

Bibliometric Analysis of Bankruptcy Prediction in Financial Institutions: Themes, Evidence, and A Future Research Agenda

Tri Gunarsih^{1*}, Rodhiyah Mardhiyah² & Fran Sayekti¹

¹*Faculty of Business and Humanities, Universitas Teknologi Yogyakarta, Indonesia.*

²*Faculty of Sains and Technology, Universitas Teknologi Yogyakarta, Indonesia.*

Abstract: Research Question: What are the dominant themes and methodological gaps revealed through co-word and bibliographic coupling analyses of Bankruptcy Prediction in Financial Institutions? **Motivation:** Starting from the need for an accurate and auditable early warning system in financial institutions, this study maps the bankruptcy prediction research landscape through a Web of Science-based bibliometric analysis (1970-2025) and VOSviewer visualization. **Idea:** This article combines performance analysis (publications, citations, and h-index) with science mapping (bibliographic coupling and co-word analysis) to explore intellectual foundations, research frontiers, and methodological gaps. **Data:** Publication record from 1970 to 2025 in Web of Science with a total of 2,410 articles. **Method/Tools:** The methods start by defining the scope of the topic (Bankruptcy Prediction in Financial Institutions) and the time horizon (1970-2025). The list of keywords is compiled iteratively by combining key terms and their synonyms. Boolean operators and wildcards are used to expand/detail the outcome. This study implemented the co-word and bibliographic coupling analyses using VOSviewer. **Findings:** The results show 2,410 publications, 42,247 citations, and an h-index of 89; output and impact have increased sharply since 2015, indicating an acceleration of interest in this topic. Four main clusters are identified: (1) Machine Learning (ML) ensembles for credit risk & bankruptcy, (2) sovereign-bank nexus, capital, and credit risk systems, (3) capital risk, governance & bank failure prediction, and (4) network-based systemic risk & tail-connectedness. The analysis also reveals divergent findings between conventional logit models and ML algorithms, the importance of addressing class imbalance, the need for temporal (out-of-time) validation, and feature selection contextualized to regulatory and systemic dynamics in the financial sector. **Contributions:** This study presents a concise taxonomy of methods and proposes a research agenda to address identified gaps and promote more accurate, transparent, and

* Corresponding author: Tri Gunarsih. Tel.: 62-274623310.

Email: trigunarsih@uty.ac.id

Acknowledgements: The authors extend their gratitude to Gusman Nawanir, M.Sc., Ph.D., for his support in this work. Funding for this work was provided by DPPM Ministry of Higher Education, Science and Technology for Fiscal Year 2025, Number 126/C3/DT.05.00/PL/2025 dated May 28, 2025.

Received 23 Oct 2025; Final revised 11 Dec 2025; Accepted 20 Mar 2025; Available online 31 Mar 2026.

To link to this article: https://www.mfa.com.my/cmr/v34_i1_a5/

© Malaysian Finance Association, 2026. This work is licensed under the terms of the Creative Commons Attribution (CC BY) (<http://creativecommons.org/licenses/by/4.0/>).

testable models across market regimes. This study provides a compass map for designing research that is both relevant and replicable.

Keywords: Bibliometric, bankruptcy prediction, financial institutions.

JEL Classification: G21, G33, C45

1. Introduction

Bankruptcy prediction has long been a significant concern in both research and practice, across the financial and non-financial sectors. Since the Z-score was introduced in the late 1960s, this approach has evolved from a simple financial ratio (Altman, 1968) towards multivariate statistical techniques, as Kim and Manganelli (2015) also with testing in different countries, Altman *et al.* (2017) then expand again using machine learning (ML) and artificial intelligence (AI) to improve the accuracy of predictions (Ahmed *et al.*, 2022; Kimura and Altman, 2017; Beutel List and von Schweinitz, 2019). Changes in approach are becoming increasingly relevant for financial institutions, including banks, financing companies, insurance companies, and microfinance institutions, because the failure of such institutions affects not only shareholders but also the stability of the financial system. The need for early warning systems that are accurate and auditable is driving the adoption of ML/AI models that are more sensitive to non-linearity and large-scale data (Petropoulos *et al.*, 2020; Chohan *et al.*, 2025; Zhao *et al.*, 2024).

