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Exploring Trends and Advancements in Financial Distress Prediction Research: A Bibliometric Study

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ABSTRACT

Due to the growing complexity and unpredictability of contemporary markets as evidenced by the financial crisis of the past 10 years, the field of financial distress prediction (FDP) research is receiving more attention. For creditors, investors, and other stakeholders to make well-informed decisions on their financial relationships with a given entity, financial distress prediction is essential. This paper identified the risk indicators that are the cause of financial distress and latest tools and methods to predict financial distress with identifying the risk management strategies for eradicate the distress condition. In this context, this study explores the landscape of the literature published in this area. We have used systematic and bibliometric approach for studying the existing literature. For the study, we have collected articles from the Scopus database for the period 1985-2022. Science mapping technique has been used for the analysis data has been conducted with the help of Vosviewer and Biblioshiny software. Various important component of a literature review like most relevant authors, most relevant sources, keywords co-occurrence network, thematic analysis and others have been explored. The study will help the scholars and future researchers in getting a comprehensive understanding and insights in the concerned field and add to the existing body of literature.

Keywords: Financial Distress Prediction, Bibliometric Analysis, Forecasting, Financial Distress, Risk
JEL Classification: G01, G17, G33, G32, G40

1. INTRODUCTION

Financial distress prediction is also known as corporate failure prediction or bankruptcy prediction, which plays a crucial role in different fields of the decision-making process, including accounting, finance, business, and engineering. Academic study on FDP has been ongoing for about 80 years (Sun et al., 2014). It is the state where a business experiences a specific financial problem. Such financial challenges include the inability to pay bills and preferred dividends and the ensuing consequences, including overdrafts on bank accounts, liquidation for creditors' interests, and even starting a statutory bankruptcy action (Beaver, 1966; Deakin, 1968; Altman, 1968). Financial Distress can have catastrophic consequences for the business and its stakeholders (Hafiz et al., 2015). The Z-score model was invented by (Altman, 1968), and different prediction models are used to predict company financial distress. Many research papers used artificial intelligence and machine learning (Aydin et al., 2022; Chen and Shen, 2020; Zhang et al., 2022) and statistical-based models (Balcaen and Ooghe, 2006) for corporate failure prediction. To differentiate distressed and non-distressed firms and create an explanatory model for business failure (Refait-Alexandre, 2004) study help in this regard. A novel financial distress prediction model is developed using the AWOA-DL (adaptive whale optimization algorithm with deep learning) approach which seeks to ascertain if a business is in financial trouble or not. The AWOA-DL technique employs a multilayer perceptron-based prediction model and AWOA-based hyperparameter tuning methods and these steps are taken in the applications of the proposed model: preprocessing, hyperparameter turning with AWOA and the prediction stage (Elhoseny et al., 2022). In addition to a new brand technique for predicting financial distress based on sparse neural networks is put forth, known as FDP-SNN. In this technique, the weight of the hidden layer is constrained with L12 regularisation to achieve sparsity, allowing the selection of pertinent and significant predictors and enhancing predicted accuracy (Chen et al., 2022). In order to predict the accuracy (Balasubramanian et al., 2019) developed a corporate financial distress prediction model using non-financial and financial parameters using a conditional logit model for Indian listed companies. With the same line the effect of annual report publication being delayed on the reliability of financial distress forecast (Nie et al., 2022a). In order to find the best weights for the feedforward neural network (FNN), this study examined the performance of the advanced cuckoo search method, In order to this models effectiveness, It was compared to backpropagation feedforward neural network (BPNN) and logistic regression (LR) by (Marso and El Merouani, 2020). Just like the above different models, tools, techniques are there for the prediction of financial distress for analyse the prediction result effectively with accuracy. In the past three decades, Researchers have produced earlier works that offer a limited number of bibliometric analyses with a sole focus on financial distress. Most of the reviews are focused on particular topics, including "Financial Distress" (Fakhar et al., 2023; Shi and Li, 2019; Sa'diyah et al., 2022) conducted a systematic literature review on financial distress. However, limited number of studies covering on risk indicator that the cause of financial distress and the latest tools and methods to predict financial distress and way to minimize risk with better predictive accuracy substantiates novel contribution of the study. This implies identifying the risk factors that lead to financial hardship and identifying the precise techniques for foreseeing financial issues. For that, we ascertain the Furthermore, we were unable to find and choose any literature that demonstrated the philosophical and conceptual foundations of this developing field of study on this particular field.

Due to these limitations, a thorough bibliometric and systematic literature review using qualitative and quantitative methodologies is required to compile the existing literature and offer precise directions for future research. The statistical analysis for the top writers, documents, and nations and most often occurring keywords are used to understand the research's present stage. As a result, this study has a significant impact on the academic literature on financial hardship prediction by offering useful insights. The study aims to capture the most recent developments in this developing field and ultimately lays up helpful advice for scholars, practitioners, investor and decision-makers, both governmental and financial organisations. To assess the intellectual structures and uncover likely future areas of research in financial distress prediction on that problem concerned, network analysis techniques including co-citation, citations, and keyword occurrences are used. As far as we are aware, this is the initial attempt to survey the area and give a thorough bibliometric analysis of financial distress prediction historically. The study uses the broad research trends in financial distress prediction to examine hidden indicators of impending financial distress. In this review paper, we want to answer the following six research questions.

- RQ1: What has happened to literature historically?
- RQ2: Which journals, Affiliations, countries and articles in this area of study have the greatest influence and impacted?
- RQ3: Which topics with in the research topic are the important ones?
- RQ4: What are the most relevant source in this field?
- RQ5: What are the most occurred keywords related to the study area?
- RQ6: What are the latest research trends and hot topics?
- RQ7: What are the risk indicators that are the cause of financial distress?
- RQ8: What are the latest methods to predict financial distress with better predictive accuracy?
- RQ9: What are the risk management strategies for minimising the distress situation which will provide an early sing?

Research objectives that follow are derived from the aforementioned research questions.

1. To study the evolution, advancement, or trends in the forecasting of financial distress.
2. To identify the risk indicators that are causing distress and the risk management strategy for overcome from that.
3. To identify the latest methods used to predict financial distress.

From Initial stage of the data source and the methodologies are used, this study gives an idea about the financial distress prediction is an important trending topic for all like rational investors, stakeholder, companies, bank and every individual etc. This study gives an insight view of past and future trend in this field of financial distress prediction. At the last, it summarises the main conclusion, as well as its recommendations for future research with implication.

2. DATA COLLECTION AND METHODS

Science mapping and performance analysis are the two important methodologies used by bibliometric methods to analyse specific scientific subjects using bibliographic data (Noyons et al., 1999; van Raan, 2005; Cobo et al., 2011). They are widely employed to assess the progress of specific scientific field (Liao et al., 2018). So bibliometric analysis gives researchers with tools and techniques to study the particular research field analysing co-citation, citation, geographical distribution, word frequency, author, co-authors details etc.

In order to rule out any researcher bias, a keyword search of the literature was done before this review began (Gallego-Losada et al., 2022). This study included scientific articles published in peer reviewed journal included in Scopus core collection, rejecting book chapters, conference paper, communication and working papers. The keyword selected for this study was "Financial Distress Prediction". The "title," "abstract," and "keywords" subfields have been used in the search process, in order to figure out that which article are matching with this study. The time period of the search was January 01, 1985-December 31, 2022. Total of 374 articles were selected in the first search results. To ruling out the potential inconsistencies, all of the results from this initial search were double checked so that it can promote objectivity by this second screening. After applying all these criteria, the total of

104 articles consisted for final sample. After this, it was carried out the bibliometric analysis. At the beginning, the software which is Bibliometrix, which was developed by (Aria and Cuccurullo, 2017), to examine the distribution of articles by journal, nations but the research area data collected from Scopus database. We have studied the absolute and relative numbers of citation of most cited articles for assess the significance and effects of various works. Secondly, we have used VOS Viewer software (van Eck and Waltman, 2010), for bibliometric mapping purpose, which allowing us to see different network connections created by co-word analysis. The subject area which was chosen for this study is business, management and accounting, economics, econometrics, finance and social science. The publication stage was final paper with source type was journal and English language selected for this study. Figure 1 depicted the methodological flowchart of this study.

3. RESULTS

3.1. Sample Characteristics

Table 1 provides an overview of the data features with 104 papers from 73 sources that were published between 1985 and 2022.

Table 1: Data characteristics on financial distress prediction

Timespan	1985-2022
Sources	73
Documents	104
Average citations per document	28.65
References	4696
Article	104
Author’s keywords (DE)	317
Authors	256
Authors of single-authored documents	6
Co-Authors per Doc	2.9

Source: Compiled by Author

The typical quantity of 28.65 citations are used for each paper. 4696 references and 317 keywords were employed in these 256-author articles, demonstrating the effectiveness of academics’ collaboration in financial distress prediction research.

3.2. Number of Publication

Taken in to consideration of the number of publications per year, a growth pattern was identified. Figure 2 indicates the annual production of research articles in the field of financial distress prediction, As it is noted that until the early 1985s, when the inquiry began and relatively few papers are published.

