

# Advancements in Bankruptcy Prediction Models and Bibliometric Analysis

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**Abstract:** Since the economic downturn of the 1930s, there has been a growing interest in predicting company bankruptcies. Though not a new topic, the prospect of business bankruptcy has gained increasing relevance due to globalisation. This study explores various methodologies employed in predicting bankruptcy. Preventing bankruptcies also bolsters economic stability by averting the adverse effects of insolvency on the community. Companies with a solid and flexible economic foundation are more likely to succeed. This article reviews existing literature, discusses prevalent predictive models, and presents a statistical analysis of bibliometric data associated with bankruptcy prediction. This work aims to answer the research question of identifying the trends over time in the econometric models used to predict bankruptcy. This article may be useful for finance and business students in providing an overview of the subject and for business managers to identify the key determinants of financial distress. Exploring the R package, *Bibliometrix*<sup>®</sup> demonstrates its efficacy as a powerful tool for science mapping.

**Keywords:** Bankruptcy prediction, Predictive models, Financial distress, Bibliometric analysis, Risk

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## 1. Introduction

Bankruptcy prediction models have been a subject of significant interest in financial literature, especially in the fields of business management and finance. This paper presents a literature review of bankruptcy prediction models from 1966 until 2024 that intends to identify trends in the most used methods and give a panorama of how this subject has been dealt with in literature. Bankruptcy prediction relies on analysing key financial indicators through various statistical and machine-learning methods, reflecting the evolution of techniques in this field. Complementary, a bibliometric analysis is presented regarding documents published in this field that are indexed in the Web of Science. The research for the bibliometric analysis was done with a set of keywords, namely Bankruptcy Prediction, Bankruptcy Prediction Models, and Financial Distress for the same period used in the literature review. It is highlighted that for the years 1966 to 1970, there are no documents with the keywords analysed. For this reason, the bibliometric analysis was conducted since 1971 until 2024.

As noted by White et al (1998), the risk of bankruptcy represents the uncertainty regarding a company's ability to sustain operations should its financial state reach a critical point. Argenti (1976) underscores the importance of examining the root causes of bankruptcy to anticipate similar drawbacks in the future. Moreover, Barros (2008) elucidates that business failure encompasses numerous factors, including deficient management practices, shortcomings in accounting systems, resistance to change, involvement in overly ambitious ventures, over-reliance on financing, and inherent risks inherent to the business landscape.

Sousa and Oliveira (2014) delineate that the causes precipitating bankruptcy proceed from both internal and external origins, classifiable as endogenous and exogenous variables. Ferreira (2016) further explains that those external factors may stem from macroeconomic influences, intense market competition, or shifts in consumer behaviour. In contrast, internal factors are linked to a company's strategic resource allocation, adaptability to market dynamics, managerial efficacy, debt burden, and operational inefficiencies. Bankruptcy causes are diverse and frequently influenced by factors such as economic crises or the volatility of the business environment (Almeida, 2010).

In the banking sector, stress tests conducted by institutions like the European Central Bank (ECB) serve as risk assessment measures, particularly in adverse scenarios. These tests measure a bank's resilience against crises, credit deterioration, and economic contractions. Thereby aiding in the evaluation of asset quality and systemic stability. This analogy underscores the significance of predictive models in averting bankruptcy and enhancing decision-making processes. Consequently, an abundance of models has been devised utilizing statistical data analysis techniques to forecast companies' susceptibility to failure or financial distress (Yang, You, and Ji, 2011).

The paper contributes to the literature review analysis from 1966 to 2024, providing insights into the evolution of bankruptcy prediction models over nearly six decades. The methodologies used in the paper offer insight into how the discourse surrounding bankruptcy prediction has evolved within the academic literature. Additionally,

it demonstrates the reliance of bankruptcy prediction on key financial indicators, elucidating the transition from traditional statistical methods to the contemporary utilization of machine learning techniques. This holistic examination enhances the understanding of the prevailing approaches to bankruptcy prediction and informs future research directions in financial analysis and risk management.