However, ML's empirical findings are inconsistent. At the country level, with a long time span, conventional logit testing can still outperform various ML algorithms in predicting systemic banking crises, such as credit spikes and asset-price booms (Beutel List and von Schweinitz, 2019). Conversely, when the analysis is conducted at the individual bank level with more granular CAMELS features, random forests and neural networks tend to outperform logit on out-of-sample and out-of-time tests (Petropoulos *et al.*, 2020). On the other hand, the bibliometric literature that captures the landscape of this study still generally relies on performance metrics, including counts of publications, citations, authors, countries, or outlets. The map that is most needed is science mapping, namely, the mapping of intellectual architecture, methodological choices, and research gaps that are truly contextual (Donthu *et al.*, 2021; Župič and Čater, 2015; Aria and Cuccurullo, 2017). In the non-financial sector, cross-industry studies have identified emerging trends and thematic clusters, but have not yet developed a neat taxonomy of prediction methods at the industry level, ranging from variable selection, validation design, to handling class imbalances (Shi and Li, 2019). Likewise, in financial institutions, bibliometric analysis of financial distress in Banking helps uncover performance trends and knowledge structures, but has not yet outlined how prediction methods are differentiated to align with regulatory characteristics, macro dynamics, and systemic linkages in the sector (Fakhar *et al.*, 2023).

Bankruptcy research on financial institutions is more important because these institutions have distinct characteristics and risks compared to the industry sector as a whole, including strict regulatory supervision, dependence on macroeconomic stability, and systemic linkages among institutions. From this, it is clear that a research gap exists: there is a lack of comprehensive literature mapping on bankruptcy prediction in the financial sector, including its connections to feature selection, evaluation methods, and future research agendas.

This research is designed to close the gap. This study aims to systematically review the academic literature on bankruptcy prediction by utilizing VOSviewer. Specifically, this study aims to (1) Describe how the research map in the field of bankruptcy prediction in the financial industry is formed and developed, including who the authors are, in what journals they work in, and what the publication flow is like, by mapping key bibliometric trends,

such as author collaboration networks, co-emergence of terms, to findings from text mining on the topic of bankruptcy prediction. (2) Discuss research spaces that are still rarely explored and formulate opportunities for future research agendas, so that the understanding of this topic is more profound and sharper. The study was compiled based on a systematic search of the Web of Science database, covering the period 1970 to 2025.

Bibliometric analysis helps assess and map a field's knowledge through performance indicators, such as the number of publications, total or average citations, and the h-index, as well as the network of expertise, including citations, co-citations, bibliographic couplings, co-words, and co-authors. The goal is not limited to calculating productivity or impact, but to reveal the knowledge base, the research frontier, and how the theme develops objectively and can be easily replicated.

2. Methodology

2.1 Bibliometric

Bibliometric analysis is one of the quantitative approaches to read the structure of knowledge through publication and citation traces, ranging from productivity calculations (number of articles, average/total citations, h-index) to the relationship of knowledge networks such as citations, co-citations, co-words, co-authors, and bibliographic couplings (Donthu *et al.*, 2021; Aria and Cuccurullo, 2017). This approach is relatively objective (citing/network-based), replicable (parameters and thresholds can be restated), and scalable for thousands of documents across decades. The results are not only who writes the most, but also what their intellectual foundations are and where the research is headed, which is important information for mapping gaps and research priorities (Donthu *et al.*, 2021; Moral-Muñoz *et al.*, 2020).

Bibliometric analysis combines several approaches, namely: (i) Citation analysis to assess the performance of the most influential fields, sources, authors, and documents (Donthu *et al.*, 2021). (ii) Co-citation analysis to uncover the knowledge base; Works that are often cited together usually form the same tradition of theory or method (Župič and Čater, 2015). (iii) Bibliographic coupling to recognize the latest "research front" through the similarity of the bibliography between new articles (Donthu *et al.*, 2021) (iv) Co-word analysis to map the conceptual structure and evolution of themes from keywords that often appear together (Aria and Cuccurullo, 2017). (v) Co-authorship analysis to map the collaboration network of authors/institutions/and countries (Perianes-Rodríguez and van Eck, 2016). One of the tools that can be used is VOSviewer to visualize large networks with stable and widely adopted association strength-based layouts (Muñoz *et al.*, 2020).

