a straightforward examination to commence the process of resolving corporate insolvency. The Code implements a default-based test to commence the corporate insolvency resolution procedure (CIRP) (Vikas, 2021). An insolvency resolution process can be initiated based on a default, allowing for early involvement when a company shows initial indications of financial crisis. Prompt identification of financial hardship is crucial for prompt settlement of insolvency (Singh, 2021).

The law establishes a comprehensive framework that assists individuals or entities holding claims in resolving unexpected disputes that arise when a company fails to make its debt payments. Furthermore, it establishes the distribution of authority over the troubled company

among different parties with claims and the degree to which market procedures are employed in resolving financial difficulties (Hotchkiss, et al., 2008). Consequently, this has an impact on the readiness of investors to contribute cash beforehand, which in turn influences the decision of enterprises about their capital structure and the cost of capital. Bankruptcy proceedings exhibit significant variation across different countries (Claessens & Klapper, 5).

Managerial ineptitude is the primary cause of a firm's suffering and potential failure. The failure of most organizations can be attributed to a variety of factors, but it is typically the flaws in management that lie at the heart of these difficulties (Altman & Hotchkiss, 1998). The primary factor leading to failure is typically a depletion of financial resources. However, there are various factors related to methods and practices which contribute to the significant number of bankruptcy and other financially troubled situations that company encounter.

In recent years, both local and foreign investment markets in India have experienced significant growth, leading to an increasing interest among individuals in making financial investments (Terrazas, 2010). There are several types of financial investment instruments, including stocks, futures, options, and bond funds. Among these, equities are the most commonly embraced investment option in society. Nevertheless, capital markets exhibit volatility, and the majority of investors become aware of a company's financial distress only upon the public release of the company's financial statement (Chen & Du, 2009). Hence, the prediction of corporate financial trouble has become increasingly crucial in contemporary society due to its substantial influence on lending determinations and the financial viability of financial institutions. The accurate prediction of bankruptcy is crucial for professionals in various fields, including "bank loan officers, creditors, stockholders, bondholders, financial analysts, governmental officials, and the general public". This ability provides them with timely warnings and alerts (Lipson, 2009).

Financial failure happens when a company consistently experiences significant losses or when it becomes bankrupt, meaning its debts outweigh its assets (Hua, et. al., 2007). Common reasons and manifestations of financial failure encompass insufficient financial literacy, failure to establish capital strategies, ineffective debt management, inadequate safeguards against unexpected circumstances, and challenges in maintaining basic financial market discipline. The prevailing assumption in predicting bankruptcy is that a company's financial statements accurately represent the aforementioned characteristics. Given the significant transformations occurring in corporate finance and the international economic landscape, essential financial ratios have the potential to fluctuate dynamically (Altman, 1968). It is

crucial and obligatory to create an evolutionary strategy for dealing with future unpredictable financial situations.

Forecasting corporate financial failure is essential for preventing or reducing the impact of adverse economic cycles on a country's economy (Borio, 2014). "Corporate insolvency prediction models" aid in the identification of forthcoming business failures and offer timely alerts of potential financial difficulties. They evaluate the financial well-being of companies in many industries, with a particular focus on the financial services industry (Simić, et. al., 2012). Predictive models typically alert auditors to a company's susceptibility and shield them from accusations of 'intentional breach of duty' for not revealing possible insolvency and corporate hardship.

The study on the “Predictive Modelling based Financial Distress Estimation System” is relevant because it deals with quite a major issue in the business world – timely identification and proper handling of potential insolvency conditions. Today’s business environment is volatile, and a firm is subjected to numerous risks within a short time, which may put the firm under financial stress due to peculiar expenses, changing economic policies and market forces. The general objectives of the study is that it seek to make a contribution in the development of a sound predictive model that will enable the assessment of a company with a view to indicating whether the company is likely to face distress or not. It creates a system by which commercial undertakers, potential investors, and policy makers can act proactively and sufficiently to reduce risks, better distribute resources, and to avoid business failure. In this way, the findings of the study enhance the financial stability and business capabilities for the stakeholders, thus strengthening the economy for the better.