## **2. Methodology**

The methodological approach chosen for this article was a literature review emphasising the bankruptcy models. This includes describing available knowledge for professional practice and identifying experts within a specific field (Fink, 2005). The data repository for the literature review was extracted from Elsevier, Science Direct, Springer and Web of Science (WoS).

The selection of the Clarivate database (WoS, Web of Science) for the bibliometric analysis in 2024 was made deliberately to ensure the validity and reliability of the data. Web of Science is renowned for its coverage and rigorous standards, providing Impact Factor (IF) metrics and enhancing the credibility of the analysis (Roldan-Valadez et al, 2018). The keywords utilized in the search were "Bankruptcy Prediction", "Bankruptcy Prediction Models", and "Financial Distress". The retrieved data included scientific articles, proceedings papers, review articles, book chapters, and early access publications from 1971 to 2024, focusing specifically on publications in finance, economics, and related fields. The search yielded 6,805 outcomes, with no language restrictions applied. Full papers were included in the review to ensure a thorough evaluation of the literature on bankruptcy prediction models. Subsequently, a bibliometric analysis was performed using the program R Studio® and the *Bibliometrix*® package. Seven papers were excluded from the analysis due to their retracted status.

## **3. Bankruptcy Prediction Models**

The introduction of financial ratios, initiated by Beaver (1966) and his seminal univariate analysis, marked a pivotal moment in corporate bankruptcy prediction. These ratios remain important in assessing companies' financial challenges, with the Cash-flow/Total Liabilities ratio emerging as particularly insightful. Altman (1968) advanced this approach by categorising ratios into five distinct groups: liquidity, profitability, indebtedness, coverage, and activity. Altman (1968) also formulated the Z Score Model, utilising Multivariate Discriminant Analysis (MDA) to evaluate the company's characteristics.

Kanitz (1974) introduced a model for predicting insolvency based on multivariate discriminant analysis (MDA), known as the Insolvency Factor. The author developed an "Insolvency Thermometer" based on the following principle: if the result of the corresponding discriminant function is between -7 and -3, there is a risk of insolvency; between 0 and -3, there is uncertainty; and if it is greater than 0, there is no risk of insolvency.

Subsequently, Ohlson (1980) and Zavgren (1985) introduced the logit regression econometric model to enhance bankruptcy prediction. While Ohlson emphasised the logistic regression model's utility in quantifying the probability of bankruptcy compared to discriminant analysis, Zavgren used a sample of solvent and insolvent companies to estimate the probability of bankruptcy. On the contrary, Platt (1985) suggested that external agents have various resources to identify signs of bankruptcy in companies. These sources can be categorised into three distinct groups: common sense, analysis of companies' published accounting statements (when available), and statistical tools. In efforts to predict bankruptcy amidst high volatility and unpredictability, Pascal (1988), in collaboration with Altman, developed a multivariate discriminant analysis model, which demonstrated reasonable effectiveness in predictions. According to the model, if Z is greater than 0.4, there is no risk of insolvency, while if Z is lower than -1.05, there is a high possibility of insolvency.

Peres (2014) underlined conditional probability models, namely Logit and Probit, as alternatives to more resource-intensive models in bankruptcy prediction. In the Logit Model, calculations involve financial ratios multiplied by coefficients resulting from estimation. Assuming bankruptcy is indicated by 0, the higher the resulting decimal is above 0.5, the less likely the company will go bankrupt. Similar conclusions to Logit are obtained with the Probit model, although the coefficients are more challenging to interpret, and a larger sample is needed for better performance. Furthermore, Logit and Probit are relatively more complex in terms of calculation compared to MDA.

The Gompertz distribution is an important growth model and has numerous applications in actuarial studies (Adham and Walker, 2001). Similar to Logit and Probit, the Gompit model employs the maximum likelihood method for estimation, generating estimated probabilities within the interval 0,1. Consequently, the Gompit model is deemed the most suitable for investigating the bankruptcy of SMEs compared to the Logit and Probit models. According to Laitinen (1991), companies do not follow a uniform pattern of behaviour. In some cases,

the deterioration of indicators is not continuous, reflecting cyclical movements that may eventually lead to bankruptcy. Additionally, Laitinen (1991) points out that the various indicators used can fluctuate over time.

