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A Bibliometric Analysis of Global Research Trends Associated with the Financial Distress and Bankruptcy Prediction

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Abstract
Financial distress and bankruptcy prediction have been studied for over half a century. However, the literature has grown rapidly and diversified methodologically in the past decade. This study combines a bibliometric analysis with a narrative review to map research on financial distress prediction published between 2015 and 2025. Following PRISMA guidelines, records were retrieved from Google Scholar, Dimensions AI and Scopus using the keywords "financial distress" AND "bankruptcy prediction" AND "financial solvency," yielding 1,319 records, of which 154 peer-reviewed, English-language journal articles met the inclusion criteria. Bibliometric mapping was conducted in VOSviewer to examine publication trends and international co-authorship networks, while the narrative review traced the theoretical and methodological development of prediction models, from early ratio-based approaches to multivariate discriminant analysis, statistical probability models and intelligent techniques such as neural networks and ensemble learning. Publication output grew unevenly over the period, with a marked increase around 2019–2020 and a further acceleration in the most recent three years. Co-authorship analysis identified a connected network of 60 countries across six clusters, led by the United States, China, Australia, Germany and India. The review shows that each generation of prediction models addressed limitations of its predecessor, with intelligent techniques offering greater flexibility at the cost of interpretability, and that model accuracy is highly sensitive to the country, industry and period of application. These findings suggest that no single model is universally superior, and that model selection should be context-specific rather than transferred unchanged across settings. The study contributes an integrated, up-to-date map of fragmented literature and identifies explainability, cross-context validation and hybrid modelling as priority directions for future research.

Keywords: Bankruptcy models, Bibliometric mapping, Distress analysis, PRISMA

Introduction

The early identification of financial distress is a condition where a firm has trouble in meeting its financial obligations and which may culminate in default or bankruptcy. This has identified as a considerable concern for investors, lenders, corporate managers, auditors, and regulatory authorities (Altman, 1968; Beaver, 1966) [2, 5].

Bellovary *et al*. (2007) [6] reviewed bankruptcy prediction studies from the 1930s to the present, and the field has since passed through several methodological generations. Univariate ratio analysis (Beaver, 1966) [5] was followed by multivariate discriminant analysis (Altman, 1968) [2] and by conditional probability models based on logit and probit estimation (Ohlson, 1980; Zmijewski, 1984) [12, 15]. Later scholarly publications assessed the single-period design of these models and proposed hazard models (Shumway, 2001) [13], as well as market-based and option-pricing measures of default risk (Campbell *et al*., 2008; Hillegeist *et al*., 2004) [7, 9].

From the early 1990s, intelligent techniques, beginning with artificial neural networks (Odom & Sharda, 1990; Tam & Kiang, 1992) [11, 14], offered a way to relax the distributional assumptions of the statistical models. Their subsequent development, including support vector machines, decision trees, ensemble learning and hybrid systems, has been reviewed by Kumar and Ravi (2007) [10] and Alaka *et al.* (2018) [1]. Barboza *et al.* (2017) [4] found that boosting, bagging and random forest models achieved higher accuracy than traditional models, whereas Alaka *et al.* (2018) [1] concluded that no single tool is superior on every criterion and that the best performance is likely to come from the informed integration of tools into hybrid models. The transferability of models across countries has also received attention. Altman *et al.* (2017) [3], for example, assessed the Z-Score model on firms from 31 European and three non-European countries.

Existing reviews have largely concentrated on the predictive performance and technical characteristics of individual models. Alaka *et al.* (2018) [1], for instance, examined 49 journal articles published between 2010 and 2015. Less attention has been paid to how the body of literature itself has developed: how research output has changed over time, which countries produce and collaborate on this research, and how these patterns relate to shifts in modelling practice. Bibliometric analysis is well suited to this task because it applies quantitative techniques to map the structure and evolution of a research field (Donthu *et al.*, 2021) [8].