The paper has been divided into seven distinct sections. Section 1 consists of the study's introduction. Section 2 of this paper presents a literature review on a financial distress determining system that uses predictive modelling to effectively handle situations of insolvency. Section 3 and 4 of the study outline the objectives and research methodology. Section 5 contains the presented results. The discussion of the results in section 6 follows the preceding material. The study's conclusion is found in Section 7. References have been added at last.

## **A. Review of Literature**

Anticipating insolvency and averting default could enable the implementation of measures to rectify the financial condition of companies. Given the importance of predicting business failure, which is seen as a critical issue in finance and economics (DI CARLO, 2018), The

results of the conceptual review indicate that when developing methods to predict and prevent default risk, it is important to consider various ways in which a company may exit the market, such as failure of payment, insolvency proceedings, and liquidation. Specifically, the study proposed that further research was needed to incorporate more dynamic models.

Keasey & Watson (2019) sought to identify the practical applications and constraints involved in implementing prediction of financial distress models for managerial purposes. In section two, the study examined the existing methods used to predict financial distress and its associated limitations. Section three analysed the significance of the anticipated occurrence (often an actual failure), the efficacy of multi-outcome models, and the suitability of different sample selection strategies. In contrast, the study conducted by Ninh, et. al. (2018) demonstrated that accounting and economic market variables, alongside macroeconomic fundamental problems, independently influence financial distress. However, in a comprehensive framework, the impact of accounting considerations seems to be more substantial than that of market-based factors. The default prediction model, which incorporates accounting elements alongside macroeconomic indicators, has superior performance compared to the model that incorporates market-based components alongside macroeconomic fundamentals.

In their study, Ashraf, et. al. (2019) sought to assess the predictive accuracy of conventional distress forecasting models for companies in different stages of distress in Pakistan's emerging market from 2001 to 2015. The results demonstrated that the three-variable probit system exhibits the highest overall predictive accuracy for the sample. However, the Z-score model demonstrates superior predictive accuracy in identifying insolvency for both early-stage and advanced-stage financially distressed firms. Conventional financial distress prediction techniques deteriorate during periods of financial crisis. In their study, Rao, et. al., (2024) introduced a "financial distress prediction (FDP) model" and approach specifically designed for "small and medium-sized enterprises (SMEs)" listed in India. The suggested approach highlights the significance of efficiency and profitability ratios for assessing financial distress, emphasizing their importance over leverage ratios. This has consequences for SME owners/managers and shareholders.

Elhoseny, et. al., (4) employed the "adaptive whale optimization algorithm with deep learning (AWOA-DL)" methodology to develop a novel financial distress prediction model in their research. The objective of the AWOA-DL technique is to ascertain the presence or absence of financial difficulty in a company. In contrast, Ogachi, et. al., (2020) aimed to implement deep learning models to predict company insolvency by analyzing textual disclosures. A thorough

predictive model for bankruptcy was developed using data from publicly traded enterprises in Kenya.

Pavlicko, et. al., (2021) sought to develop an ensemble model for predicting financial crisis. The proposed model functions as a predictive model for one year in advance and may be readily utilized by firms as a versatile tool to assess the risk of financial distress, not just in Central European countries but also in other nations. The prediction model's main advantages are its interpretability and excellent accuracy in performance. In contrast, Arora & Saurabh (2022) conducted a study on the financial hardship of listed Indian companies on the "Bombay Stock Exchange (BSE)". They selected a representative sample of companies to ensure balance in their analysis. The random forest bagging model attained the maximum reliability, recalled, as well as "area under the curve (AUC)" for the "receiver operating characteristic (ROC)" curve in terms of model performance. The boosting model attained the utmost precision.