By introducing the non-parametric method known as data envelopment analysis (DEA) in conjunction with mathematical programming, Paradi et al (2004) demonstrated the feasibility of comparing pairs of companies, evaluating their relative efficiencies regarding financial bankruptcy by measuring the distance to the efficient frontier. The authors noted that bankrupt companies exhibit significantly lower average efficiency scores than non-bankrupt companies. Hence, low-efficiency scores in the worst practice models indicate that companies excel at being inefficient.

Du Jardin (2015) employed financial ratios encompassing key dimensions influencing bankruptcy, including liquidity, solvency, profitability, financial structure, activity, and turnover. The pioneering use of neural networks was conducted by Odom and Shard (1990); Tam and Kiang (1990), that used this model to predict bank failure. Similarly, Du Jardin (2015) utilised neural networks to forecast company bankruptcy, employing financial data as input and a Z-score to determine the probability of bankruptcy. The network adjusts its weights through training to minimise the disparity between predictions and actual outcomes. Despite the utility of Artificial Neural Networks highlighted in various studies, Peres (2014) emphasised their limitations, including the challenge of identifying the optimal model amidst diverse network topologies, methods, and learning parameters.

Du Jardin (2015) explains a limitation in traditional failure modelling methods, where each company is represented by variables measured only once, thus excluding time as an explanatory factor. However, it was noted that survival analysis allows for incorporating time by employing longitudinal data. The author further explained that the Cox model estimates the risk function based on explanatory variables as an example of survival analysis, assuming proportional hazards where the relationship between risk rates remains constant over time. First introduced by Cox in 1972 for measuring bank failures, this model is known for predicting proportional risks using failure rates, employing a semi-parametric approach that does not necessitate specifying the data distribution (Andersen, 1982).

Cortes and Vapnik (1995) proposed the concept of support-vector networks, which operate on the following principle: it transforms the input vectors into a high-dimensional feature space  $Z$  via a predetermined non-linear mapping. Within this space, a linear decision surface is crafted, possessing unique characteristics that guarantee the network's strong generalisation capability. Wang et al (2005) inspired by the technique named Support Vector Machine (SVM), grounded on the principle of minimising structural risk as opposed to empirical risk. SVM is acknowledged as a potent and promising tool for data classification and function estimation, even with limited samples.

Coad et al (2013) argue that firm performance is more appropriately modelled as a random walk process, while survival is determined non-randomly and depends mainly on the stock of accumulated resources. The Gambler's Ruin theory is applied, combining two elements: random company growth and survival (Akhundjanov and Toda, 2019). Inspired by Wilcoxon (1971), this approach uses the metaphor of a group of players gathered around a gaming table, each with a set of resources. Like business people, players in this game of chance tend to be optimistic about their chances of winning, although they have little or no control over the outcome.

The Kaplan-Meier method serves as a non-parametric estimator of the survival function, analysing the time elapsed from the beginning of a study to a specific event. According to Correia (2016), this estimator has gained increasing reliability. However, the model needs to be revised to handle multiple covariates, requiring the creation of several strata, which may lead to small sample sizes and hinder comparison. Nevertheless, the Kaplan curve remains a viable tool for analysing company survival (Gonçalves et al, 2017).

Kaski et al (2001) devised a method based on Fisher's information matrix to derive a metric in the data space, employing the Self-Organising Map (SOM) to explore companies' financial statements. This metric evaluates local distances considering changes in the distribution of an auxiliary random variable, reflecting data significance. Chen et al (2013) described the Self-Organising Map as a non-parametric neural network used for visual clustering in various applications. The authors' studies analysed changes in companies' financial situations and trajectory patterns through a clustering process with the self-organising map, evaluating potential bankruptcy scenarios by examining temporal changes in financial indicators. Initially, the Self-Organising Map characterises bankruptcy risk, followed by projecting instantaneous observations onto the map to form a trajectory vector.