Compared to narrative review, the bibliometric approach offers several advantages, including (i) being more objective because it relies on citation data and networks to reduce narrative bias; (ii) it can be repeatable because parameters, thresholds, and algorithms can be restated; (iii) scalability for thousands of documents across decades; and (iv) being able to trace the dynamics of the field through theme maps and time tracks. The software ecosystem is also maturing, including Bibliometrix/Biblioshiny, VOSviewer, and CiteSpace, so that the flow from descriptive statistics to thematic evolution runs more standard and transparent (Donthu *et al.*, 2021; Muñoz *et al.*, 2020). These advantages are particularly relevant to fast-changing areas such as bankruptcy prediction and banking crises, which demand a systematic, auditable, and easily updated synthesis (Donthu *et al.*, 2021).

2.2 Search Strategies and Data Collection Procedures

A search strategy starts by defining the scope of the topic and the time horizon. The time period spans from 1970 to 2025, covering the latest research trends. The list of keywords is

compiled iteratively, combining key terms and synonyms, including bankruptcy, insolvency, financial distress, corporate failure, business failure, default, and credit risk. Boolean operators and wildcards are used to expand/detail the outcome, e.g., "bankrupt*". The main database used is the Web of Science.

Search results are downloaded in a complete bibliographic format (title, abstract, author/keywords, affiliation, source, year, and reference list). All track records were put together, deduplicated based on DOI/title-year-author, and then filtered in stages: (i) title/abstract screening to check the suitability of focus (prediction of bankruptcy with intelligent/quantitative techniques), (ii) full-text screening if the scope is ambiguous. Ready-to-use outputs for performance analysis (publications/citations), co-citations, bibliographic coupling, co-wording, and co-author networking. The summary of data collection, including the Search String in the WoS Database, is shown in Table 1.

Table 1: Data collection parameters

Basis data	Web of Science
Download date	21 April 2025
Year range	1970–2025
Document type	Article
Subject area	Financial Institutions
Language	English
Search String in WoS Database	
Keywords	Justification
"bankrupt*" OR "insolvenc*" OR "financial distress*" OR "corporate failure*" OR "business failure*" OR "default*" OR "credit risk*" OR "predict*" OR "forecast*" OR "model*" OR "assess*" OR "detect*" OR "estimat*" OR "classifi*" OR "early warning*" OR "financial institution*" OR "commercial bank*" OR "investment bank*" OR "insurance compan*" OR "credit union*" OR "microfinance institution*" OR "financial firm*" OR "financial service* firm*" OR "financial sector*"	To identify literature related to bankruptcy To identify literature related to prediction To identify literature related to financial institutions

3. Findings and Discussion

3.1 Descriptive Analysis

This section explains the articles used in the bibliometric analysis, which are divided into two categories: article description and number of publications cited.



Figure 1: Article description

Figure 1 shows the publication track record from 1970 to 2025. The total number of publications is 2,410, with 42,247 citations, of which 39,155 are from outside parties (excluding self-citations). The publication in Figure 1 has a broad impact, with 29,741 articles citing it, of which 28,499 are non-self-citations, averaging 17.53 citations per item. The quality and consistency of contributions are also reflected in the H-index of 89, which means that 89 publications have been cited at least 89 times each. In summary, the combination of a large volume of works, the spread of citations across articles, and the dominance of external citations indicates a sustained and credible academic influence.