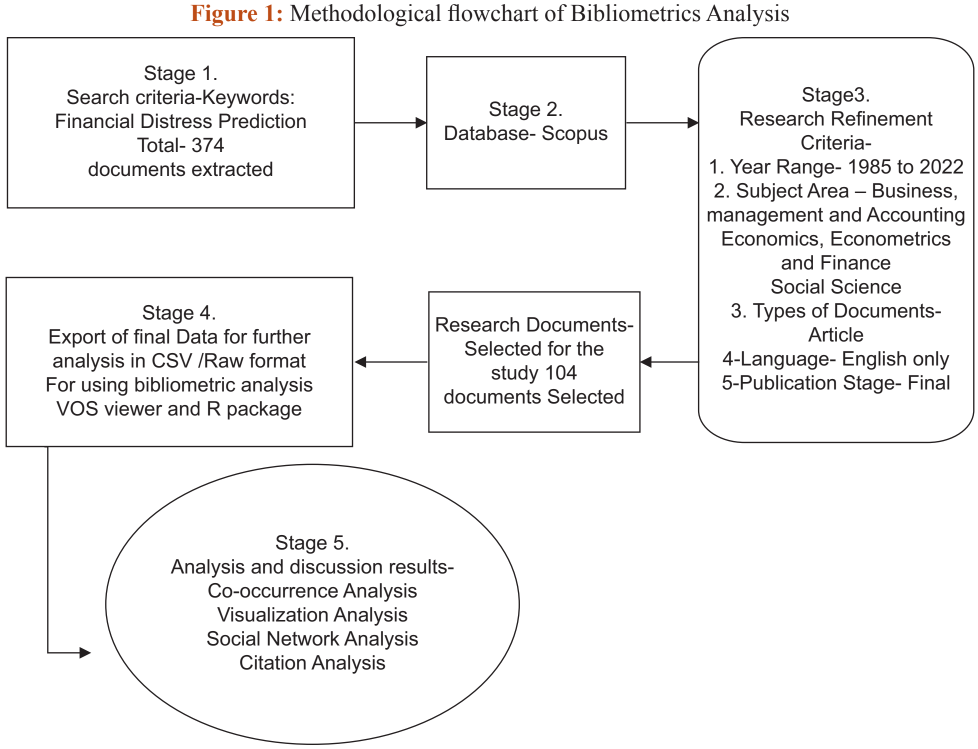
The first article (Whittred and Zimmer, 1985), this study relatively less focused in the following 10 years. The next studied on using artificial intelligence approach in financial distress predicted by (Zhu et al., 2021), Italian industrial districts: influence of the governance on performance by (Pastore and Tommaso, 2013) these are like papers which was most helpful and providing a boosting for further literature in this field. This study didn’t consider the current year as it is not complete yet. The trend was growing in a fluctuating way i.e some year its trend was increased and then decreased. The highest number of articles published in the year of 2021 which was 15.

3.3. Author’s Country and about Journals

As seen in the Table 2, China was the country which have more number of published article in the field of financial distress prediction. Most of the study based on artificial intelligence and machine learning using in financial distress prediction for that reason also China was more potential not only this field but also in different field of research and innovation with development.

It seen that on attention of most potential journals, Table 2 indicates the most efficient sources which have published articles on this research topic. We can differentiate and create a linked between Journals and

Figure 1: Methodological flowchart of Bibliometrics Analysis



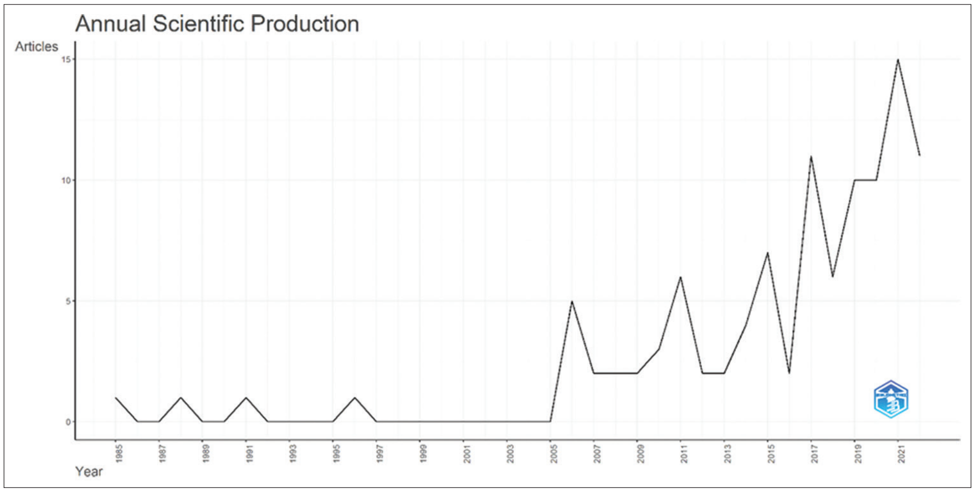
Source: Compiled by Author

research areas, like finance, management, computer science and psychology. That's why financial distress prediction currently positioned between behavioural science, cognitive science, psychology, neuro finance and financial management. We observed that, still there is a minimal numbers of particular publication in that above field, that's why its signify the chance to filled the gap in near future.

3.4. Most Influential Sources (Journal Local Impact)

The sources are crucial to how a stream of research develops. The top 10 sources, as measured by the total number of publications, are shown in the Table 3. An h-index and citations can be used to evaluate a journal's quality. An article's relevance is determined by the citations it obtains from other academic works. The H-index measures the proportion of scholarly papers with h or more citations (Egghe, 2008). The G-index shows the number (n) of publications with the most square (n × n) citations (Nalubega and Evans, 2015). M-index is an additional way to mention the h-index. It displays the h-index annually starting with the 1st year of publication (Egghe, 2008). With 9 papers and 927 times cited, the journal Knowledge Based Systems is at the top of the list. The fact that it began publishing in this field in 2008 and is currently ranked top is an intriguing fact. Only 44 papers have been produced

Figure 2: Historical evolution of scopus publication about financial distress prediction



Source: Compiled by authors from Biblioshiny

Table 2: Article distribution based on the most influential Countries, Journals and Research areas

S. No	Countries	n	%	Journals	n	%	Research area	n	%
1	China	31	29.8	Knowledge-based systems	9	8.6	Business, management and accounting	66	63.4
2	United States	12	11.5	Investment management and financial innovations	4	3.8	Economics, econometrics and finance	63	60.5
3	Taiwan	9	8.6	Managerial finance	4	3.8	Computer science	17	16.3
4	Australia	8	7.7	Economic modelling	3	2.8	Decision sciences	16	15.3
5	Malaysia	7	6.7	Economic papers	2	1.9	Social sciences	13	12.5
6	India	5	4.8	Information processing and management	2	1.9	Engineering	6	5.7
7	United Kingdom	5	4.8	International review of financial analysis	2	1.9	Mathematics	6	5.7
8	Finland	4	3.8	Journal of business research	2	1.9	Environmental science	3	2.8
9	Indonesia	4	3.8	Journal of credit risk	2	1.9	Energy	2	1.9
10	South Korea	4	3.8	Journal of forecasting	2	1.9	Psychology	2	1.9

Source: Compiled by authors

Table 3: Top 10 influential journal with H-index, G-index and M-index

Journal	h-index	g-index	Im-index	TC	NP	PY-start
Knowledge-based systems	9	9	0.563	927	9	2008
Managerial finance	4	4	0.308	67	4	2011
Economic modelling	3	3	0.3	137	3	2014
Investment management and financial innovations	3	4	0.214	29	4	2010
Information processing and management	2	2	0.667	38	2	2021
International review of financial analysis	2	2	0.182	300	2	2013
Journal of business research	2	2	0.5	66	2	2020
Journal of credit risk	2	2	0.25	35	2	2016
Journal of forecasting	2	2	0.5	39	2	2020
Journal of international financial management and accounting	2	2	0.286	322	2	2017

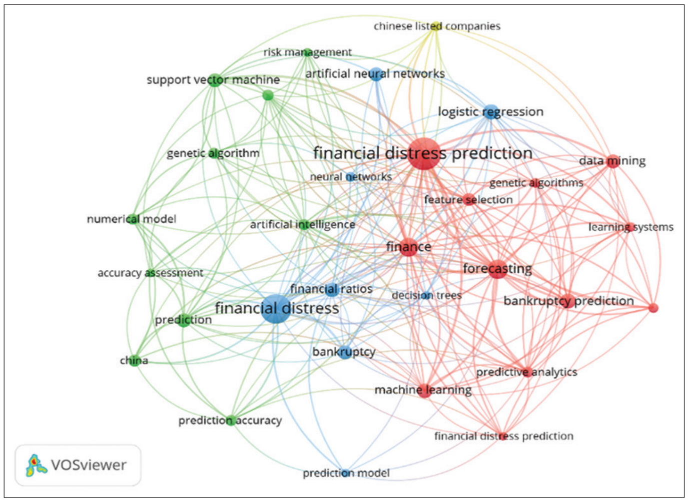
The top 10 journals for financial difficulty are shown in this table according to metrics for citations between 1985 and 2022; TC stands for total citations and NP for number of publications.
Source: Compiled by Author

since the Managerial Finance was founded in 2011. However, this journal's h-index is 4 and it has been cited 67 times. The reputable journal Economic Modelling is another with an h-index of 3, it has only produced 3 papers but 137 times cited.

3.5. Publications by Author

The 104 articles were written by 256 authors. Table 4 shows the most influential authors, which have at least three and more than three articles on the research topic. Li, Hui is most prominent author out of them. These are the authors which have mostly collaboration with other authors. So there is an proper connection among researchers community.