This study therefore combines a bibliometric analysis of the financial distress prediction literature published between 2015 and 2025 with a narrative review of the theoretical foundations and methodological development of prediction models. The objectives are (i) to describe the growth of publications over time, (ii) to identify the countries that lead the field and the collaboration networks among them, and (iii) to trace the development of prediction models from early ratio-based studies to statistical and intelligent technique-based models.

The remainder of the paper is organised as follows. The methodology, including the PRISMA-based selection of articles, is described first, followed by the bibliometric analysis. The paper then discusses the theories used to analyse financial distress, the early development of prediction models, and the statistical and intelligent technique-based models. The final section presents the conclusions.

Methodology

The Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA) guidelines were followed to screen documents for the literature review and bibliometric analysis (Page, McKenzie, *et al*., 2021; Page, Moher, *et al*., 2021). Google Scholar, Dimensions AI and Scopus databases were used to search for literature. The keywords “Financial Distress” AND “ Bankruptcy prediction ” AND “Financial Solvency” were used to find the relevant literature. Searches were restricted to full-text English publications issued from 2015 onwards. The literature search was conducted in April 2026. The inclusion and exclusion criteria and the number of articles selected at each step of the PRISMA presented in Figure 1. The bibliometric analysis was conducted in VOSviewer 1.6.20.

The specific inclusion criteria for bibliometric analysis identified peer reviewed journal articles that explicitly focused on Financial distress analysis, and directly addressed financial distress and bankruptcy modelling. Articles were excluded if they were duplicated across databases, were non-English, were published before 2015, were conference abstracts and if they explicitly integrate tangential or unrelated financial topics. Grey literature (including policy briefs, government reports, working papers, and institutional reports) identified during the search process was screened but omitted from the bibliometric dataset to maintain methodological consistency and comparability.

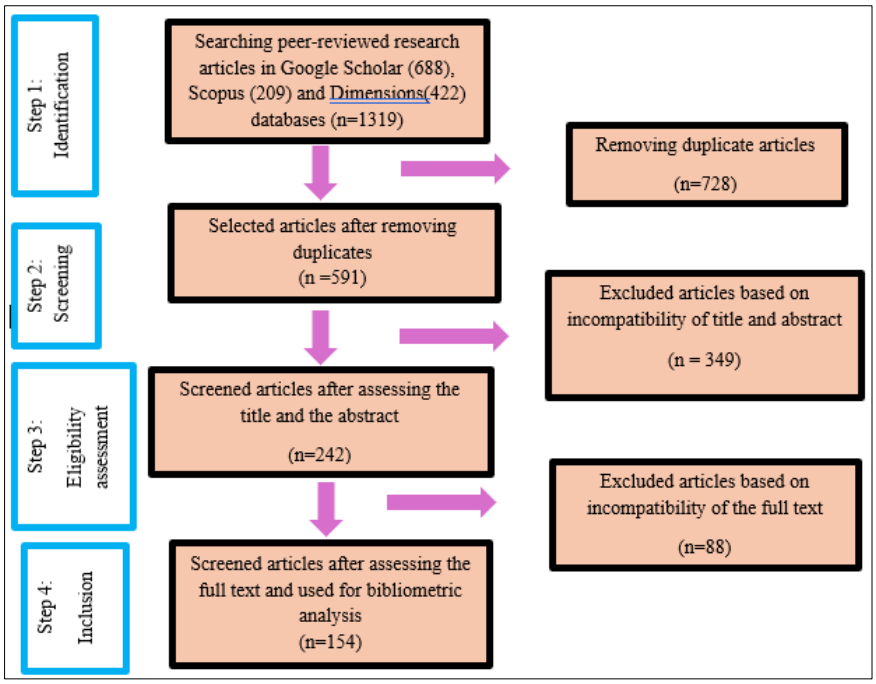


Fig 1: The Flow diagram indicating the steps of selecting articles for the bibliometric analysis based on Preffered Reporting Items for Systematic Reviews and Meta-Analysis (*PRISMA*)

Bibliometric Analysis

The initial search of Google Scholar (n = 688), Dimensions AI (n = 422) and Scopus (n = 209) databases resulted in 1319 articles. At the screening step, 728 duplicate articles were removed, and the remaining 591 articles were assessed for eligibility by assessing title and abstract, and 349 articles were removed due to non-compatibility with the objectives of the literature review and unavailability of full papers. After reading the full text, 88 articles were excluded because of grey literature and non-compatibility of the full text with the inclusion criteria, and a total of 154 articles were selected for bibliometric analysis (Figure 1).