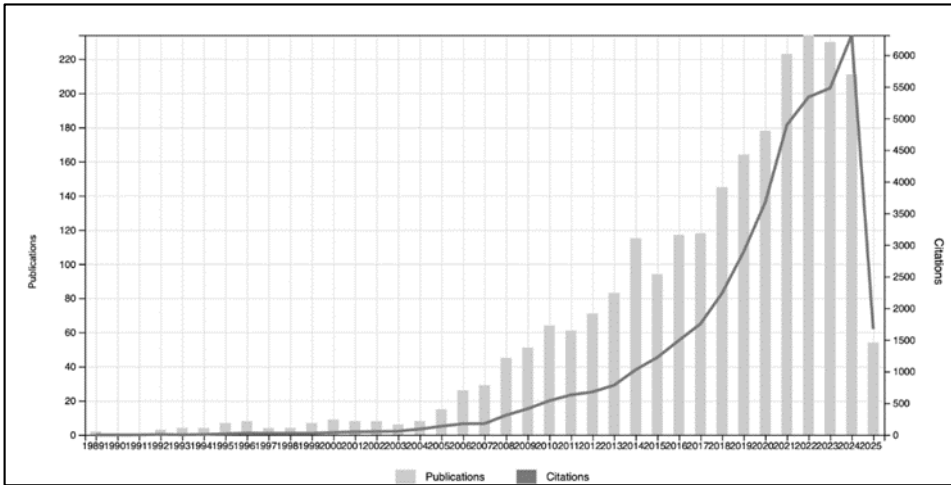


Figure 2: Number of publications and citations Bankruptcy Prediction in Financial Institutions in the WoS database retrieved on 21 April 2025

Figure 2 shows the data artifact of publications (purple bars with Y-axis on the left with units 0 to 220) and citations (blue lines with Y axis on the right with units 0 to 6,000) over the period 1989-2025. In 1989-2005, the volume of publications was very low (fewer than 10 per year), then gradually increased in 2006-2014 (about 60-80 per year). The sharp acceleration began in 2015 and peaked in 2020-2024, when output exceeded 200 publications per year (the peak occurred around 2022-2024). This indicates an increasing trend in research on bankruptcy prediction in financial institutions, as measured by volume. This data supports the statement in the background section about the importance of this research to financial institutions.

The citation line indicates that citations remained relatively flat until 2014, then increased rapidly, with a lag in publication growth, peaking around 2023-2024 to exceed 6,000 citations per year. The figure for 2025 appears to be declining for both metrics, possibly because the data was downloaded in April 2025 and the current year is not yet complete. Overall, the graph illustrates the robust growth in research capacity and scientific impact over the past decade, exhibiting a classic pattern: production initially increased, followed by a surge in citations a few years later.

3.2 Bibliometric Coupling

The results of the bibliometric coupling are summarized in Table 2, which presents the ranking of the 10 highest papers by number of citations and total link strength. Table 2 shows two main research tracks. First, the ensemble method for credit scoring, such as Ala'Raj and Abbod (2016), Xia *et al.* (2018), Abelián and Castellano (2017) and Papouskova and Hajek (2019). These works have a strong connection to quotations, often serving as references. Second, research on systemic risks and the fragility of banking, for example, Anginer and Demircuc-Kunt (2014) and Huang and Zhu (2009), Huang and Zhu (2012), attributes company-level findings to financial system stability. Next, Iturriaga and Sanz (2015) demonstrated predictions of bankruptcy using neural networks, and Imbierowicz and Rauch (2014) highlighted the link between credit liquidity risk. Duan and Wang (2012) introduced a method to visualize the probability of default across periods. The study's results can be summarized as follows: the ensemble approach is closely related to financial stability.

Table 2: Top 10 papers in bibliographic coupling analysis

Ranking	Publication	No. of Citation	Total link strength
1	Ala'Raj and Abbod (2016): Classifiers consensus system approach for credit scoring	141	66
2	Xia <i>et al.</i> (2018): A novel heterogeneous ensemble credit scoring model based on the bstacking approach	147	57
3	Abelián and Castellano (2017): A comparative study on base classifiers in ensemble methods for credit scoring	145	41
4	Papouskova and Hajek (2019): Two-stage consumer credit risk modelling using heterogeneous ensemble learning	131	40
5	Anginer and Demirguc- (2014): Has the global banking system become more fragile over time?	325	40
6	Huang <i>et al.</i> (2009): A framework for assessing the systemic risk of major financial institutions	294	37
7	Iturriaga and Sanz (2015): Bankruptcy visualization and prediction using neural networks: A study of US commercial banks	128	35
8	Imbierowicz and Rauch (2014): The relationship between liquidity risk and credit risk in banks	168	34
9	Huang and Zhu (2012): Systemic Risk Contributions	136	32
10	Duan and Wang (2012): Multiperiod corporate default prediction: A forward intensity approach	183	31