Figure 3: Co-word analysis



Source: prepared using VOSviewer software

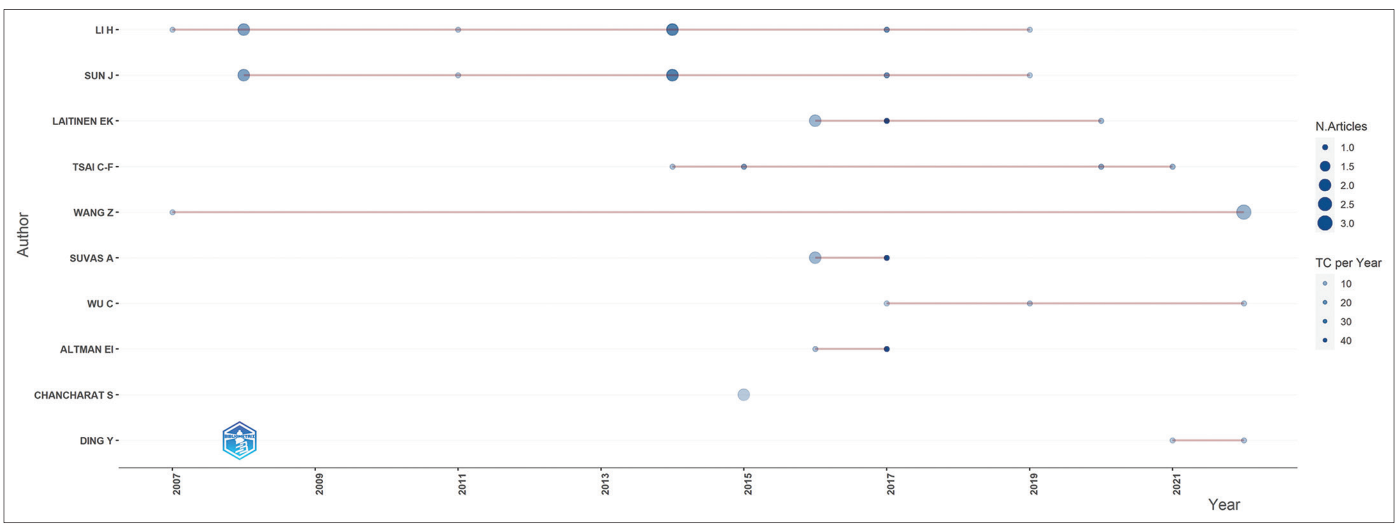
3.6. Top Authors Production Over the Time

Figure 4 Presents the most active authors in financial distress prediction based on the number of publications. A small number of early contributors who were allegedly reliable from the early 2000s have improved at predicting financial distress. Most of the articles were written by the author, who remained active throughout the time, such Li H. Another steady writer who frequently made contributions to the growth of the field of financial distress prediction is Sun J. Since 2013, many more researchers have become interested in this topic and are routinely researching the numerous facets of predicting financial distress.

3.7. Most Cited articles

The top 10 internationally cited documents and the most globally cited documents between 0 and 300 are displayed in Figure 5 above. With 297 worldwide citations in 2017, Ei. Altman is the author of the most often cited paper in the field of financial distress prediction, as indicated by the black bar chart. The Journal of International Financial Management Accounting published that article. The authors Tinoco and Wilson (2013) and Sun et al. (2014) have received 220 and 215 citations, respectively, for their papers worldwide in the international review of financial analysis and

Figure 4: Authors production over time



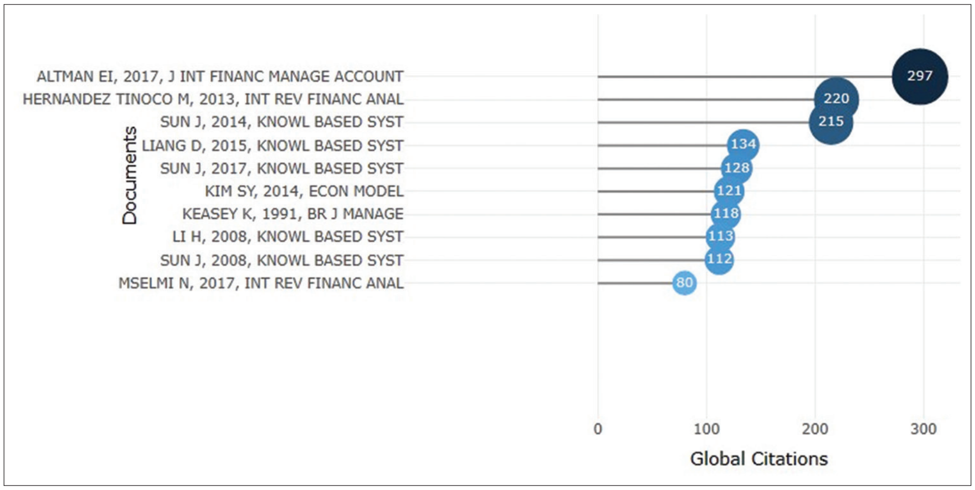
Source: Compiled by Author from Biblioshiny

Table 4: Most productive authors in financial distress prediction

Rank	Name of author	Country of author	University/Institution	Number of publications
1	Li, Hui	China	Nankai University, Tianjin, China	8
2	Sun et al.	China	Tianjin University of Finance and Economics, Tianjin, China	7
3	Laitinen, Erkki K.	Finland	Oulun Yliopisto, Oulu, Finland	4
4	Tsai, Chihfong	Taiwan	National Central University, Taoyuan, Taiwan	4
5	Zhao et al.	China	Hefei University of Technology, Hefei, China	4
6	Suvas, Arto	Finland	Vaasan Yliopisto, Vaasa, Finland	3
7	Wu et al.	China	Harbin Institute of Technology, Harbin, China	3

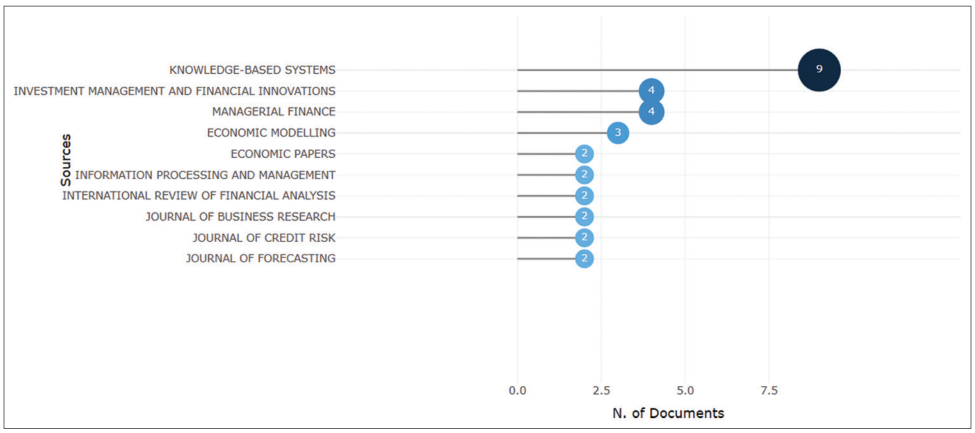
Source: Compiled by authors

Figure 5: Most 10 cited documents



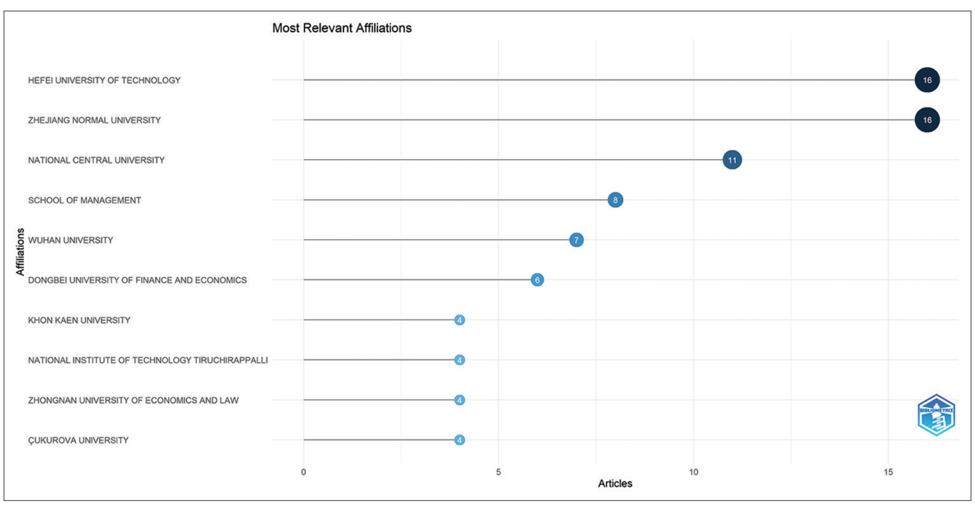
Source: Compiled by authors from Biblioshiny

Figure 6: Top 10 journals incorporate with number of publications, prepared using Biblioshiny



Source: Compiled by Author from Biblioshiny

Figure 7: Most relevant affiliation



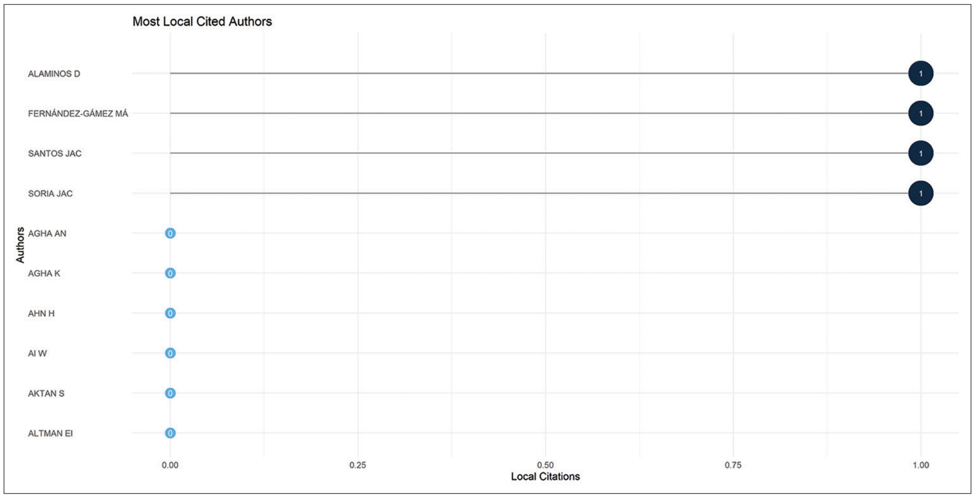
Source: Compiled by Author from Biblioshiny

knowledge-based systems; these results are displayed in the indigo bar chart. Six documents have citation counts ranging from 135 to 110, with the remaining documents receiving citation counts less than 100 worldwide.

3.8. Keyword Co-occurrence Analysis

Since keyword is the primary theme and hotspot in the topic of interest. For the support of that researcher go through in to the topic and followed as per his or her research field on the basis of that.