Shetty & Vincent (2021) conducted a study to examine how non-financial measures might be used to anticipate financial distress in the Indian manufacturing sector. The study's findings demonstrate that incorporating the two non-financial variables enhanced the effectiveness of the financial distress prediction model. In a similar vein, Balasubramanian, et. al. (2019) sought to construct a corporate financial distress model specifically for Indian listed businesses. They accomplished this by employing a conditional logit regression technique and included both financial and non-financial characteristics. The findings demonstrated that models incorporating financial factors achieved prediction accuracies of 85.19% and 86.11%, whereas models incorporating a combination of financial and non-financial variables exhibited higher prediction accuracies of 89.81% and 91.67%. The crucial indicators of financial crisis include "net asset value, long-term debt–equity ratio, return on investment, retention ratio, age, promoters holdings pledged, and institutional holdings".

While significant progress has been made in developing predictive models for financial distress estimation, several research gaps remain. One key gap is the limited exploration of non-traditional data sources, such as social media, customer sentiment, and alternative credit data, which could enhance the accuracy and timeliness of predictions. Additionally, existing models often rely heavily on financial ratios and historical data, which may not fully capture the complexities of modern business environments, especially in the context of rapid technological and economic changes. There is also a need for more comprehensive approaches that integrate machine learning techniques with traditional financial analysis to improve the predictive power of these models. Furthermore, the ethical implications of using

advanced predictive models in financial distress estimation, such as potential biases and data privacy concerns, require further investigation. Addressing these gaps could lead to more robust and equitable systems for managing insolvency situations.

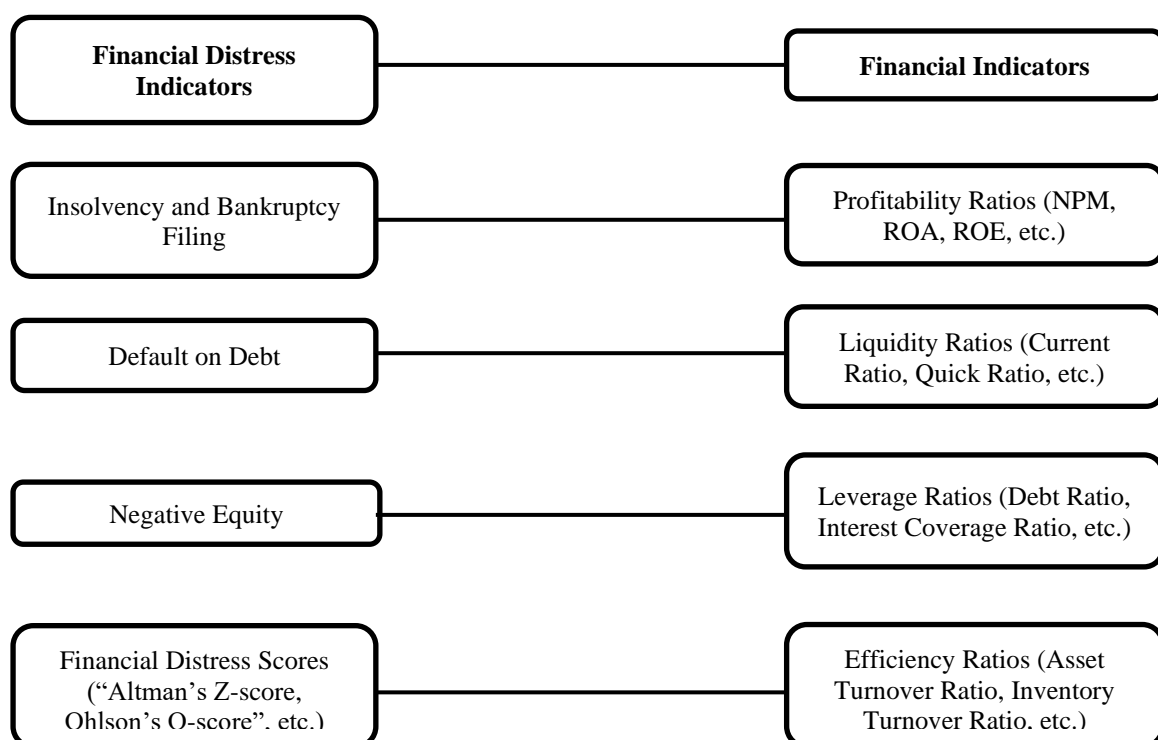
## B. Research Objectives

- a) To create a robust predictive model that accurately estimates financial distress in companies using various financial indicators.
- b) To offer policy recommendations to improve financial distress management and insolvency resolution processes at organizational and regulatory levels.