Result network (VOSviewer) Bibliographic Coupling of Bankruptcy Prediction in Financial Institutions is presented in Figure 3. The map displays a grouped reference network or co-citation in four colored clusters. The size of the node reflects the relative weight or strength of the citation of each reference, while the thickness and number of lines indicate the proximity/topic that often comes up together. Each cluster is described as follows: (1) Red Cluster (right), collecting credit risk modeling literature and modern data analytics (Khandani and Lo, 2010) be a strong node that connects to Li (2021) and Malhotra and Malhotra (2003), signifying a focus on default prediction with statistical/ML techniques and credit scoring applications. (2) The Green Cluster (center), serves as a conceptual bridge between the regulatory literature and modern modeling. Diamond and Rajan (2000) and Acharya and Schnabl (2014) appear as a hub node, connected to Wahlen (1994), Milevsky and Promislow (2001), Serrano-Cinca *et al.* (2015), until Ma *et al.* (2018). This cluster represents intermediation/risk theory and empirical work widely cited across topics. (3) Blue Cluster (left/top), pivoted to banking, regulation, and stability literature. Names such as Wheelock and Wilson (2000), Muravyev *et al.* (2009), Flannery and Rangan (2008) and Cihák and Hesse (2010) closely interconnected, describing the basis for bank supervision, risk, and prudential policy studies, and (4) the Yellow Cluster (bottom/left), a relatively new group of derivative applications/themes, with Chava (2014), Amini and Minca (2016) and Ando (2022). Its connectivity to green clusters suggests that these works draw heavily from the foundations of risk/intermediation theory.

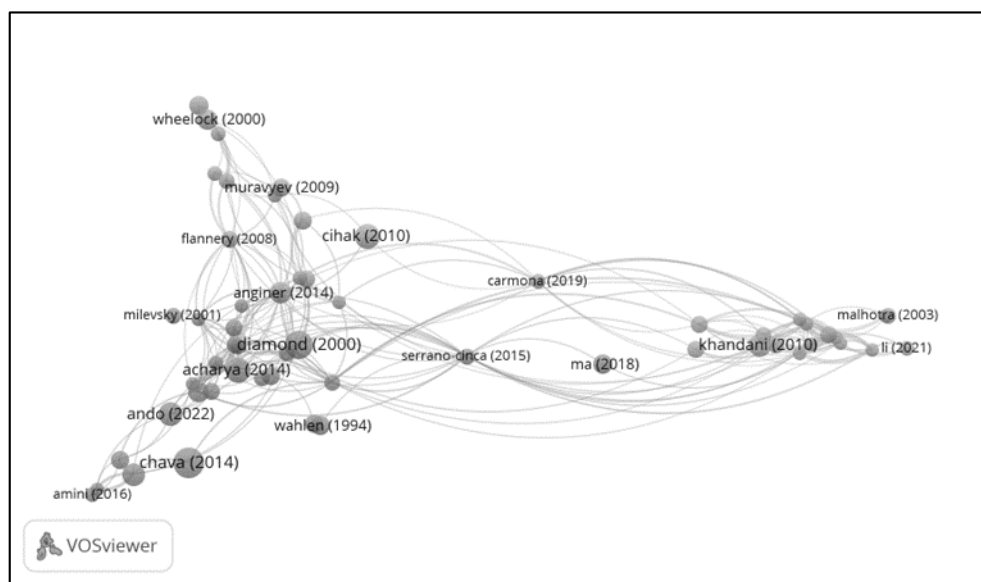


Figure 3: Bibliographic Coupling of Bankruptcy Prediction in Financial Institutions