Figure 8: H-index analysis of authors' local impact



Source: Compiled by Author from Biblioshiny

Figure 9: Visualization of the words that have been used the most frequently in articles on Financial Distress Prediction

Source: Compiled by Author from Biblioshiny

Figure 3 shows that the connection of keyword extracted from the search articles. In this network, all keywords are divided in to four groups and highlighted by four distinct colours (Red, Blue, Green and Yellow). The term "Financial Distress Prediction' is the one that is used most. which indicates red cluster group. The red cluster group also includes forecasting, bankruptcy prediction, data mining, machine learning etc. Financial ratios, neural networks, decision trees, artificial neural networks etc. are often used terms from the blue cluster group. In the green cluster group, terms like support vector machine, genetic algorithm, risk management, numerical model etc. are commonly employed. The yellow clusters has only one important term, which is Chinese listed companies. But It has more networks like others. The thicker lines in between the nodes represents that those keywords have a greater thematic link, which have high frequency of co-occurrence and vice versa.

3.9. Most Relevant Sources

Figure 6 shows the top 10 journals as per the highest volume of publication. Knowledge based system (Impact Factor=8.8) is the paper which have included more paper in this field (9). Investment management and Financial Innovations (Impact Factor=2023 Evaluation Pending) and Managerial Finance (Impact Factor=1.5) are the journals which secured second position with each of 4 publications occupied second and third position. With 3 publications, the Journal Economic Modelling (Impact Factor=4.7) comes in third. Economic Paper (Impact Factor=0.9), Information Processing and Management (Impact Factor=8.6), International Review of Financial Analysis (Impact Factor=8.2), Journal of Business Research (Impact Factor=11.3), Journal of Credit Risk (Impact Factor=0.264), and Journal of Forecasting (Impact Factor=3.4) are the Journals which are positioned accordingly after the third journal with 2 publication each.

3.10. Countries Collaboration World Map

The collaboration of countries are seen in Figure 12. It shows the international partnerships. The map's blue colour symbolises international research collaboration. The degree of the authors' participation is also shown by the pink border separating the states. The dark blue colour indicates great collaboration (China), however the grey signifies non- collaborating countries (Greenland, Mexico, Brazil, South Sudan etc). China with USA has the greater collaboration. However USA mostly collaborated with others country which is Finland, Poland, Korea and China have collaboration with Japan after USA.

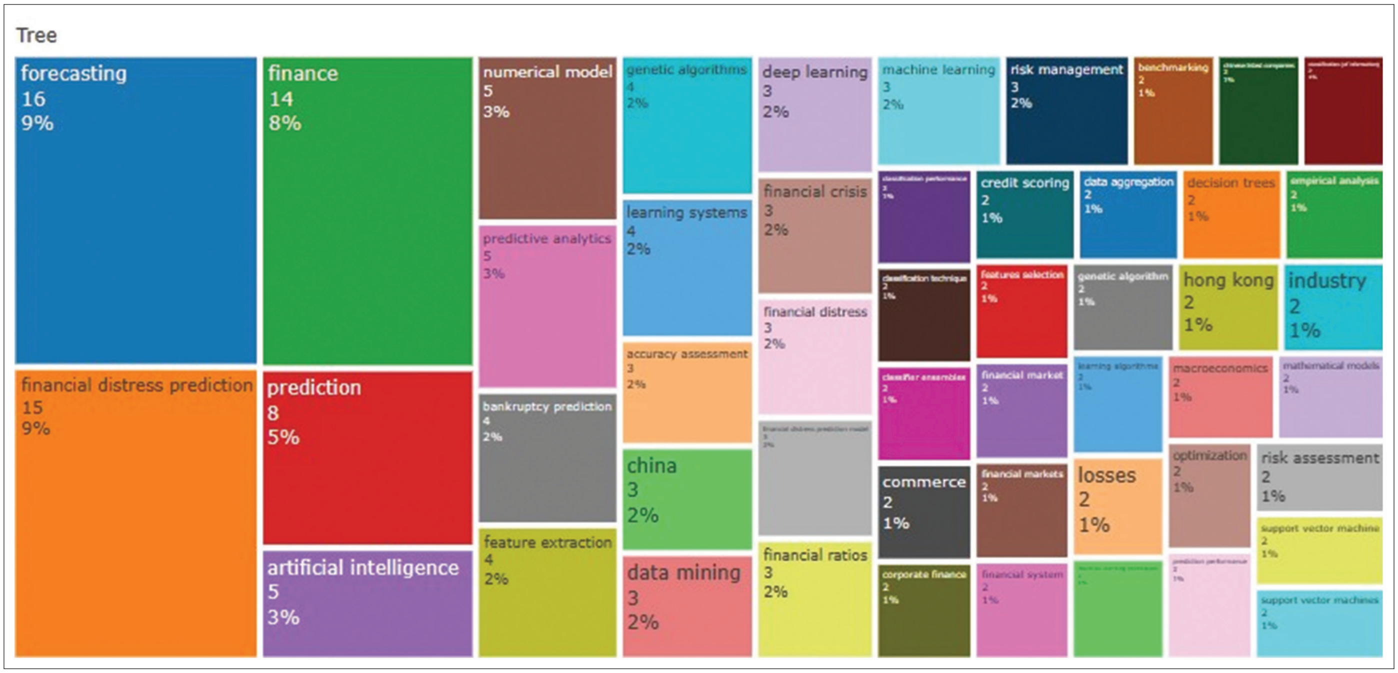
3.11. Country Scientific Production

The above graph shows the scientific output of the various countries. The countries on the map with the highest rates of paper publication are marked with indigo colour. The results of several countries contributions to the study of financial distress prediction are shown in Figure 13. China, USA, Malaysia, Australia, Indonesia, and India are the top six countries contributing the most to this newly booming field of study.

3.12. Thematic Map Analysis

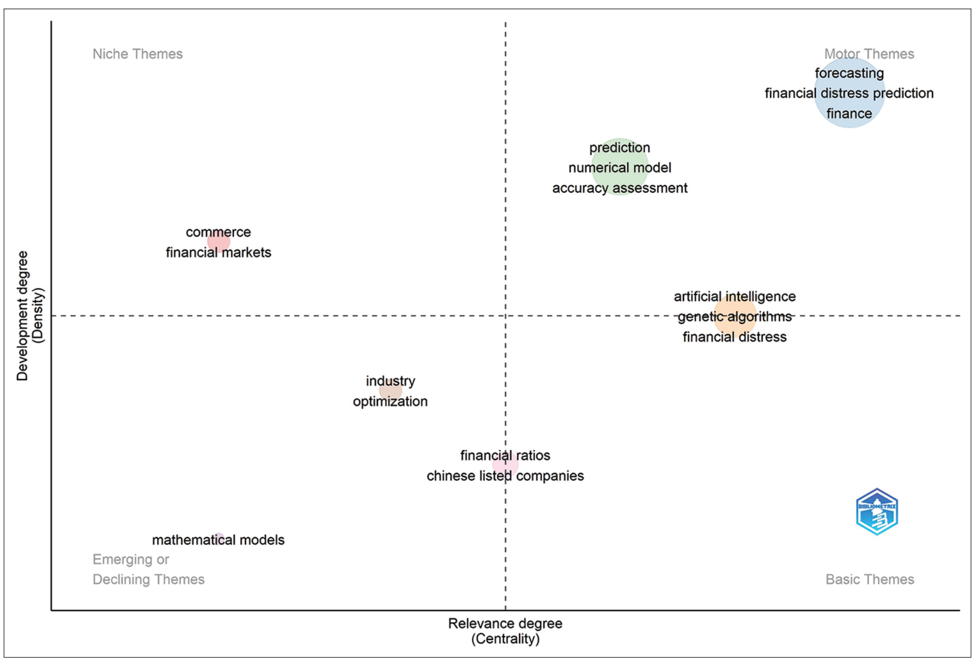
A two dimensional plot serves as the foundation for the idea of a thematic map (Cobo et al., 2011). Seven themes are created based on co-word analysis and keyword clustering, as illustrated in Figure 11. "Forecasting," "financial distress prediction," "finance," "prediction," "numerical model," "accuracy assessment," fall in Quadrant 1 (motor theme), Which shows these themes are

Figure 10: Word tree map



Source: Author's Complilation

Figure 11: Thematic map



Source: Compiled by authors from Biblioshiny

fully developed and important for research field. There is non availability under Quadrant 2 (basic theme). Artificial intelligence, genetic algorithms and financial distress fall on the border of basic and motor themes, which indicates that there is still much work to be done in this crucial areas. Industry, optimization and mathematical models that belongs in Quadrant 3 (which are emerging and declining themes). Researchers must pay attention to this area. Commerce and financial markets comes in Quadrant 4, which is niche themes, they are highly developed but isolated problems. At the last, financial ratios and Chinese listed company fall in both emerging and basic theme, which shows that lots of work has to be done in this context. Based on thematic analysis, it can be observed that financial distress prevails in silos with every quadrant presence except 2 i.e., Quadrant 1-Financial distress prediction, Quadrant 3-Optimization, Quadrant 4-Financial market.

3.13. Thematic Evolution

The above picture Figure 14 how the themes have evolved between 1985 and 2022. The information reveals several frequently used themes. On the left, you can see some of the themes that will be prominent from 1985 to 2018. There are six themes offered, and the magnitude of each one varies according to how frequently it is used. The right column lists the current themes in use from 2019 through 2022. Each of the five themes is given with a different size depending on how it will be used. The theme of financial distress prediction and bankruptcy prediction has ties to several machine learning tools to accurately evaluate the distress prediction, which infers the thematic evolution.

3.14. Most Frequent Keywords

The words' frequency reveals the development and central idea of a certain field of study (Kumar et al., 2021).Gaining information from this study will help you understand which research streams and sub-streams are most popular, as well as what terms writers use most frequently in their titles, abstracts, and keywords (Wu et al., 2021). In the 104 articles analysed we obtained 480 keywords, out of which 22 met the threshold of a minimum of 5 occurrences. By maintaining the lowest frequency, the Biblioshiny application generates the words that are most frequently used. The keywords "financial distress prediction" (44 occurrences and 94 total link strength), and others are like "forecasting" (16 and 60) and "finance" (15 and 55) form the core and so on. Financial distress Prediction, Forecasting, Finance, Financial Distress, Bankruptcy Prediction are the most frequent words in this area, as depicted in Table 5.