Time series analysis of the scientific literature related to financial distress prediction is presented in Figure 2. The time series analysis identifies the current status and helps to predict future research prospects in the related field (Donthu *et al*., 2021) [8]. According to the annual number of publications in the field of "financial distress prediction", four main phases can be identified: Phase 1 – steady early growth phase (2015-2019), Phase 2 – Development phase (2019-2020), Phase 3 – Growth plateau (2020-2022) and Phase 4 – Renewed acceleration phase (2022-2025). In the steady early growth phase, from 2015 to 2019 this field showed a slow development which shows a 6-8% increase of publications over this period. However, in the development phase (2019 -2020), a surge of number of publications can be observed which accounts for 14% growth in the number of publications over a single year. The observed rapid increase of research output likely coincides with the global wave of research activity following COVID-19, when publication volumes rose sharply across many fields. After 2020, the number of publications in this field become noticeably stable resulting in only 3-4% increase in the number of publications in Phase 3 (2020-2023). This growth plateau can be considered as a period of consolidation after the earlier surge, rather than a decline. However, in the renewed acceleration phase there is a 20% growth of the number of publications over the past three years.

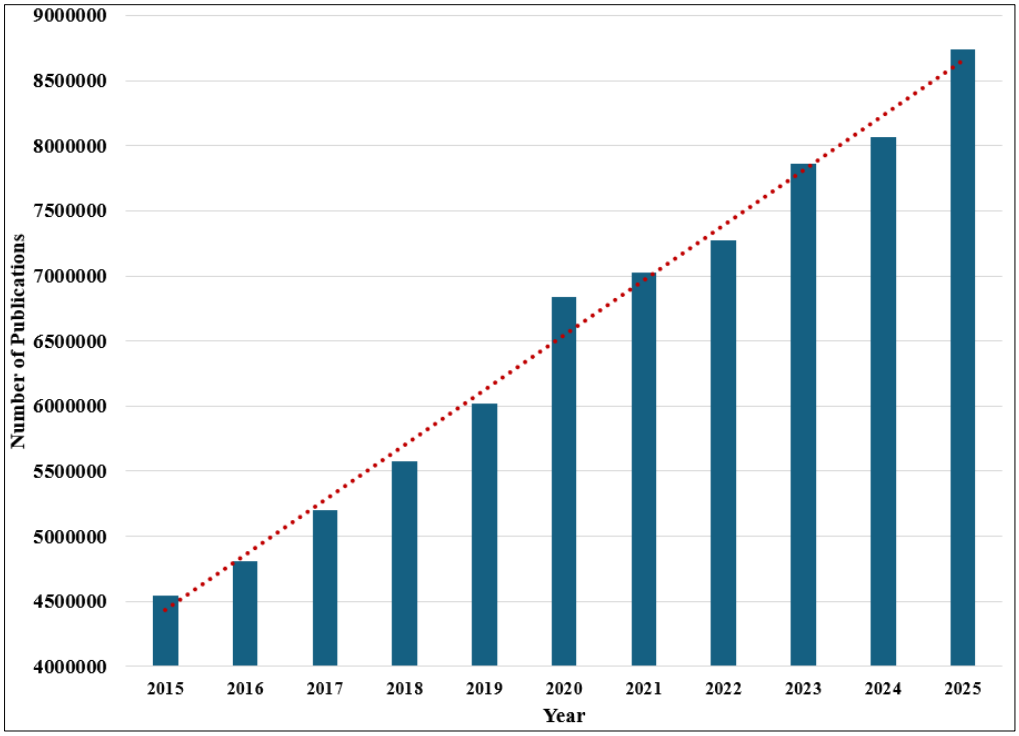


Fig 2: Annual number of publications related to financial distress prediction from 2015-2025