Nodes such as Carmona and Momparler (2019) and Cihák and Hesse (2010) seem to link the cluster, while Diamond and Rajan (2000) and Acharya and Schnabl (2014) act as a central binder. Overall, the map shows an evolutionary path: from the banking stability and regulatory literature (blue) to the strengthening of systemic and risk theoretical frameworks (green), then to a wave of predictive modelling for credit risk (red), with some contemporary applications (yellow) spreading and taking references from network centers. The four clusters in the Bibliographic Coupling of Bankruptcy Prediction in Financial Institutions are summarized in Table 3. The explanation of each cluster is as follows.

Table 3: Bibliographic coupling analysis on Bankruptcy Prediction in Financial Institutions

Cluster No and color	Cluster label	Number of publications	Representative publication
1 (Red)	ML Ensembles for Credit Risk & Bankruptcy Prediction	16	Xia <i>et al.</i> (2018); Ala'raj and Abbod (2016); Chang and Wu (2018); Papouskova and Hajek (2019); Li <i>et al.</i> (2019); Liang <i>et al.</i> (2016)
2 (Green)	Sovereign Bank Nexus, Bank Capital & Credit-Risk Systems	16	Acharya and Schnabl (2014); Gennaioli and Rossi, (2014); Diamond and Rajan (2000); Bangia <i>et al.</i> (2002); Mishkin (2011); Veronesi and Zingales (2010); Serrano-Cinca and López-Palacios (2015); Umar <i>et al.</i> (2021)
3 (Blue)	Bank Capital Risk, Governance & Failure Prediction	15	Anginer and Demircuc-Kunt (2014); Barry and Tarazi (2011); Kwan and Eisenbeis (1997); Imbierowicz and Rauch (2014); Palvia and Vähämaa (2015); Flannery and Rangan (2008); Betz <i>et al.</i> (2014); Carmona and Momparler (2019)
4 (Yellow)	Network-Based Systemic Risk & Tail-Connectedness	10	Ando (2022); Kim and Manganelli (2015); Amini and Minca (2016); Bardoscia <i>et al.</i> (2017); Huang and Zhu (2012); Huang and Zhu (2009); Jorion and Zhang (2009); Glasserman and Young (2015)

3.2.1 Cluster 1 (Red)

The theme of this cluster is the use of ML ensembles for credit scoring and bankruptcy prediction. The common thread of this cluster is the use of multiple classifier systems, ranging from stacking and bagging/boosting to feature engineering, to address class imbalance and capture non-linear patterns in customer or company data. The essence of this theme is to bring together a diverse group of basic learners who complement each other to improve generalizations. For example, bstacking combines the power of bagging and stacking and has been proven to be effective for credit scoring because meta-learners can refine signals from different models (Xia *et al.*, 2018). Similarly, the consensus system that assembles several MCS (Multiple Classifier Systems) and cross-architecture features for more stable performance (Ala'Raj and Abbod, 2016). On the boosting path, XGBoost often achieves higher accuracy/AUC (Area Under the ROC Curve) scores than the classic model. Therefore, many researchers have made gradient boosting the 'backbone' of modern pipelines (Chang and Wu, 2018).

The direction of research has also shifted from just Probability of Default (PD) towards a more complete loss estimate through a two-stage architecture (PD to EAD/LGD (Exposure at Default or Loss Given Default)), so that the need for risk management practices is closer (Papouškova and Hajek, 2019). On the feature side, transfer learning helps improve model transferability across credit-business domains by leveraging information from traditional credit products to build training sets for data-scarce new products (Li *et al.*, 2019), while the addition of the aspect of mutual governance of financial ratios increases the discriminatory power of the model (Liang *et al.*, 2016). Overall, this cluster emphasizes ensembling, temporal validation, and handling imbalances as a standard practice, from banking to P2P lending, to enable more reliable, out-of-the-box risk prediction.