Table 5: Most frequent keywords on financial distress Prediction (Top 10)

Keywords	Frequency
Financial Distress Prediction	44
Forecasting	16
Finance	15
Financial distress	36
Bankruptcy Prediction	10
Machine Learning	9
Financial Ratios	9
Predictive Analytics	5
Support Vector Machine	8
Logistic Regression	10

Source: Compiled by authors

3.15. Most Relevant Affiliations

The top relevant affiliate articles are shown in Figure 7. The affiliation that received the most citations is 16 and is reflected in the black bar chart which is claimed by the Hefei University of Technology and Zhejiang Normal University. The second largest affiliation is claimed by National Central University which is shown on the blue bar chart. The third largest affiliation is School of management with citation is 8. The 4th and 5th affiliations are claimed by Wuhan University and Dongbei University of Finance and Economics. Remaining four articles have same numbers of affiliates at levels four indicated by light blue colours.

3.16. H-index Analysis of AUTHORS' Local Impact

The ensuing influence as determined by the h-index can also be used to sort authors whose papers were published which is shown in Figure 8. The h-index in the current study spans from 0 to 1. The size of this influence is depicted in dark blue on the bar graph above. The authors with the greatest h-indexes are shown in the figure above. They are Alaminos D, Fernandez-Gamez MA, Santos JAC, Soria JAC, who each have an h-index of 1.

3.17. Word Cloud

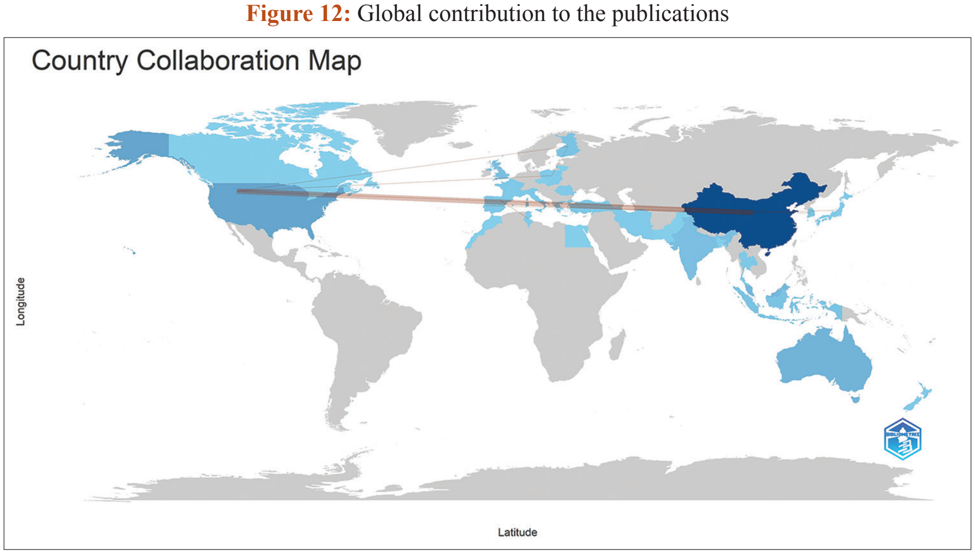
The size of the terms in this word cloud corresponds to how often they are used. Despite the rather random sequence of the sentences, the most crucial ones are given a large size and positioned in the centre to stand out more. The words that were most frequently used in the paper's discussion of financial distress prediction are shown in the word cloud in Figure 9.

The most frequent words are "Forecasting," "Finance," and "Prediction," coming in first, second and third, respectively. This implies that researchers have looked at this financial distress prediction. Researchers should focus more in this area with using different numerical models and AI with ML tools and technique.

3.18. Tree Map

Indexers and search engines can identify pertinent papers with the use of the author's keywords in their writings. The manuscript will be accessible to readers if database search engines are able to

Figure 12: Global contribution to the publications

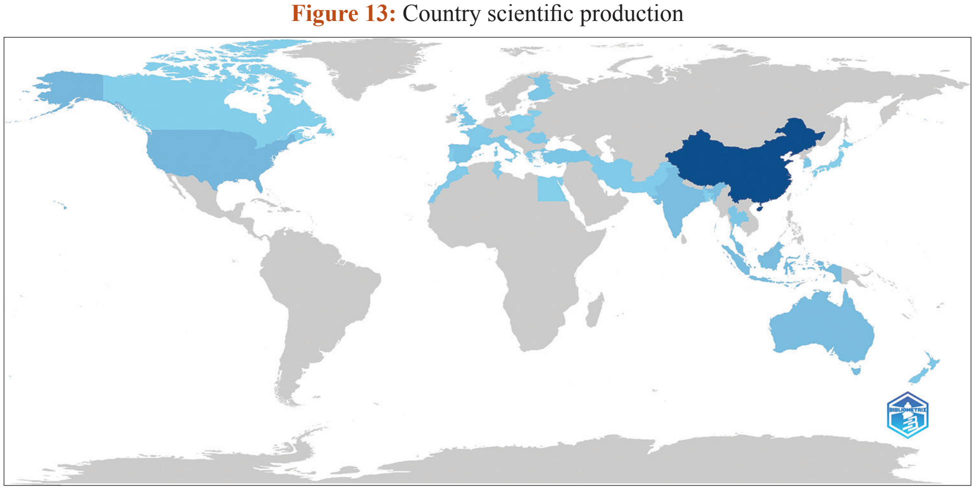


Source: Compiled by authors from Biblioshiny

Table 6: Research Trends 2022 and 2023

S. No	Reference	Objective
1	(Zhao et al., 2023)	A study demonstrate the idea about existence of extensive financial data reduces the incremental utility value of textual disclosure in financial crisis prediction.
2	(Ding et al., 2023)	It investigate the time varying prediction features during pre-covid and post covid periods.
3	(Ragab and Saleh, 2022)	This study explored using logistic regression to investigate the impact of nonfinancial factor connected to governance on precision of financial distress prediction among Egyptian listed SMES.
4	(Wang et al., 2022)	The impact of pledging controlling shareholders stock on raising financial distress prediction accuracy empirically examined by this study.
5	(Ben Jabeur and Serret, 2023)	This study examines the performance of 4 common feature selection techniques for financial distress prediction (t- test, stepwise logistic regression, stepdisc discriminant analysis and partial least square discriminant analysis).
6	(Al Ali et al., 2023)	In order to determine the best hypermeter configuration for LSTM, this research blends GA with LSTM.
7	(Jiang et al., 2023a)	This study present a methods for mining the statistical features and semantic aspects in the text of the patients.
8	(Liu et al., 2023)	This study used financial data of listed companies in China and 5 different prediction time spans to build financial distress prediction model using 4 popular tree based gradient boosting models: Gradient boosting decision tree.
9	(Bin Yousaf et al., n.d.)	The effectiveness of dynamic, static and machine learning models in predicting financial distress of enterprises was compared in this study.
10	(Kang et al., 2022)	This paper used a distress indicator , which was Merton Distance to default (Merton DD) to forecast the financial distress of credit unions in Taiwan.
11	(Zhao et al., 2022)	This study propose a novel framework , which integrates sentiments tone data taken from comments on online stock discussion and analysis, and financial statement notes.
12	(Wu et al., 2022)	This study proposes stock market forecasting model that combines the conventional Altman Z-Score model with a multilayer perception artificial neural network (MLP-ANN).
13	(Nie et al., 2022b)	This study investigates the effects of annual report disclosure delays on the reliability of financial distress forecasting.
14	(Jiang et al., 2022)	This study addressed the issue of predicting the financial distress of Chinese listed businesses utilising unbalanced data, an unique hybrid model was developed.
15	(Sun et al., 2022)	In order to create MFDP models, this study develops an improved decision-directed acyclic graph (IDDAG) fusion based approach on maximising generalisation ability and integrates it with the one versus one (OVO) decomposition method.(OVO-IDDAG).
16	(Lagasio et al., 2023)	This paper study the effect of the composition and functioning of board committees on firms financial distress.
17	(Nurhayati et al., 2022)	This study explored with used Altman modified Z Score, Springate and Zmijewski techniques to assess how well healthcare sub- sector organisations can predict their financial difficulties.
18	(Zhang et al., 2022)	This paper explored the explainable AI approach for financial distress prediction is to create a model that accurately predicts financial distress while also providing transparency and interpretability in its predictions, assisting stake holders in making informed decisions and reducing financial risks.
19	(Hassan et al., 2023)	This study analyse the scenario of financial distress prediction by focusing on Pakistan's biggest sectors (textiles, sugar and cements) listed on Pakistan stock exchange.
20	(Jiang et al., 2023)	This study analyses whether variable taken from question and answer text may considerably increase the performance of financial distress prediction (FDP) models and represent a framework for predicting the financial distress of businesses.