The global collaborative network map based on co-authorship between countries is given in Figure 3. The size of a circle representing a country is positively correlated with the number of publications. The largest set of connected countries consists of 60 countries in 6 clusters based on collaborations. The USA, China, Australia, Germany and India are the countries with the highest number of publications (Figure 3).

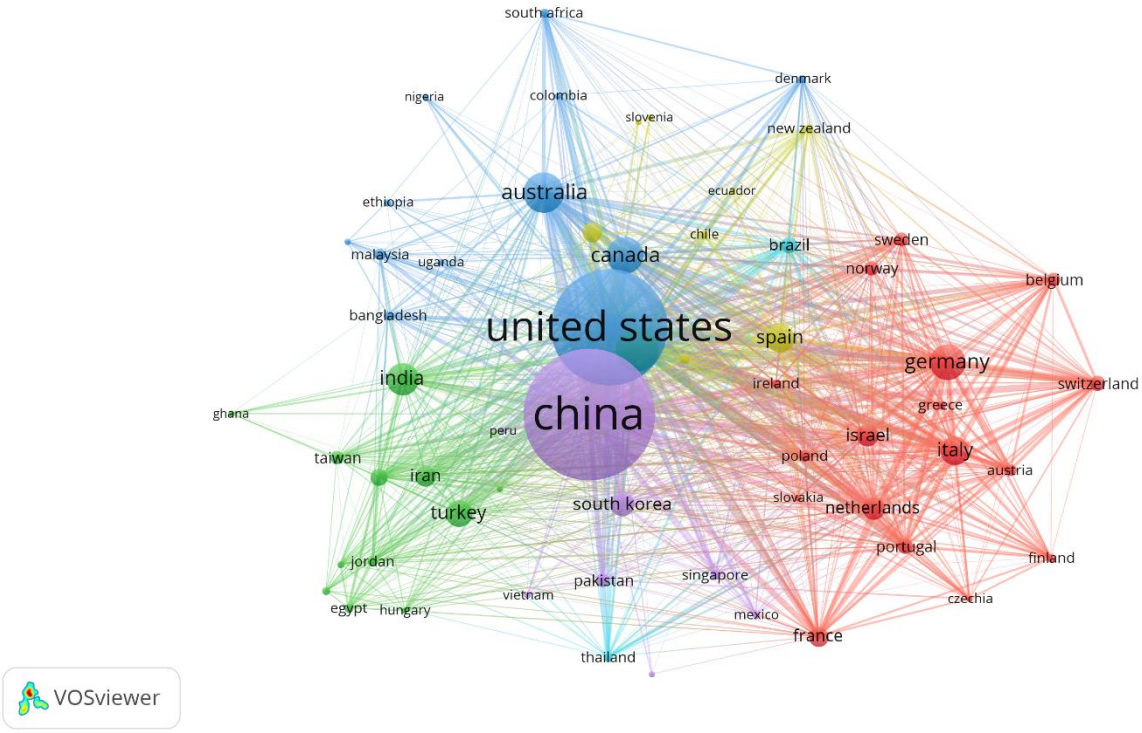


Fig 3: The global collaborative network map based on co-authorship between countries

The overlay visualization map of counties is presented in Figure 4. This map provides a visualization of research productivity related to financial distress prediction at different countries over the 2015–2025 period. The contribution of China to the field has significantly increases during the year 2025, while the United States, Australia and Canada have significantly contributed to publications during the past three years (Figure 4).