## C. Research Methodology

The research methodology for the study titled "Predictive Modelling Based Financial Distress Estimation System to Better Deal with Insolvency Situations" will employ a descriptive and exploratory research design. This approach will enable an in-depth analysis of current predictive models and the exploration of new methodologies. The study utilized both qualitative and quantitative data, ensuring a comprehensive understanding of financial distress factors. Data collection primarily involves secondary sources, including financial reports, industry analyses, and existing literature. The study area encompasses the entirety of India, providing a broad view of regional economic dynamics and insolvency trends.

## II. RESULTS



**Figure- 1-** Predictive Model based on financial distress estimation system to deal with insolvency situation - **Source-** Self prepared by Author



The figure above shows a conceptual model which aims at developing a sound forecasting model that will enable one to estimate financial prognosis of company distress from financial ratios. This framework is divided into two primary categories: That consists of elements that exhibit special importance in developing financial health of a company includes Financial Distress Indicators and Financial Indicators.

#### *A. Financial Distress Indicators*

These are very important indices for establishing the presence and extent of financial problems in an organisation. They are the dependent variables or the outcome in the predictive model of analysis. The figure highlights four key indicators:

##### *a) Insolvency and Bankruptcy Filing:*

This is established as to whether the company has stated officially that it is insolvent, or if it has declared bankruptcy. It is a dichotomous variable and equals 1 if the firm filed for the corresponding legal action; otherwise, it is 0 and can be considered one of the most unambiguous indicators of financial trouble.

##### *b) Default on Debt:*

This measure reveals the basic aspects of a firm's credit risks, or in other words, whether it has failed to pay back its debts. Unnamed dummy is also a binary variable with 1 if default occurs during the 2nd year, and 0 otherwise. A default happens when the business cannot pay for the existing debts which to indicate that it is in grave trouble.

##### *c) Negative Equity:*

Business negative equity refers to a situation where the liability position in the business is higher than the equity position meaning that the business has more debts than it has assets. This is another dichotomous variable where 1 will be given to households with negative equity and 0 to those with positive equity, and this is one of the measures of financial vulnerability.

##### *d) Financial Distress Scores:*

Previous financial predicament scores include Altman's Z-score and Ohlson's O-score are a composite numeral that minimizes several saving ratios. These scores are calculated quantitatively depending on the firms' past financial records and prior research findings. It can also be utilised in assessing constant variables that would reflect different levels of distress.

#### *B. Financial Indicators*

These are the independent variables or the predictors of the model. These are extracted from the income statement and balance sheet and provide information on the various aspects of a firm's performance and financial position. The figure categorizes these indicators into four main groups:

**a) Profitability Ratios:**

- i.** Net Profit Margin (NPM): Measures the proportion of the business's total income that eventually becomes profit after all costs have been deducted. It is determined by net income and revenue where net income is subtracted from revenue to arrive at the figure.
- ii.** Return on Assets (ROA): Shows the extent to which a firm can utilise its assets to make profit and is measured as, Net income divided by total assets.
- iii.** Return on Equity (ROE): Shows Return on shareholders, the amount which is being earned for their investment through the ratio of Net Income to Shareholders' Equity.

These ratios are very important in evaluating the companies' capacity to make profit out of its generated revenues or generated sales, assets and equity.