Figure 13: Country scientific production



Source: From Biblioshiny

Table 7: Risk Indicators that have been connected to financial Distress

Risk indicators	Potential exploration	References
Working capital to assets	This ratio evaluates a company's capacity to pay short-term debt. A lower ratio suggests that a business would be having trouble making its bill payments, which could put it in financial jeopardy.	(Deakin, 1968)
Cash flow to sales	This ratio assesses how well a business can turn a profit from its activities. Financial distress may result from a company's inability to generate profits, as indicated by a falling cash flow to sales ratio.	(Beaver, 1966)
Interest coverage ratio	The ability of a business to pay its interest is gauged by this ratio. A reduced interest coverage ratio suggests that a business would struggle to make its debt payments, which could put it in danger of going bankrupt.	(Edward I. Altman, 1968)
Poor Profitability	Declining net income and profit margins	(Ohlson, 1980)
Operational Inefficiencies	Decline in operational efficiency, low asset turnover ratios	(Zmijewski, 1984)
Market-Based Factors	Stock price underperformance, negative market sentiment	(Campbell et al., 2008)
Macroeconomic Conditions	Economic downturns affecting the industry and overall economic conditions.	(Beaver, 1966)
Industry-Specific Factors	Negative alterations to the business environment and technical setbacks.	(Shumway, 2001)
Management Effectiveness	Inadequate leadership and absence of strategic focus	(Whited, 1992)
Legal and Regulatory Risks	An increase in court cases, fines from regulations, or legal disputes	(R. J. Taffler, 1982)

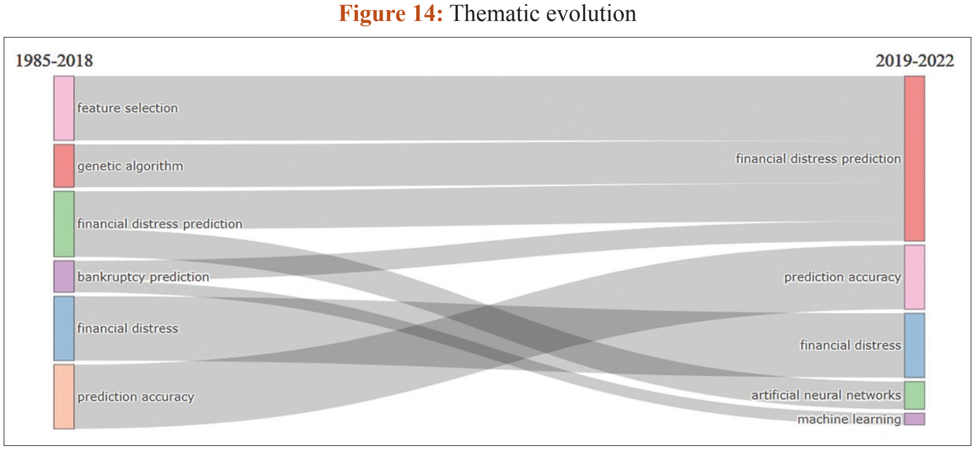
Source: Compiled By Author

Table 8: Risk management strategies to prevent financial distress

	Key factor strategy	References
Managing Cash Flow Effectively	By Using effective cash flow management techniques to make sure the company can pay its immediate debts.	(Mian and Smith Jr., 1992)
Sensible Debt Handling	Remain cautious when managing your debt, making sure that your debt levels are manageable and in line with your organization's cash flow.	(Deakin, 1968)
Diversification of Revenue Streams	Expand into new markets and diversify your offerings of goods and services to lessen your reliance on a single source of income.	(Cummins and Weiss, 2009)
Methodical Cost Control	Optimize resource usage by implementing cost-cutting initiatives and operational efficiencies.	Horngren et al., (2016)
Continual Stress Assessment	To determine potential weaknesses and evaluate the organization's adaptability to different economic scenarios, conduct periodical stress testing.	(Daníelsson et al., 2002)
Strategies for Mitigating Risks	Use risk-reduction techniques, such hedging and insurance, to guard against certain financial hazards.	(David Cummins and Mahul, 2003)
Flexibility in Corporate Governance	Continue to follow good corporate governance procedures, with special focus on risk management and having a flexible, adaptable governance framework.	Hitt *et al*. (2016)
Constant Tracking and Documentation	To identify early indicators of financial hardship, implement a system for ongoing monitoring of financial measurements and reporting procedures.	Lam (2003)
Awareness and Training for Employees	To make sure that every employee is aware of their responsibilities for risk management and financial stability, invest in employee awareness and training programmes.	Colquitt et al. (2014)

Source: Compiled by author

Figure 14: Thematic evolution



Source: Compiled by Author From Biblioshiny

Table 9: These are a few of the most recent techniques for anticipating financial issues

Techniques	Derivation	References
Sparse Algorithm and Support Vector Machine	Due to performance degradation caused by numerous redundant and irrelevant information, sparse algorithms are crucial in classification learning. Reducing computing complexity and increasing classification accuracy are two benefits of a strong feature selection technique. When dealing with high-dimensional data, where the number of features is significantly greater than the number of samples, traditional models could find it difficult to perform. In order to deal with such circumstances, sparse algorithms encourage sparsity in the model, which means that just a portion of the features are deemed crucial for generating predictions.	Hastie et al. (2013)
Random forests, gradient boosting machines, and deep learning	The use of machine learning methods, including deep learning, gradient boosting machines, and random forests, for financial distress prediction has been the subject of numerous studies. These methods can manage intricate data interactions and identify patterns that conventional models would overlook. Random Forest Compared to certain other conventional techniques, Random Forests are less prone to overfitting. By constructing several decision trees and combining their forecasts, they enhance generalisation. • Non-linearity- While typical linear models could have trouble capturing complicated, non-linear relationships in the data, Random Forests can. • Features' Significance-They help identify important variables for financial distress prediction by offering a feature importance measure. Gradient Boosting machines • High Prediction Accuracy- Gradient Boosting Machines, like LightGBM and XGBoost, frequently attain excellent predicted accuracy by gradually strengthening the model's shortcomings. • Features' Significance- Similar to Random Forests, gradient boosting models help with interpretability by offering insights on feature importance. • Handling Imbalanced Data- Unbalanced datasets, which are typical in financial distress prediction scenarios, can be handled using gradient boosting. Deep Learning • Automated Character Recognition- Manually constructing features is no longer necessary since deep learning models especially neural networks can automatically build hierarchical representations from unprocessed data. • complicated patterns Deep learning algorithms are well-suited for financial distress prediction in dynamic contexts because they are excellent at identifying complex patterns and relationships in data. • Metamorphosis- Deep learning models are scalable to handle big datasets and intricate architectures.	(Altman et al., 1994) (Liaw and Wiener, 2002) (Chen and Guestrin, 2016) (Lecun et al., 2015)
Engineering Features and Choosing Them	The effectiveness of financial distress prediction models can be significantly increased by utilising sophisticated feature engineering and selection techniques. The most pertinent features are found by methods like recursive feature reduction and LASSO (Least Absolute Shrinkage and Selection Operator). By including a penalty term based on the absolute values of the coefficients, the Least Absolute Shrinkage and Selection Operator (LASSO), a regularisation approach used in linear regression, promotes sparsity in the coefficient estimations. It is especially helpful in feature selection, assisting in the identification and retention of the most crucial variables within a mode.	(Tibshirani, 2016)
Hybrid feedforward neural network, cuckoo search algorithm	Predicting financial distress is still a topic of ongoing research. Because of their propensity to identify intricate patterns, artificial neural network (ANN) models make excellent candidates for modelling financial crisis. According to experimental findings, a FNN model's cuckoo search algorithm may be taken into consideration for foretelling future financial difficulties. One optimization algorithm that draws inspiration from nature and is frequently used to solve optimization problems is the Cuckoo Search Algorithm.	(Marso and El Merouani, 2020)
Catboost, Ada Boost	Catboost- Yandex created CatBoost, a gradient boosting technique that works especially well with category features. Considering that it frequently requires less hyperparameter tuning than other gradient boosting implementations, it is a strong and effective approach. • Managing Classific Features- When working with financial datasets, CatBoost's innate ability to handle categorical features eliminates the need for human encoding.	(Prokhorenkova et al., 2017) (Freund and Schapire, 1997)

(Contd...)

Table 9: ***(Continued)***

Techniques	Derivation	References
	• Strong enough to overfit- In order to avoid overfitting, CatBoost has built-in regularisation techniques that can be useful when working with sparse financial data. AdaBoost- Adaptive Boosting, or AdaBoost, is an ensemble learning method that turns a weak learner into a strong one. To enhance overall model performance, it focuses on modifying the weights of incorrectly categorised cases in subsequent training rounds. • Weighted Training- AdaBoost emphasises the significance of incorrectly categorised examples in later rounds by allocating weights to training instances. This has potential applications in the forecast of financial hardship, where accurate identification of problematic situations is crucial. • Group Variability- AdaBoost combines several weak models, which may enhance generalisation and overall prediction performance.	

Source: Compiled by Author

locate the authors' keywords. As a result, more individuals will read the manuscript, which will probably result in more citations. The research trend, discussion gaps, and related fields that would be interesting for future research could all be determined with the help of this data. A Word TreeMap is used to display the top 50 frequently used keywords in the articles. The word tree map below (Figure 10) describes a list of terms that are used in various ways in a number of the articles from the current study. First, the term "Forecasting" is widely used 16 times which is 9% of total usage. The word "Financial Distress Prediction" is the second most used word used for 15 times which is also 9%. And in third place, there is the word "Finance". Similarly, the words "Prediction", "Artificial Intelligence" "Numerical Model "and "Predictive Analysis" ranges from 8 to 5 times.

3.19. Current Research Directions

We thoroughly analysed the content of the papers which was the published in 2022 and 2023 (January to September), extracted the key research strands, and summarised them in Table 6 in order to identify the most current research directions and hottest topics.

4. RISK INDICATOR

There are several risk factors that might lead to financial distress, and these elements have been thoroughly researched by researchers in order to find trends and create prediction models. These are some typical risk factors for financial trouble, accompanied by pertinent article references mentioned in Table 7.

4.1. Risk Management Strategy

In order to prevent financial suffering, risk management solutions include proactive steps to recognise, evaluate, and reduce risks before they become more serious. Key tactics are listed below in Table 8, accompanied by selected article references:

5. LATEST METHODS FOR FINANCIAL DISTRESS PREDICTION

For enterprises, investors, and financial institutions to reduce risks and make well-informed decisions, financial difficulty prediction is essential. Financial ratios and statistical models have been the mainstays of traditional financial distress prediction techniques, but recent developments in artificial intelligence (AI) and machine learning (ML) have created new opportunities for more thorough and accurate forecasts. Table 9 highlights the latest method for predicting financial distress.