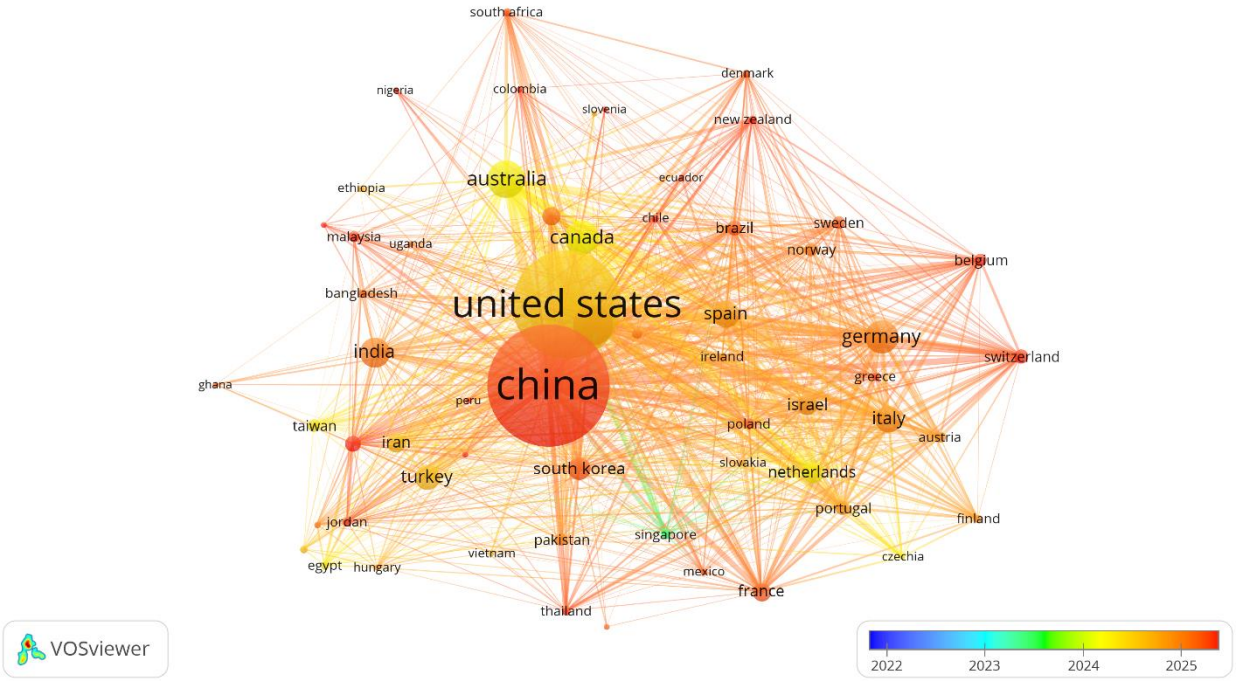


Fig 4: The overlay visualization map of the countries according to the number of publications in each year.

Theories for Analyzing Financial Distress

There are limited theories in literature which relate to prediction of financial distress in the corporate world.

Gamblers Ruin theory, which was based on probabilities was developed by Feller (1968). This theory assumes the firm is assumed as a Gambler and it has a certain amount of money for its operation. Depending on cash inflows and cash outflows the firm will experience positive or negative cash flows. If the cash flow is continually negative and the firm declares bankruptcy but continues operation if the net worth is greater than zero. Financial distress occurs when a firm will continue to operate until its net worth is zero or until it goes bankrupt (Chi & Pozdnyakov, 2026).

This theoretical perspective is applicable to the corporates. Excessive expenses above its revenue results in a situation of negative operational cash flows. To overcome this phenomenon, corporations acquire debt without considering its capital structure. When these debts fall due, due to the shortage in cash, the corporate will default its debt repayment commitment. This results in the company been bankrupt (Ahmed *et al*., 2024; Li *et al*., 2023).