Advancing on the models, Chen (2011) reported that Decision Tree is a standard data mining methodology that simultaneously offers classification and prediction functions. Analysing the provided data constructs a tree-like structure model through inductive reasoning. This technique is systematically employed, constructing the tree from a training sample until the terminal nodes. It exclusively contains companies of two specific types: bankrupt or non-bankrupt. New entities are classified based on the terminal node in which they fall in the tree, identifying the group to which they belong and the associated probability. However, this progressive selection approach can expose the tree to the problem of overfitting since it requires reconsidering the analysed variable later. Peres (2014) explored the use of Decision Trees in the context of corporate bankruptcy, emphasising their effectiveness in classifying companies based on financial data. Additionally, Peres implies that using Genetic Algorithms in corporate bankruptcy research aims to enhance this process by extracting a set of rules or conditions for classification. These conditions, which are linked to specific cut-off points, enable the model to more accurately predict whether a company is likely to fail or not.

Another approach is the Rough Set, developed to generate rules distinguishing between healthy and failing companies, aiming to predict corporate bankruptcy. Dimitras et al (1999) applied the Rough Set theory to construct bankruptcy prediction models in Greece. It observed many advantages, including comprehensible decision rules and integrating qualitative and quantitative variables. However, challenges such as variability in rule sets and redundancies were noted. The method underscored the significance of financial profitability, liquidity, debt capacity, and working capital ratios without necessitating prior assumptions. Moreover, the Rough Set method can analyse new datasets and generate suitable rules as needed, representing the requisite expertise.

Tian, Shi, and Liu (2012) accentuate that machine learning represents one of the most important and impactful advancements. Barboza et al (2017) conducted a study employing machine learning to differentiate between bankrupt and non-bankrupt companies, focusing on business characteristics like profitability, liquidity, leverage, size, and growth measures. The authors exploited potential discriminant variables and identified weights or coefficients applicable in mathematical functions to separate groups, such as bad borrower vs. good borrower or bankrupt company vs. non-bankrupt company.

Computational methods handle imprecise problems, incomplete data, and uncertainty, which are common traits in predicting corporate bankruptcies. According to Korol (2013), while statistical models prioritise accuracy and reliability, artificial intelligence models thrive on the premise that accuracies enable the management of imprecise data and uncertainty, distinguishing them from statistical models. The integration of these models has been instrumental in advancing bankruptcy prediction, offering significant insights into corporate risk mitigation. From the early contributions of Altman to contemporary methods like neural networks and genetic algorithms, this synergy has continuously underscored the importance of this interdisciplinary approach.

#### **4. Bibliometric Analysis**

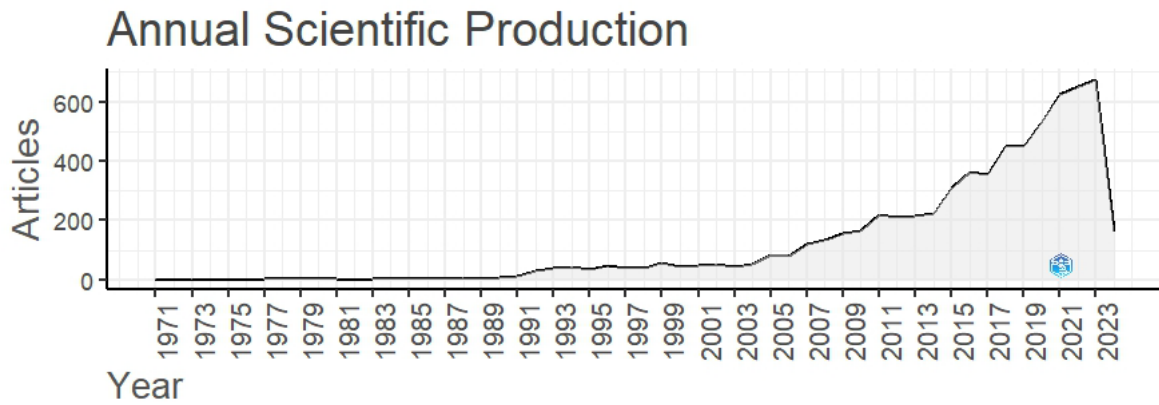
According to Craine (1972), bibliometrics studies provide a more objective and reliable analysis. The vast volume of thematic research, conceptual developments, and data form the milieu in which bibliometrics becomes useful by providing structured analysis to a large body of information, allowing inference of trends over time. Aria and Cuccurullo (2017) argue that science mapping nowadays is indispensable for scholars in every scientific field. With the rapid growth of publications and the fragmented development of knowledge, accumulating and organizing information becomes ever more challenging.