6. CONCLUSION AND FUTURE RESEARCH DIRECTION

Using bibliometric analysis covering 1985-2022, this study examined current trends and difficulties and gaps in financial distress prediction. We have utilised RStudio packages for visualising trends, clusters, most recent topics, and the progress of financial distress prediction using the keyword selection and theme. Prediction of financial difficulties and important prolific authors with important prolific affiliations. we discovered via an examination of the most popular keywords. Finally, we studied the risk indicators that are the cause of financial distress and what are the risk management strategy to avoid that distress situation and latest methods to eradicate financial distress. The primary areas were largely examined financial distress prediction, forecasting, and finance, according to the studies.

The evolution of the number of publications in this field was not a growing level. Its an important area of focus for researchers due to its major value for enterprise and stakeholders including lenders, bankers, investor and participants of capital markets (Waqas and Md-Rus, 2018). There have been many research studies in the context of financial distress prediction but still there is need to explore more in this area. Previous studies have explored this area with using AI and ML techniques used for predict financial distress (Zhang et al., 2022), (Tran et al., 2022). Some advanced AI model (weighted boosted tree-based tree) used for distress prediction which was given by (Liu et al., 2022), for Deep learning (Li and Wang, 2023). Future gaps can be fulfilled with taking others industries with product and patents (Jiang et al., 2023b). (Tang and Xie, 2023) emphasized future research on different industries in MSME'S. To improve the accuracy of distress prediction models, researchers and practitioners are increasingly using other data sources, including as social media sentiment, news sentiment, and macroeconomic indicators, in addition to traditional financial statements. Most commonly employed are ensemble approaches, which mix many models to increase forecast accuracy. The best algorithm will rely on the particulars of the dataset, the nature of the problem, and the available computing power. For your particular use case, it is advised that you experiment with various methods, do cross-validation, and adjust hyperparameters to find the optimal model. Using ensemble techniques, including merging predictions from several algorithms, can also help increase accuracy overall. Financial distress prediction models have been used in conjunction with strategies including stacking, bagging, and boosting. To provide light on model choices, methods like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) are employed.

The different bibliometric indicators that were used in this study gives us a overview of the subject area (Maharana and Pal, 2023). A growing trend has been observed for the publication which shows that more studies should be undertaken in this research field. We identified the top authors, top nations, most cited papers and significant themes that should be taken in to consideration when starting with new investigations in this area. The motifs identified by the study of keyword co-occurrence and thematic map should be given emphasis on future study in this area. A large portion of the effort will go into creating algorithms that can predict financial crisis in real-time or almost real-time. In financial markets that are active and undergoing rapid change, this is particularly crucial. Investigating how external factors, which can have a significant impact on financial stability, such as climate change, geopolitical events, and pandemics, affect the prediction of financial crisis. incorporating behavioural finance insights into models for predicting financial hardship can help us better understand how market oddities, investor biases, and investor sentiment can all contribute to financial distress. Studying how new technologies, such as blockchain and cryptocurrencies, affect financial distress prediction is important since these assets present special difficulties and opportunities, which offering multiple future research avenues. With these guiding principles in mind, the current study shows the rising appeal of financial distress prediction and suggests new directions for academics, practitioners, investors, and policymakers.

This research gives emphasis on the following conclusions for future research from both management practices and theory development perspectives based on the systematic examination of the literature on financial distress prediction. We acknowledge the limitations that still exist in our study. Firstly, the research presented findings derived from information sourced from the Scopus database. The possibility that use a different database could yield completely different results is one of the research's drawbacks. Second, while our study aligns with the objectives and values of the bibliometric analysis, we encourage future researchers to employ scientometric analysis, meta-analysis, and topographic view to provide a comprehensive overview of the financial distress literature. Our study uses bibliometric analysis and systematic literature review to present the current state and future directions of research in financial distress.

6.1. Implications for Theory Development

This study has number of implications in theoretical background. Since it aids decision making by consumers, regulators and companies. Our grasp of the forecast of financial trouble must be advanced through implications for this field theory development. First, it contributes to the multidisciplinary approaches. This financial distress prediction models can gain by incorporating knowledge from variety fields, including economics, psychology, sociology, and data science. The development of more thought theories taken in to account both financial and non-financial elements. Second, theories from behavioural finance perspective can assist in illuminating the causes of financial difficulties. Research can look in how cognitive, heuristic biases affect decision making and which leads to financial misery. Third, from literature review various author used different machine learning and AI tools for prediction financial distress so it could be gives more accurate result than traditional tools and techniques. Fourth, Impact of government regulations and policies on risk of financial distress should be taken in to account in theoretical models. Investigating the effects of bankruptcy laws, government actions and banking regulations during economics crises are all part of this. It is a dynamic process. It influenced by change in firm specific factor, industry trend and economic condition etc. Government actions, interest rates, and inflation into account might offer important insights towards anticipating financial distress. Predictive models can be improved by understanding how macroeconomic issues affect businesses and industries. This study helps to gives an insight view of this field. It requires a proper depth study relating to this area so that all the stake holders have get proper knowledge in this concern field.

6.2. Implications for Management Practice

The review should help to understand and creating a proper awareness among all stakeholders, individual and investor etc. in the context of this study worldwide. The information provided here will help to all stakeholders in identify the variable and model that enable and those that are impeding the implementation. These models can be used by management to spot distress indicators and warning signs early on.so that, it allows to prevent financial crises and it can help to implement cost reduction strategies.

REFERENCES

Al Ali, A., Khedr, A.M., El Bannany, M., Kanakkayil, S. (2023), GALSTM-FDP: A time-series modeling approach using hybrid GA and LSTM for financial distress prediction. International Journal of Financial Studies, 11(1), 11010038.

Altman, E.I. (1968), American finance association. The Journal of Finance, 23(4), 589-609.

Altman, E.I. (1968), Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance, 34(2), 78-86.

Altman, E.I., Marco, G., Varetto, F. (1994), Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). Journal of Banking and Finance, 18(3), 505-529.

Aria, M., Cuccurullo, C. (2017), Bibliometrix: An R-tool for comprehensive science mapping analysis. Journal of Informetrics, 11(4), 959-975.

Aydin, N., Sahin, N., Deveci, M., Pamucar, D. (2022), Prediction of financial distress of companies with artificial neural networks and decision trees models. Machine Learning with Applications, 10, 100432.

Balasubramanian, S.A., Radhakrishna, G.S., Sridevi, P., 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.

Balcaen, S., Ooghe, H. (2006), 35 years of studies on business failure: An overview of the classic statistical methodologies and their related problems. British Accounting Review, 38(1), 63-93.

Beaver, W.H. (1966), Financial ratios as predictors of failure. Journal of Accounting Research, 4, 71-111.

Ben Jabeur, S., Serret, V. (2023), Bankruptcy prediction using fuzzy convolutional neural networks. Research in International Business and Finance, 64, 101844.

Bin Yousaf, U., Jebran, K., Wang, M. (2021), A comparison of static, dynamic and machine learning models in predicting the financial distress of chinese firms. Romanian Journal of Economic Forecasting, 25(1), 122-138.

Campbell, J.Y., Hilscher, J., Szilagyi, J. (2008), In search of distress risk. Journal of Finance, 63(6), 2899-2939.

Chen, T., Guestrin, C. (2016), XGBoost: A Scalable Tree Boosting System. In: Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. p. 785-794.

Chen, Y., Guo, J., Huang, J., Lin, B. (2022), A novel method for financial distress prediction based on sparse neural networks with L1/2 regularization. International Journal of Machine Learning and Cybernetics, 13(7), 2089-2103.

Chen, S., Shen, Z.D. (2020), Financial distress prediction using hybrid machine learning techniques. Asian Journal of Economics, Business and Accounting, 16(2), 1-12.

Cobo, M.J., López-Herrera, A.G., Herrera-Viedma, E., and Herrera, F. (2011), Science mapping software tools: Review, analysis, and cooperative study among tools. Journal of the American Society for Information Science and Technology, 62(7), 1382-1402.

Colquitt, J.A., LePine, J.A., Wesson, M.J. (2014), Organizational Behaviour Improving Performance and Quality. Vol. 53. PPI Pulp and Paper International.

Cummins, J.D., Weiss, M.A. (2009), Convergence of insurance and financial markets: Hybrid and securitized risk-transfer solutions. Journal of Risk and Insurance, 76(3), 493-545.

Daníelsson, J., Jorgensen, B.N., De Vries, C.G. (2002), Incentives for effective risk management. Journal of Banking and Finance, 26(7), 1407-1425.

David Cummins, J., Mahul, O. (2003), Optimal insurance with divergent beliefs about insurer total default risk. Journal of Risk and Uncertainty, 27(2), 121-138.

Deakin, E.B. (1968), A discriminant analysis of predictors of business failure. Journal of Accounting Research, 34(2), 78-86.

Egghe, L. (2008), The influence of transformations on the h-index and the g-index. Journal of the American Society for Information Science and Technology, 59, 1193-1361.

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. https://doi.org/10.1007/s10479-022-04766-5, 1-23

Fakhar, S., Mohd Khan, F., Tabash, M.I., Ahmad, G., Akhter, J., Al-Absy, M.S.M. (2023), Financial distress in the banking industry: A bibliometric synthesis and exploration. Cogent Economics and Finance, 11(2), 2253076.

Freund, Y., Schapire, R.E. (1997), A decision-theoretic generalization of on-line learning and an application to boosting. Journal of Computer and System Sciences, 55(1), 119-139.

Gallego-Losada, R., Montero-Navarro, A., Rodríguez-Sánchez, J.L., González-Torres, T. (2022), Retirement planning and financial literacy, at the crossroads. A bibliometric analysis. Finance Research Letters, 44, 102109.

Hafiz, A., Lukumon, O., Muhammad, B., Olugbenga, A., Hakeem, O., Saheed, A. (2015), Bankruptcy Prediction of Construction Businesses: Towards a Big Data Analytics Approach. In: Proceedings - 2015 IEEE 1st International Conference on Big Data Computing Service and Applications, BigDataService 2015. p. 347-352.

Hanson, D., Hitt, M.A., Ireland, R.D., Hoskisson, R.E. (2016), Strategic Management: Competitiveness and Globalisation. United States: Cengage AU.