**b) Liquidity Ratios:**

- i.** Current Ratio: Determine the solvency level in which the company's ability to discharge its short-term liabilities are obtained by accessing Current Assets to Current liabilities ratio.
- ii.** Quick Ratio: Comparable to the current ratio but inventory is not included in the numerator, given by  $(\text{Current Assets} - \text{Inventory}) / \text{Current Liabilities}$ .

These ratios illustrate the ability of the company to discharge short-term obligations with its easy resources in the shortest possible time.

**c) Leverage Ratios:**

- i.** Debt Ratio: Shown as the percentage of overall resources acquired through loans;  $\text{Total Debt} / \text{Total Assets}$ .
- ii.** Interest Coverage Ratio: Assesses the business's capacity to meet interest on its borrowings calculated as EBIT divided by Interest Expense.

These ratios assist in evaluating the extent of financial risk involved in the firm's capital structure and its capacity to cope up with the debt.

**d) Efficiency Ratios:**

- i. Asset Turnover Ratio: Analyses the extent to which a business corporation is capable of utilizing its assets in increasing sales, determined by dividing the Revenues by Total Assets.
- ii. Inventory Turnover Ratio: Procedure that determines how fast goods are sold and replaced in a given period, which is  $\text{COGS}/\text{Average Inventory}$ .

These ratios explain efficiency of central operations of the company and its performance in managing asset base and inventory.

### ***C. Integrating the Indicators***

To build the model, financial data from several other companies both the potential FDIs and financials will be gathered and used. Logistic regression, decision tree, random forest, neural net or any other machine learning algorithm can be used to train the model with this data. The objective is to find out the association between the chosen financial variables and the emergence of financial trouble.

Therefore, through the use of seven financial ratios, the analysis seeks to substantiate that financial health and distress has various dimensions. The model will be checked for consistency, validity, and reliability to diagnose the likelihood of financial distress which can assist companies and stakeholders managing their firms' affairs effectively.

### ***D. Outcomes***

#### ***a) Development of a Predictive Model:***

- i. Development of an effective set of variables that can be used to forecast the instances of financial distress and classifying the firms into distress and no distress types.
- ii. Test regarding fitting the correspondences by means of machine learning algorithms, for instance logistic regression, decision trees, random forests or neural networks which will help to find out an interdependence between the variables representing financial performance and occurrences of financial distresses.

#### ***b) Identification of Key Financial Indicators:***

- i. Determination of the most important financial ratios that help in predicting financial failure, the company's profitability, its solvency, its financial structure, and its efficiency.
- ii. A quantitative method used to determine the level of significance of each of the financial ratios in illustrating firms' vulnerability to financial problems, thus allowing for proper attention to be placed on the major indicators.

**c) *Assessment of Financial Distress Indicators:***

- i.** Analysis of the viability of employing different financial distress signals including: insolvency filing and bankruptcy; failure to meet the payment of debts; negative shareholders' equity; and existing scores for financial distress at the time of the year under observation (Altman's Z-score, Ohlson's O-score).
- ii.** Setting up of specific cut off point for these indicators that gives a warning of an organization's predicament of financial insecurity.

**d) *Enhanced Accuracy and Robustness:***

- i.** Enhancement on the precision and quality of the financial distress prediction from the existing models through the use of various financial variables as well as the integration of complex automated algorithms.
- ii.** On this stage, the model is checked on the historical data of the financial market to confirm its efficiency and effectiveness in real conditions.

**e) *Proactive Financial Management:***

- i.** Offering a useful framework for the firms and their stakeholders to watch and prevent the signs of financial problems.
- ii.** Timely decision-making as well as the intervention strategies with regard to the risk of insolvency and bankruptcy.

**f) *Comprehensive Financial Health Assessment:***

- i.** Combining one or more indexes of its financial standing into a single predictive model for a better evaluation of the company's financial stability.
- ii.** This model improves the knowledge of the complex causes of financial distress and contributing factors.