Designed by Aria and Cuccurullo in 2017, the *Bibliometrix*<sup>®</sup> package is known for conducting inclusive science mapping and bibliometric analyses. Programmed in R, the proposed tool is flexible and can be promptly updated and integrated with other statistical R packages. Therefore, it proves useful in a constantly evolving science such as bibliometrics.

#### **5. Results**

This section presents the findings of the bibliometric analysis conducted on the dataset obtained from the Clarivate database (WoS), using statistical techniques in R Studio<sup>®</sup> and the *Bibliometrix*<sup>®</sup> package. The aim is to uncover significant trends and patterns in the research landscape surrounding the articles analysed. It provides an overview of the scholarly activity in this domain over the past decades with results from computing key metrics, such as publication trends, most productive countries, and keyword co-occurrences, among other topics. These results offer insights into the evolution, impact, and direction of research in the field of financial distress and bankruptcy prediction.

The analysis covered the temporal range from 1971 to 2024, incorporating diverse sources, including journals, book chapters, proceeding papers and early access. A dataset of 6,805 documents revealed an annual growth rate of 10,05%. The average document age is 8,47 years, suggesting a continuous influx of recent research. Each document received an average of 25.86 citations, emphasising its impact and relevance. Moreover, considering citations per year, an average of 2.318 citations were observed, indicating the continuing influence of the research. These findings emphasise the depth and breadth of scholarly contributions in the field, reflecting a rich landscape of research and knowledge dissemination.



**Figure 1: Annual Articles Scientific Production**

The Annual Scientific Production chart shown in Figure 1 informs us about the tendency of publication spread through the years and reflects a steady and remarkable growth over time. It started gradually increasing, with occasional fluctuations, until the late 1990s. From the turn of the millennium onwards, there has been a noticeable flow, indicating an increasing interest and investment in scientific research. 2024 shows a notable decrease compared to the previous year, but this could be attributed to various factors such as shifts in research priorities, external circumstances, methodological changes in data collection, or the fact that it is still only the first semester of the year. This trend underscores the enduring commitment to advancing knowledge and innovation in the scientific community.

**Table 1: Top 10 Sources Publication with the Highest Number of Articles in this Field**

Top 10	Most Relevant Sources	Articles
1	Expert Systems with Applications	182
2	Journal of Banking & Finance	145
3	Journal of Financial Economics	104
4	Journal of Corporate Finance	88
5	European Journal of Operational Research	82
6	Sustainability	77
7	Review of Financial Studies	74
8	Journal of Finance	70
9	International Review of Financial Analysis	51
10	Applied Economics	48

Table 1 presents the top 10 most relevant publication sources based on the number of articles contributed to this topic, their respective scientific areas, and their quality indicators. "Expert Systems with Applications" leads with 182 articles, followed by "Journal of Banking & Finance" with 145, and "Journal of Financial Economics" with 104. Other significant sources include "Journal of Corporate Finance" (88 articles), "European Journal of Operational Research" (82 articles), and "Sustainability" (77 articles). Rounding out the list are "Review of Financial Studies" (74 articles), "Journal of Finance" (70 articles), "International Review of Financial Analysis" (51 articles), and "Applied Economics" (48 articles). These sources collectively represent a significant body of literature in finance, economics, and related fields.

Table 1: Top 10 most relevant keywords in the articles analysed.