Hassan, E., Awais-e-Yazdan, M., Birau, R., Paliu-Popa, L. (2023), Anticipating financial distress in monster sectors of Pakistan's economy: An application of logit. Industria Textila, 74(3), 363-370.

Hastie, T., Tibshirani, R., Friedman, J.H., Friedman, J.H. (2009), The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Vol. 2. New York: Springer. p.1-758.

Hitt, M.A., Carnes, C.M., Xu, K. (2016), A current view of resource based theory in operations management: A response to Bromiley and Rau. Journal of Operations Management, 41(10), 107-109.

Horngren, C.T., Datar, S.M., Rajan, M.V. (2016), Cost Accounting: A Managerial Emphasis. United Kingdom: Pearson.

Jiang, C., Lyu, X., Yuan, Y., Wang, Z., Ding, Y. (2022), Mining semantic features in current reports for financial distress prediction: Empirical evidence from unlisted public firms in China. International Journal of Forecasting, 38(3), 1086-1099.

Jiang, C., Ma, L., Wang, Z., Chen, B. (2023), Financial distress prediction using the Q&A text of online interactive platforms. Electronic Commerce Research and Applications, 61, 101292.

Jiang, C., Zhou, Y., Chen, B. (2023a), Mining semantic features in patent text for financial distress prediction. Technological Forecasting and Social Change, 190, 122450.

Jiang, C., Zhou, Y., Chen, B. (2023b), Mining semantic features in patent text for financial distress prediction. Technological Forecasting and Social Change, 190, 122450.

Kang, C.M., Wang, M.C., Lin, L. (2022), Financial distress prediction of cooperative financial institutions-evidence for Taiwan credit unions. International Journal of Financial Studies, 10(2), 10020030.

Kumar, S., Pandey, N., Lim, W.M., Chatterjee, A.N., Pandey, N. (2021), What do we know about transfer pricing? Insights from bibliometric analysis. Journal of Business Research, 134, 275-287.

Lagasio, V., Brogi, M., Gallucci, C., Santulli, R. (2023), May board committees reduce the probability of financial distress? A survival analysis on Italian listed companies. International Review of Financial Analysis, 87, 102561.

Lecun, Y., Bengio, Y., Hinton, G. (2015), Deep learning. Nature, 521(7553), 436-444.

Li, J., Wang, C. (2023), A deep learning approach of financial distress recognition combining text. Electronic Research Archive, 31(8), 4683-4707.

Liao, H., Tang, M., Luo, L., Li, C., Chiclana, F., Zeng, X.J. (2018), A bibliometric analysis and visualization of medical big data research. Sustainability (Switzerland), 10(1), 1-18.

Liaw, A., Wiener, M. (2002), Classification and regression by randomForest. R News, 2(3), 18-22.

Liu, J., Li, C., Ouyang, P., Liu, J., Wu, C. (2023), Interpreting the prediction results of the tree-based gradient boosting models for financial distress prediction with an explainable machine learning approach. Journal of Forecasting, 42(5), 1112-1137.

Liu, W., Fan, H., Xia, M., Pang, C. (2022), Predicting and interpreting financial distress using a weighted boosted tree-based tree. Engineering Applications of Artificial Intelligence, 116, 105466.

Maharana, A.K., Pal, S. (2023), Application of bibliometric analysis in the study of climate change and sustainable development practices. International Journal of Environment and Climate Change, 13(6), 361-368.

Marso, S., El Merouani, M. (2020), Predicting financial distress using hybrid feedforward neural network with cuckoo search algorithm. Procedia Computer Science, 170, 1134-1140.

Mian, S.L., Smith, C.W. Jr. (1992), Accounts receivable management policy: Theory and evidence. American Finance Association, 47(1), 169-200.

Nalubega, S., Evans, C. (2015), Participant views and experiences of participating in HIV research in sub-Saharan Africa: A qualitative systematic review. JBI Database of Systematic Reviews and Implementation Reports, 13(5), 330-420.

Nie, Z., Yan, L., Wang, Z., Li, B. (2022a), Disclosure delay and financial distress prediction: Based on Chinese annual reports disclosure system. Applied Economics Letters, 30(15), 2098-2101.

Nie, Z., Yan, L., Wang, Z., Li, B. (2022b), Disclosure delay and financial distress prediction: Based on Chinese annual reports disclosure system. Applied Economics Letters, 30(15), 2098-2101.

Noyons, E.C.M., Moed, H.F., Luwel, M. (1999), Combining mapping and citation analysis for evaluative bibliometric purposes: A bibliometric study. Journal of the American Society for Information Science, 50(2), 115-131.

Nurhayati, I., Endri, E., Suharti, T., Sundarta, I., Rinda, R.T. (2022), The accuracy of financial distress prediction during the COVID-19 pandemic on healthcare sub-sector companies. WSEAS Transactions on Business and Economics, 19, 1463-1475.

Ohlson, J.A. (1980), Financial ratios and the probabilistic prediction of Bankruptcy. Journal of Accounting Research, 18(1), 109.

Pastore, P., Tommaso, S. (2013), Italian industrial districts: Influence of the governance on performance and financial distress of firms. An explorative study. Corporate Ownership and Control, 11(1), 962-991.

Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A.V., Gulin, A. (2018), Catboost: Unbiased boosting with categorical features. Advances in Neural Information Processing Systems, 2018-Decem(Section 4), 6638-6648.

Ragab, Y.M., Saleh, M.A. (2022), Non-financial variables related to governance and financial distress prediction in SMEs-evidence from Egypt. Journal of Applied Accounting Research, 23(3), 604-627.

Refait-Alexandre, C. (2004), La prévision de la faillite fondée sur l'analyse financière de l'entreprise: Un état des lieux. Économie and Prévision, 162(1), 129-147.

Sa'diyah, C., Widagdo, B., Rahadjeng, E.R. (2022), Financial distress: From bibliometric analysis to current research, future and trends research directions and content analysis. In: Social and Political Issues on Sustainable Development in the Post Covid-19 Crisis. London: Routledge. p. 131-138.

Shi, Y., Li, X. (2019), A bibliometric study on intelligent techniques of bankruptcy prediction for corporate firms. Heliyon, 5(12), e02997.

Shumway, T. (2001), Forecasting bankruptcy more accurately: A simple hazard model. Journal of Business, 74(1), 101-124.

Sun, J., Li, H., Huang, Q.H., He, K.Y. (2014), Predicting financial distress and corporate failure: A review from the state-of-the-art definitions, modeling, sampling, and featuring approaches. Knowledge-Based Systems, 57, 41-56.

Sun, J., Li, J., Fujita, H., Ai, W. (2022), Multiclass financial distress prediction based on one-versus-one decomposition integrated with improved decision-directed acyclic graph. Journal of Forecasting, 57, 41-56.

Taffler, R.J. (1982), Forecasting company failure in the UK using discriminant analysis and financial ratio data. Journal of the Royal Statistical Society, 145(3), 342-358.

Tang, Y., Xie, M. (2023), Financial Distress Prediction of Small and Medium- Sized Enterprises Based on Artificial Intelligence Technology. In: International Conference on Applied Intelligence and Sustainable Computing, ICAISC 2023.

Tibshirani, R. (2016), Regression Shrinkage and Selection via the Lasso. Journal of the Royal Statistical Society, 58(1), 267-288.

Tinoco, M.H., Wilson, N. (2013), Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. International Review of Financial Analysis, 30, 394-419.

Tran, K.L., Le, H.A., Nguyen, T.H., Nguyen, D.T. (2022), Explainable machine learning for financial distress prediction: Evidence from Vietnam. Data, 7(11), 7110160.

Trevor H, Robert T, Jerome JH. (2009), The Elements of Statistical Learning: Data Mining, Inference, and Prediction. 2nded. Springer Series in Statistics.

van Eck, N.J., Waltman, L. (2010), Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics, 84(2), 523-538.

van Raan, A.F.J. (2005), For your citations only? Hot topics in bibliometric analysis. Measurement: Interdisciplinary Research and Perspective, 3(1), 50-62.

Wang, Z., Wang, Q., Nie, Z., Li, B. (2022), Corporate financial distress prediction based on controlling shareholder's equity pledge. Applied Economics Letters, 29(15), 1365-1368.

Waqas, H., Md-Rus, R. (2018), Predicting financial distress: Importance of accounting and firm-specific market variables for Pakistan's listed firms. Cogent Economics and Finance, 6(1), 1-16.

Whited, T.M. (1992), American Finance Association debt, liquidity constraints, and corporate investment : Evidence from panel data. The Journal of Finance, 4(4), 1425-1460.

Whittred, G., Zimmer, I. (1985), The implications of distress prediction models for corporate lending. Accounting and Finance, 25(1), 1-13.

Wu, D., Ma, X., Olson, D.L. (2022), Financial distress prediction using integrated Z-score and multilayer perceptron neural networks. Decision Support Systems, 159, 113814.

Wu, M., Long, R., Bai, Y., Chen, H. (2021), Knowledge mapping analysis of international research on environmental communication using bibliometrics. Journal of Environmental Management, 298, 113475.

Zhang, Z., Wu, C., Qu, S., Chen, X. (2022), An explainable artificial intelligence approach for financial distress prediction. Information Processing and Management, 59(4), 102988.

Zhao, Q., Xu, W., Ji, Y. (2023), Predicting financial distress of Chinese listed companies using machine learning: To what extent does textual disclosure matter? International Review of Financial Analysis, 89, 102770.

Zhao, S., Xu, K., Wang, Z., Liang, C., Lu, W., Chen, B. (2022), Financial distress prediction by combining sentiment tone features. Economic Modelling, 106, 105709.

Zhu, F.J., Zhou, L.J., Zhou, M., Pei, F. (2021), Financial distress prediction: A novel data segmentation research on chinese listed companies. Technological and Economic Development of Economy, 27(6), 1413-1446.

Zmijewski, M.E. (1984), Methodological issues related to the estimation of financial distress prediction models. Journal of Accounting Research, 22, 59-82.