**g) *Data-Driven Insights and Recommendations:***

- i.** Production of hypotheses and conclusions that will be based on the data collection method in relation to financial stability enhancement and distress prevention.
- ii.** Offering the discovered predictions in the form of a set of strategy recommendations that would help the companies increase profitability, liquidity, and leverage ratios, as well as minimise the level of inefficiency.

### **III. DISCUSSION**

The model presented in the study helps in identifying the relevant financial indicators that provide insight into firm soundness and helps predict insolvency risk. Essentially, the implementation of this model into the field of insolvency calls for a number of organized and structured steps so that to ensure accurate and reliable predictions, the first of which is the gathering of comprehensive data on the financial statements of a sample of companies, both insolvent and solvent. These should include a set of financial indicators that measure profitability ratios, liquidity ratios, leverage ratios, efficiency ratios, financial distress indicators, insolvency and bankruptcy filings, debt defaults, negative equity, and financial distress scores, among others. Secondly, upon collection of the data, clean and pre-process it for missing values, outliers, and inconsistencies to ensure quality and reliability. This also includes data normalization so that different financial metrics can be on a comparable scale, which helps in the accuracy of model training.

The next step after data preprocessing in applying statistical methods or machine learning algorithms is the development of predictive models. In this stage, the prepared dataset gets trained to recognize patterns and interrelated relationships between financial indicators and insolvency risk. Logistic regression, decision trees, random forests, and support vector machines are some of the common methods applied to this. Later, model performance will be evaluated against performance metrics for classification problems such as accuracy, precision, recall, and F1-score. This stage of validation confirms whether the model can rightly make a prediction about insolvency and generalize well on new data. Cross-validation techniques can further provide a robust evaluation in this aspect. Finally, the fitted best model is integrated into a decision support system that allows users to provide the financial details of a company in order to get the predicted insolvency probability with relevant recommendations and insights. This will enable one to make judgments in real-time and proactively act on risk management. This shall be monitored and updated continuously with new data so that the model remains very effective and accurate over time.

The financial distress model shows due use in the formulation of insolvent prevention and management recommendations. The model serves as an early warning system aimed at the identification of possible signs of financial distress long before the event, hence providing the business organization with the opportunity to take corrective action early to enhance their business performance for avoidance of insolvency. Moreover, it is possible to use it for a study on the credit value of borrowers, which means the base for decisions on the giving out

of loans and significantly reduces the risks of default. In addition to this, this model in general terms allows for the efficient allocation of resources with other related mechanisms targeting specifically companies at higher risk of being insolvent. This ensures that the intervention and support programs are directed to the places where they are most needed. Thirdly, policy may be guided by the insights of the model in the creation of effective insolvency prevention and remediation frameworks that contribute to overall financial stability.

The study involved the development of a reliable predictive model that effectively predicts financial hardship in organizations by utilizing a range of financial indicators. On the other hand, Situm's (2015), in their study examined the disparities between troubled and recovered enterprises and insolvent firms by analyzing several accounting ratios that have been identified as significant predictors in previous research. Subsequently, an endeavor was undertaken to construct prediction models utilizing linear discriminant analysis and logistic regression, with the objective of categorizing a company into one of these two conditions.

In 2016, the Government of India introduced the IBC, and the “Insolvency and Bankruptcy Board of India (IBBI)” was subsequently established to oversee its implementation, which provides a framework for financially distressed Indian corporations to achieve solvency or resolution. Subsequently, around three hundred companies have initiated the process of bankruptcy resolutions in India in accordance with the IBC, 2016 (Arora & Saurabh, 2022). The IBC adheres to the creditor-in-control framework. In bankruptcy law that favors creditors, liquidation mostly occurs as a result of insolvency and the bankruptcy process. A sequence of liquidations has the potential to trigger a significant economic crisis. Identifying corporate financial difficulties at an early stage might decrease the probability of bankruptcy and ultimately prevent the business from being liquidated, hence safeguarding the overall economy (Shetty & Vincent, 2021).