3.2.2 Cluster 2 (Green)

The theme of this cluster is Sovereign Bank Nexus, Bank Capital & Credit-Risk Systems. The sovereign bank nexus illustrates the interconnectedness of risk: a bank bailout burdens the fiscal and adds to the risk of sovereignty, while a correction in the price of government bonds immediately erodes the balance sheets of the banks that hold them, creating a doom loop when domestic exposure to sovereign bonds is enormous (Acharya and Schnabl, 2014; Gennaioli and Rossi, 2014). At the institutional level, capital theory highlights a tipping point: too thin capital triggers fragility and impetus risk-shifting, while too thick capital can suppress the intermediation function and liquidity creation (Diamond and Rajan, 2000). The cyclical dynamics of rank migration also explain why stress testing must be sensitive to the business phase, because the opportunity to downgrade increases during contraction (Bangia *et al.*, 2002).

The lessons of the 2007-2009 crisis show how housing shocks, securitization, and money-market runs can escalate into a systemic crisis. Public intervention is indeed necessary, but it raises the trade-off between stability and taxpayer burdens (Mishkin, 2011; Veronesi and Zingales, 2010). Beyond banking, FinTech is expanding credit while bringing new sources of risk: in P2P lending, default is greatly influenced by the character of the borrower and the grade platform, so that transparency and protection of retail investors are crucial (Serrano-Cinca and López-Palacios, 2015). The use of non-traditional methods, such as mobile phone footprints, has been shown to improve the accuracy of default predictions in environments with high information asymmetry (Ma *et al.*, 2018). The dimensions of the green transition and commodity cycle also shape risk: low-carbon financing correlates with better asset quality in the Eurozone, while the commodity boom in resource-rich countries can decrease efficiency and increase the probability of failure (Umar *et al.*, 2021).

3.2.3 Cluster 3 (Blue)

The theme of this cluster is Bank Capital Risk, Governance & Failure Prediction, which strings together three axes: rules, structure, and behavior. In terms of rules, the FDICIA framework (Federal Deposit Insurance Corporation Improvement Act.) and prompt corrective action, encouraging banks to thicken capital while curbing risk appetite, as market discipline goes hand in hand with regulatory sanctions (Aggarwal and Jacques, 2001). Healthy competition also helps, i.e., higher competition tends to lower systemic risk through diversification, not uniformity of behavior risk-taking (Anginer and Demirguc-Kunt, 2014). But governance and ownership remain decisive; Private banks show a risk profile that is more sensitive to internal mechanisms than public banks (Barry and Tarazi, 2011).

At the micro level, operational inefficiencies often coexist with risk-taking and capital-raising incentives, which align with the hypothesis of moral hazard in underperforming banks (Kwan and Eisenbeis, 1997). The relationship between risks is also nonlinear; for instance, in US banks from 1998 to 2010, liquidity risk did not always move in tandem with credit risk in the short term. However, both increase the chance of failure (Imbierowicz and Rauch, 2014). Elements that people take part in; banks led by female CEOs or board chairmen tend to hold more risk, resulting in higher equity capital and a lower probability of failure during times of crisis (Palvia and Vähämaa, 2015).

In the long horizon, weakening implicit guarantees and increased monitoring of counterparties help explain the accumulation of U.S. bank capital in the (Flannery and Rangan, 2008). For early detection, the model maps bank and country indicators of distress that go beyond formal bankruptcy, including state intervention and mergers in distress (Betz Oprica *et al.*, 2014). Last machine learning, like XGBoost, improves accuracy in failure prediction and highlights key ratios as early warnings (Carmona and Momparler, 2019).

3.2.4 Cluster 4 (Yellow)

The theme of this cluster was Network-Based Systemic Risk & Tail-Connectedness. Systemic risk is essentially network-based. Shocks in one institution can propagate through balance sheet linkages, and tail-connectedness captures how strong that contagion is when the market is at extremes, rather than the daily average (Ando, 2022; Kim and Manganelli, 2015). The shape of the network helps determine the threshold for a chain failure: the concentration of relationships, the strength of capital cushions, and the asset recovery process all contribute to "resilience to contingency" (Amini and Minca, 2016). At the mechanism level, a decline in market value and a tightening of leverage can magnify small surprises into widespread instability through a repetitive feedback trajectory (Bardoscia *et al.*, 2017).