Top 10	Most Relevant Keywords	Articles
1	Financial Distress	729
2	Bankruptcy	627
3	Bankruptcy Prediction	253
4	Credit Risk	163
5	Financial	150
6	Capital Structure	147
7	Machine Learning	140
8	Corporate Governance	139
9	Covid 19	106
10	Prediction	106

Table 2 presents the top 10 most relevant keywords in articles analysed in the bibliometric study. These keywords are "Financial Distress", "Bankruptcy", "Bankruptcy Prediction", "Credit Risk", "Financial", "Capital Structure", "Machine Learning", "Corporate Governance", "Covid 19" and "Prediction". These keywords indicate a focus on understanding and predicting financial distress and bankruptcy, assessing credit risk, optimizing capital structure, applying machine learning techniques in finance, examining corporate governance practices, and studying the impact of events like COVID-19 on financial markets and predictive models. The table provides insights into the trends and areas of interest within the academic community, but it might also assist researchers in directing their studies towards relevant topics.

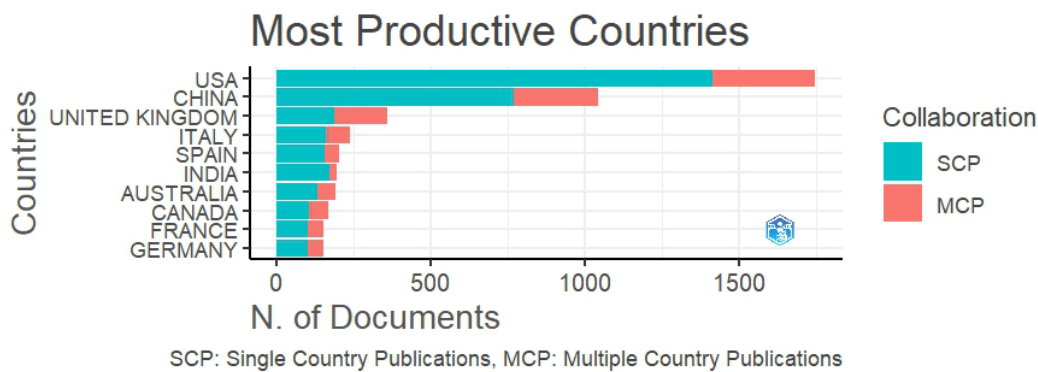


Figure 2: The Most Productive Countries

The Most Productive Countries chart, shown in Figure 2, demonstrates that the USA, China, and the United Kingdom, respectively, have the highest number of single and multiple-country publications in scientific articles addressing bankruptcy prediction. This indicates that these countries are prolific in publishing articles independently and collaborating internationally on scientific research. The countries were selected by the analysis using the R Studio® program based on their number of contributions to the literature on the topic. It was determined by assessing the number of publications retrieved in the WoS search originating from each country. This chart contributes to indicate each country's geographical distribution and scholarly activity. The visual representation enhances the understanding of the global research landscape and the importance of international collaboration in advancing knowledge and addressing complex issues in the field.