Early Development of Prediction Models

The earliest available study in the field of prediction model dates back to 1930s. Twenty nine firms were analyzed on the failure characteristics of firms which was performed by Bureau of Business Research. The analysis was performed using twenty nine ratios and concluded that eight ratios were good indicators to represent weakening firms. The eight ratios were Working Capital to Total Assets, Surplus and Reserves to Total Assets, Net Worth to Fixed Assets, Fixed Assets to Total Assets, the Current Ratio, Net Worth to Total Assets, Sales to Total Assets, and Cash to Total Assets. Among the eight ratios, Working Capital to Total Assets was the more superior in the prediction of the firm as per the analysis done by Bureau of Business Research (Braunsberger & Aschauer, 2025). Furthermore, there were research studies performed based on the sizing of the organization. Once such study was carried out by Merwin (1942) focusing on small manufacturers. During his study he observed that failure signals could be witnessed four to five years prior to the actual event when compared with successful firms. He concluded that ratios of Net Working Capital to Total Assets, Current Ratio, and Net Worth to Total Debt had significant predictive power of providing early warning signals of failing firms. A similar study was performed by on small manufacturing firms and concluded that the three ratios of Net Working Capital to Total Assets, Current Ratio, and Net Worth to Total Debt had superior prediction power and detection of failure could be predicted four to five years before the actual event.

Chudson *et al*.(1945) conducted the first study on Financial structures and concluded that though no general financial structure on an economy wide level is present, clustering on an industry basis is possible considering industry, size and profitability. The study results were a significant finding for the prediction model development. The author concluded that models developed for general applications cannot be used for prediction of industry specific applications. A comparative study of successful and unsuccessful firms were performed by Jackendoff (1962). The author concluded

that Current Ratio and Net Working Capital to Total Assets ratio were lower for unsuccessful firms when compared to successful firms while Debt to Net worth ratios were higher for failure firms.

Statistical models

Early research on bankruptcy prediction models focused on univariate studies (Beaver, 1966; Altman, 1968; Ravi Kumar *et al*., 2007; Behr *et al*., 2017) [2, 5]. They focused on individual ratio analysis and compared ratios of failed firms with the ratios of successful firms.

The univariate model is built on individual signals of failure where it measures each ratio separately. A firm is classified as either failed or non- failed depending on an 'optimal cut off point' of the ratio. If the ratio is below the cut-off point the firm is classified as fail and if the firm's ratio is above the cut-off point the firm is classified as non- failed. Simplicity is one key advantage of the univariate model while the firm classification can be evaluated for one ratio at a time which could give inconsistent and confusing results is a key disadvantage of the model. Furthermore, importance of ratios cannot be identified in the model as all are assume to have equal importance, 'cut-off points' are identified through trial and error method are other disadvantages of the univariate model. In his scholarly article on univariate study, Beaver (1966) [5], evaluated 79 failed firms and 79 successful firms which spanned over 38 industries. He used the mean values of 30 ratios and considered the predictive power of these ratios for bankruptcy prediction. Among the 30 ratios, Net Income to Total Debt had the highest predictive ability of 92% accuracy one year prior to failure. Total Debt and Cash Flow to Total Assets all had an accuracy of 90% in predicting failure one year prior to the occurrence. Further univariate studies have been used by Pinches *et al*.(1975) and Chen and Shimerda (1981) which has yielded similar results as Beaver (1966) [5].

Stemming from Beaver's 1966 study and his recommendation that combining multiple ratios may have higher prediction ability, E. Altman developed the first multivariate study in 1968 (Altman,1968) [2]. characteristics. The multivariate discriminant analysis (MDA) introduced the concept of "Z-score". This consisted of a collection of variables capable of providing a classification of successful and failure firms. There are several key assumptions in the MDA model: The data set is discrete, non-overlapping and identifiable;The independent variables follow a normal distribution; Covariance's are equal across the failing and the non-failing group; The prior probability of failure and the misclassification costs are known.