Bankruptcy prediction is crucial for all stakeholders in the insurance business, such as insurance regulators, customers, intermediaries, and insurance companies. Nevertheless, consumers express significant apprehension over the future financial capability of insurance companies to fulfill their obligations when acquiring insurance products, as the service period of these products occurs subsequent to the purchase (Ogachi, et. al., 2020). The prediction of a company's financial state, particularly the risk of financial distress, is currently a significant concern. This is important not only for company management to make informed decisions, but also for all stakeholders to understand the financial condition of the company and its potential future growth (Pavlicko, et. al., 2021).

The prediction of financial distress has been a subject of considerable attention for several decades because to its importance to publicly traded companies, stakeholders (such as financial institutions, investors, government, and researchers), and the national economy (Balasubramanian, et. al., 2019).

#### **IV. CONCLUSION**

Several policy recommendations should be implemented for the improvement of financial distress and insolvency management at the organizational and regulatory levels. Advanced machine learning techniques and the addition of more relevant data increase the predictive model's power, which turns to provide an improved accuracy in the prediction of insolvency. In view of this enhanced accuracy, early intervention and recovery strategies of those companies at risk from insolvency can be developed and hope for more recovery of these companies in face of insolvency. It can also be used by financial institutions to underpin enhanced risk assessment practices and to price their products more effectively, thus supporting more efficient risk management practices. Second, it will help governments design sound insolvency regimes and support programs and optimize policy frameworks in a way that better fosters economic stability and growth.

At the organizational level, there is a need to encourage the development of reliable advanced tools and techniques used in predictive analytics using both the traditional and the new data sets for early warning signals of organizational distress. Simple and comprehensive financial health check-ups along with stress testing procedures can assist business organisations in minimising more chances of insolvency. It also means that organisations should strive to maintain accuracy in their financial reports and establish proper ways of informing the stakeholders during distressed situations.

At the regulatory level, the policymakers should deliberate on how to revise the insolvency laws in order to enhance the efficiency of the legal structures pushing for resolution of cases without much delay. In this regard, other scholars have suggested the development of best practices for the use and implementation of the FDIs and early warning systems to help forestall such events. Governments need to call for cooperation between financial institutions, businesses, and credit agencies, where they can report on distress signals. Moreover, offering seminars and information to the top management of the corporations regarding ways to prevent and handle the financial distress, as well as the proper ways of ethical use of Big Data and predictive models may also enhance the stability of the financial realm. In their ensemble, these measures might contribute to building a stronger informational platform for addressing

problems related to insolvency and to achieving more fair and efficient outcomes of corporate bankruptcies.

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## V. REFERENCES

1. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance*, 23(4), 589-609.
2. Altman, E. I., & Hotchkiss, E. (1993). *Corporate financial distress and bankruptcy* (Vol. 1998, pp. 105-110). New York: John Wiley & Sons.
3. Arora, P., & Saurabh, S. (2022). Predicting distress: A post insolvency and bankruptcy code 2016 analysis. *Journal of Economics and Finance*, 46(3), 604-622.
4. Ashraf, S., GS Félix, E., & Serrasqueiro, Z. (2019). Do traditional financial distress prediction models predict the early warning signs of financial distress?. *Journal of Risk and Financial Management*, 12(2), 55.
5. Balasubramanian, S. A., GS, R., P, S., & Natarajan, T. (2019). Modeling corporate financial distress using financial and non-financial variables: The case of Indian listed companies. *International Journal of Law and Management*, 61(3/4), 457-484.
6. Bhagwati, J. (2022). *Insolvency and Bankruptcy Code (IBC) and Long-Term Bulk Lending in India*. Centre for Social and Economic Progress.
7. Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of banking & finance*, 45, 182-198.
8. Chen, W. S., & Du, Y. K. (2009). Using neural networks and data mining techniques for the financial distress prediction model. *Expert systems with applications*, 36(2), 4075-4086.
9. Claessens, S., & Klapper, L. (2002). *Bankruptcy Around the World. Explaining Its Relative Use*, World Bank Policy Research Working Paper, 2865.
10. DI CARLO, A. (2018). Forecasting and preventing bankruptcy: A conceptual review. *African journal of business management*, 12(9), 231-242.
11. Elhoseny, M., Metawa, N., Sztano, G., & El-Hasnony, I. M. (2022). Deep learning-based model for financial distress prediction. *Annals of Operations Research*, 1-23.
12. Goel, S. (2017). *The Insolvency and Bankruptcy Code, 2016: Problems & Challenges*. Imperial Journal of Interdisciplinary Research (IJIR), 3, 2454-1362.
13. Hotchkiss, E. S., John, K., Mooradian, R. M., & Thorburn, K. S. (2008). Bankruptcy and the resolution of financial distress. *Handbook of empirical corporate finance*, 235-287.