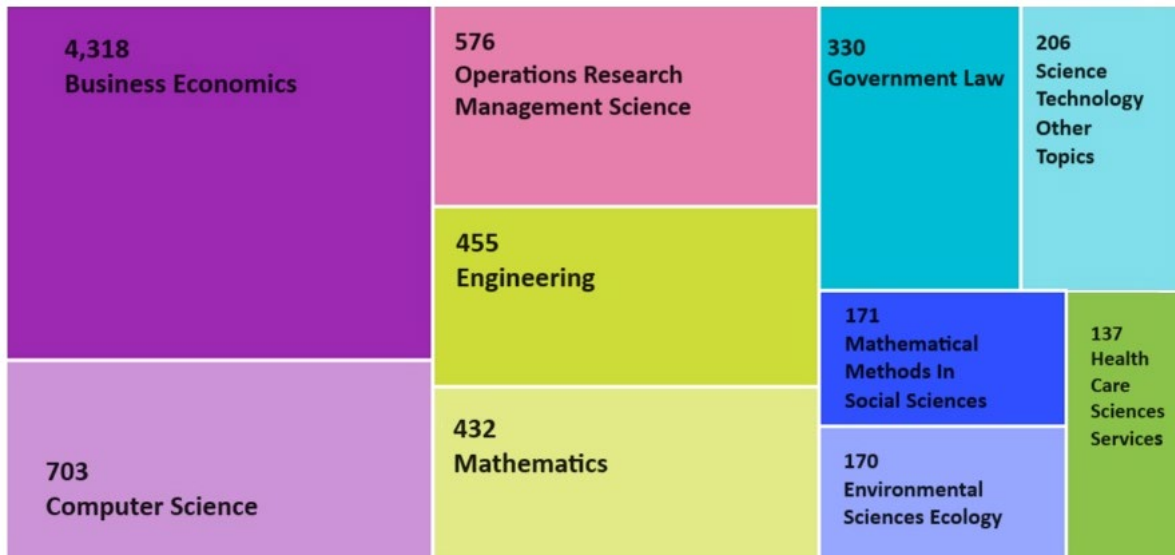


Figure 4: The Main Research Areas (WoS)

Figure 4 is a Tree Map Chart retrieved from WoS, showing ten diverse research areas and disciplines, offering insights for bankruptcy prediction across relevant fields of study. The categorization includes Business Economics and Computer Science as the research areas most connected with the topic of bankruptcy prediction. Other research areas connected with the topic are Operations Research Management Science for organizational optimization; Engineering for technological development; Mathematics for numerical relationships; Government Law for legal systems; Mathematical Methods in Social Sciences for mathematical applications in social phenomena; Environmental Sciences Ecology; Science Technology - Other topics for diverse scientific studies; and Sciences Service for scientific knowledge delivery. The analysis aids researchers, policymakers, and stakeholders in understanding academic research and innovation.



Figure 5: Sustainable Development Goals (WoS)

The Tree Map Chart shown in Figure 5 demonstrates the ten critical importance of Sustainable Development Goals (SDGs) in contemporary research and academic discussion. Through the analysis, valuable insights were uncovered into how researchers are addressing and contributing to attaining SDGs towards a more sustainable future. The figure reveals that the majority of papers in the field of bankruptcy prediction (2836 papers) are related to SDG 08, “Decent Work and Economic Growth”, as expected. However, predicting bankruptcy can also help in achieving other sustainable development goals, such as SDG03 “Good health and well-being”, SDG01 “No poverty”, SDG10 “Reduced inequality” and SDG09 “Industry innovation and infrastructure”.

## 6. Limitations

Firstly, due to restricted database access from our institute, data extraction for the bibliometric analysis was limited to the Web of Science (WoS) database. Therefore, while it is acknowledged that other databases are valuable, the lack of access led us to make this decision. Consequently, selecting articles for bibliometric analysis only partially represents all research conducted in the bankruptcy field regarding the keywords added. Additionally, the temporal scope of the study, covering bankruptcy prediction models from 1971 to 2024, must consider the advancing economic and financial conditions over time. Furthermore, the generalizability of the findings and conclusions drawn from the literature review and bibliometric analysis may be limited, as it may only be universally applicable to some industries, sectors, or regions. Finally, challenges related to data availability, model complexity, and interpretability may need to be improved to ensure the use of these models in real-world business settings.

## 7. Conclusion

The article overviews bankruptcy prediction models, tracing their evolution from classical statistical methods to more advanced techniques, such as artificial neural networks and genetic algorithms. While traditional models such as multivariate discriminant analysis and logistic regression remain popular due to their effectiveness, there is a growing trend towards more complex approaches like artificial neural networks and genetic algorithms. The continuous improvement of these models is crucial to providing practical tools to companies to identify and mitigate financial risks, thus contributing to their long-term sustainability. However, challenges persist, including the complexity of models and imprecise data. Nevertheless, these tools offer a promising path to strengthen management in the face of a dynamic and competitive business environment.

The results of the bibliometric analysis indicate that the field of bankruptcy prediction is constantly progressing, with a substantial increase in the number of publications over the decades. This reflects the growing academic interest in understanding corporate financial difficulties. However, despite the progress, there are opportunities for more thorough longitudinal studies to fully capture the evolution of the field over time. In summary, the findings of bibliometric analysis offer perceptions for researchers and professionals interested in mitigating financial risks and promoting the financial health of organisations.

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