Alman (1968) [2] model used five factors in predicting bankruptcy in the manufacturing sector. This was used to predict the prediction ability and if it fell within a certain range had a 95% accuracy in the predictive power one year before failure. Similar to other models, the predictive ability decreased to 72% in year two,48% and 29% respectively in year three and four prior to the actual event of bankruptcy. The accuracy of prediction was at 79% for a holdout sample. Subsequently many researchers used the MDA model with different factors. Daniel (1968) used a ten factor multivariate discriminant analysis (MDA) which had a prediction power of 91.8% on failed firms which 100% for successful firms.

Deakin (1972) used a 14 factor multivariate discriminant analysis to predict the bankruptcy of firms. The model used 11 failed and 23 non-failed firms during the period of 1963 and 1964 which were randomly selected from Moody's industrial manual. The model had a classification accuracy

for failed firms of 77%, 96%, 94%, 91% and 87% for years one to five prior to failure whilst the accuracy for non-failed firms were 82%,92%, 82%, 67% and 78% respectively for years one to five prior to failure. Using the above results, he concluded that the variables used were able to predict as far as three years prior to the event.

The Linear Probability based Models (LPM) focus on expressing the probability of failure or success of a firm as a dichotomous variable. Failure and success were defined by obtaining boundary values. The major strength of the LPM model is that it defines failure or success as a probability. The complexity of interpretation for an average person was a major drawback in LPM. There have been several studies in model building using LPM in the prediction of financial distress and bankruptcy domain (Maddala, 1983; Theodossiou, 1991; Gujarati, 1998; Morris, 1998).

Edmister (1972) used Linear Discriminant Analysis (LDA) and used the 19 ratios which are the quick, current, inventory/net working capital, net working capital/total assets, current assets/total debt, total debt/equity, fixed assets/equity, cash flow/ current liabilities, current liabilities/equity, equity and long-term debt/ fixed assets, inventory/sales, fixed assets/sales, total assets/sales, net working capital/sales, equity/sales, earnings before taxes (EBT)/sales, EBT/total assets, EBT/equity, and EBT plus depreciation/total debt.

Starting from 1980s, model building shifted from the traditional MDA models to Logit, Probit and Neural networks. Furthermore, industry specific models targeting banking, manufacturing, hospitality etc. emerged during this period. A trend emerged developing country specific models. These were developed targeting countries such as Australia, Austria, Finland, Canada, Japan, Korea, Belgium, Greece, Singapore, Spain, Sweden etc.

A nine factor LDA model was developed by Raja and Goureia (1980) concluded that Cash flow/Total Debt was the most significant univariate ratio capable of predicting bankruptcy. Their model was able to predict "Problem firm" with a 79% accuracy while "Growth firm" with a 65% accuracy. The nine factor logit model of Ohlson (1980) [12] had a prediction accuracy of 96% for year one and year two prior to bankruptcy and 93% accuracy for one or two years prior to bankruptcy.

Intelligent Technique-Based Models

The move towards intelligent techniques related prediction models are less vulnerable to the above assumptions and thus opened many news studies in literature. Artificial neural networks, Fuzzy inference systems, Genetic algorithms (GAs), their hybridizations (neuro-fuzzy, neuro-genetic, fuzzy-genetic), computationally intelligent methodologies such as support vector machines, boosted decision trees, random forests are some of the intelligent techniques found in the literature.

The initial work to predict financial distress and bankruptcy through the usage of Neural Network based models were developed by Odom and Sharda (1990) [11] and Tam and Kiang (1992) [14], Wilson and Sharda (1994) developed a model using five accounting ratios, resampling and neural networks. The model yielded higher prediction accuracy compared to MDA when used on a sample of 65 bankrupt firms and 64 non-bankrupt firms. Nine financial ratios were used on a neural network by Cinca *et al*. (2005) targeting 66 Spanish banks and concluded that the model had a higher predictive power compared to LDA. In his study, Charalambous *et al*. (2000) compared five neural network methods, namely; Learning Vector Quantization, Radial Basis Function, Feed- forward networks that use the conjugate gradient optimization algorithm, the back-propagation algorithm and the logistic regression. He used 139 matched pairs of bankrupt and non-bankrupt firms in his analysis.