14. Hua, Z., Wang, Y., Xu, X., Zhang, B., & Liang, L. (2007). Predicting corporate financial distress based on integration of support vector machine and logistic regression. *Expert Systems with Applications*, 33(2), 434-440.
15. Keasey, K., & Watson, R. (2019). Financial distress prediction models: a review of their usefulness 1. *Risk Management*, 35-48.
16. Lipson, J. C. (2009). The shadow bankruptcy system. *BUL Rev.*, 89, 1609.
17. Ninh, B. P. V., Do Thanh, T., & Hong, D. V. (2018). Financial distress and bankruptcy prediction: An appropriate model for listed firms in Vietnam. *Economic Systems*, 42(4), 616-624.
18. Ogachi, D., Ndege, R., Gaturu, P., & Zoltan, Z. (2020). Corporate bankruptcy prediction model, a special focus on listed companies in Kenya. *Journal of Risk and Financial Management*, 13(3), 47.
19. Pavlicko, M., Durica, M., & Mazanec, J. (2021). Ensemble model of the financial distress prediction in Visegrad group countries. *Mathematics*, 9(16), 1886.
20. Rao, S., Satya Nandini, A., & Zachariah, M. (2024). Predicting Indian SME financial distress: an ex-ante approach. *Vilakshan-XIMB Journal of Management*.
21. Ravi, A. (2015). Indian insolvency regime in practice: An analysis of insolvency and debt recovery proceedings. *Economic and political weekly*, 46-53.
22. Sehgal, S., Mishra, R. K., Deisting, F., & Vashisht, R. (2021). On the determinants and prediction of corporate financial distress in India. *Managerial Finance*, 47(10), 1428-1447.
23. Shetty, S. H., & Vincent, T. N. (2021). The role of board independence and ownership structure in improving the efficacy of corporate financial distress prediction model: evidence from India. *Journal of Risk and Financial Management*, 14(7), 333.
24. Shukla, R. (2020). Individual Insolvency-The next Big Thing. *Issue 4 Int'l JL Mgmt. & Human.*, 3, 2179.
25. Simić, D., Kovačević, I., & Simić, S. (2012). Insolvency prediction for assessing corporate financial health. *Logic Journal of the IGPL*, 20(3), 536-549.
26. Singh, V. K. (2021). Modern Corporate Insolvency Regime in India: A Review. *NLS Bus. L. Rev.*, 22.

27. Situm, M. (2015). Recovery from distress and insolvency: A comparative analysis using accounting ratios. In *Proceedings of the 6th Global Conference on Managing in Recovering Markets, GCMRM* (pp. 589-606).
28. Terrazas, A. (2010). Diaspora investment in developing and emerging country capital markets: Patterns and prospects. *Migration policy institute*.
29. THOMAS, R. (2008). *The Securitisation & Reconstruction of Financial Assets And Enforcement of Security Interest Act, 2002-A Critique* (Doctoral dissertation, National law school of India University).
30. Vikas, J. (2021). Resolution of Debts and Insolvency and Bankruptcy Code, 2016: The Status of Government Dues and Taxes. *Journal of National Law University Delhi*, 8(1-2), 29-44.

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