Lipmann (1987) defined Artificial Neural Networks as an information processing system that is used to mirror human reasoning. They are modelled on the functions and activities of the human brain. Development of prediction models incorporating classification techniques similar to brain functionality using Neural Networks (NN) was further researched by Bell *et al*.(1990) and Khanna (1990). NN use past data to learn relationships and detect patterns in the data set.

As per Zhang *et al*.(1999) the capability to induce algorithms for recognizing patterns were the major strength in NN. The "black box" phenomena in models developed using NN, which lack transparency, is one of the major weaknesses. Among the NN base techniques Case-based reasoning (CBR) has been used in literature by researchers due to the following advantages. Among the advantages of CBR is that it uses a data-driven approaches because it is easy to apply, has no possibility of overfitting and provides good explanation for the output while the low prediction accuracy is a weakness. Bhattacharjee and Han (2014), and Chiu and Wu (2002) are some examples of literature where CBR has been used in models to predict financial distress and bankruptcy.

A distribution-free technique applicable under less restrictive conditions regarding population distribution and data measurement was used by Tam and Kiang (1992) [14] in their model built using K-nearest neighbour (KNN). The KNN used a non-parametric method for classifying observations that relaxes the normality assumption as well as eliminates the functional form required in DA and logit was a key advantage. The model suffered from lack of transparency as NN models were characterized as "black boxes". Genetic Algorithm (GA) is another neural network technique which has been used in model building exercise in the area of financial distress and bankruptcy prediction. GA uses a stochastic search technique to find an optimal solution to a given problem from a large number of existing solutions. The main advantage of GA is that the optimized linear function without restrictive statistical hypotheses such as normality of explanatory variables or the equality of the variances/co-variances matrix though the lack of transparency similar other NN models was the main disadvantage.

Conclusion

This study reviewed the financial distress and bankruptcy prediction literature published between 2015 and 2025 by combining a PRISMA-guided selection process, a bibliometric analysis and a narrative review of prediction models. Of the 1,319 records retrieved from Google Scholar, Dimensions AI and Scopus, 154 peer-reviewed articles met the inclusion criteria and were analysed.

The bibliometric results show that research output has grown unevenly. Publications rose slowly between 2015 and 2019, increased by about 14% over a single year between 2019 and 2020, and then levelled off, with growth of only 3–4% during the consolidation phase. Over the most recent three years, output has accelerated again by roughly 20%, which suggests

that interest in the topic is being renewed rather than fading. The co-authorship analysis identified a connected network of 60 countries in six clusters. The USA, China, Australia, Germany and India produced the most publications, China's contribution increased markedly in 2025, and the USA, Australia and Canada were particularly active in the past three years.

The review of the literature shows that prediction models have evolved from the comparison of individual financial ratios in early studies, through Altman's multivariate discriminant analysis and probability-based models, to intelligent techniques such as neural networks, case-based reasoning, k-nearest neighbour and genetic algorithms. Each generation addressed limitations of the one before it. Multivariate models overcame the inconsistency of single-ratio classification, and intelligent techniques removed the restrictive distributional assumptions of statistical models. However, the gain in flexibility came at the cost of transparency, since many intelligent models operate as "black boxes". The studies reviewed also indicate that models re-estimated for a local context, such as the Indian manufacturing sector, tend to be more accurate than the original models, that combining non-financial and financial variables can improve accuracy, as in the Ghanaian mixed model, and that uniform cross-country models can achieve acceptable accuracy across many national settings.

Taken together, the evidence indicates that no single model is universally superior. Model choice involves trade-offs between accuracy, transparency, data requirements and the assumptions an analyst is prepared to accept, which is consistent with the conclusion of Alaka *et al*. (2018) [1]. For researchers and practitioners, the practical implication is that models should be selected and calibrated for the industry, country and period to which they will be applied, rather than adopted unchanged from the setting in which they were developed.

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