To assess vulnerabilities without mapping the entire network, node-level information (the degree of connectivity and loss-absorbing capacity) can provide a rapid test of worst-case scenarios for policymakers (Glasserman and Young, 2015). On the market-based measurement side, premium distress insurance extracts the implicit price of systemic losses and divides the risk contribution to each bank (Huang and Zhu, 2012), in line with a framework that emphasizes the importance of combining individual failure probabilities and default correlations that change with market (Huang and Zhu, 2009). Micro evidence is also consistent: the bankruptcy of one company immediately suppresses the value of creditors directly through the other party's channels (Jorion and Zhang, 2009). For dynamic monitoring, a decomposition-based measure of variance mapping spillover between institutions (Diebold and Yilmaz, 2015), while quantile models, such as quantile VAR, are more sensitive to capturing transmission of extreme shocks (Ando, 2022; Kim and Manganelli, 2015).

3.3 Co-word Analysis

Co-word analysis can map research topics by looking at keywords that often appear together, thereby revealing interrelated themes and which ones are most central. The results of the analysis are usually presented as maps or clusters that show the group of topics and how the research focus has evolved. The fifteen highest keywords based on occurrences, accompanied by total link strength, are summarized in Table 4.

From Table 4, the top 15 keywords indicate that the research landscape is dominated by the theme of credit risk. The term credit risk ranked first with 412 appearances, followed by risk (362), which actually had the highest total link strength (TLS) (1,031), indicating its role as a link between topics. The direction of research was strong on performance and efficiency (249 and 136 appearances; TLS 957 and 538), determinants of search (231; TLS 858), and impact (153; TLS 502), indicating a focus on impact evaluation and determinants in risk management.

From a methodological perspective, the terms model/models (231/146; TLS 633/420), prediction (126; TLS 423), and machine learning (115; TLS 345) affirm the orientation toward predictive modeling. It is intertwined with the distress domain: default (146; TLS 433), bankruptcy (125; TLS 384), and bankruptcy prediction (117; TLS 424), which signifies a strong interest in early warning of failure. The existence of systemic risk (TLS 331) indicates an expansion of perspective from idiosyncratic risk to inter-institutional linkages and potential transmission at the system level.

Table 4: Top 15 keywords in the co-word analysis

Rank	Keyword	Occurrences	Total Link Strength
1	credit risk	412	1018
2	risk	362	1031
3	performance	249	957
4	determinants	231	858
5	model	231	633
6	impact	153	502
7	default	146	433
8	models	146	420
9	systemic risk	142	331
10	efficiency	136	538
11	prediction	126	423
12	bankruptcy	125	384
13	bankruptcy prediction	117	424
14	machine learning	115	345
15	credit	110	317

Notes: Sorted based on number of occurrences.

Overall, these patterns form four major clusters: (1) credit risk, risk, default, bankruptcy, (2) performance, efficiency, impact, determinants, (3) predictive modeling, and (4) systemic risk. TLS's high levels of "risk" and "performance" indicate these two terms as central nodes in a co-occurrence network. Meanwhile, "machine learning" has medium frequency and solid connectivity, describing methods increasingly embedded across various topics, especially those related to bankruptcy/credit risk prediction. This narrative suggests a research agenda that balances model accuracy, understanding of determinants, and systemic implications for financial stability.

The co-word visualization is shown in Figure 4. The keynote map forms a landscape centered on credit risk, with the model(s) serving as the connecting node. From the center emanates three groups: on the top-middle side (green), there is the realm of risk and system stability, which includes default, banks/banking, liquidity, systemic risk, contagion,

financial stability/crisis, market, and debt. On the left-bottom (red) side, the theme of performance and determining factors is gathered, including performance, determinants, efficiency, non-performing loans, profitability, management, governance, corporate governance, capital structure, growth, and competition. While on the right (blue), there is a predictive modeling cluster, marked by machine learning, credit scoring, bankruptcy prediction, classifiers, neural networks, regression, feature selection, financial ratios, and discriminant analysis, all related to financial distress.

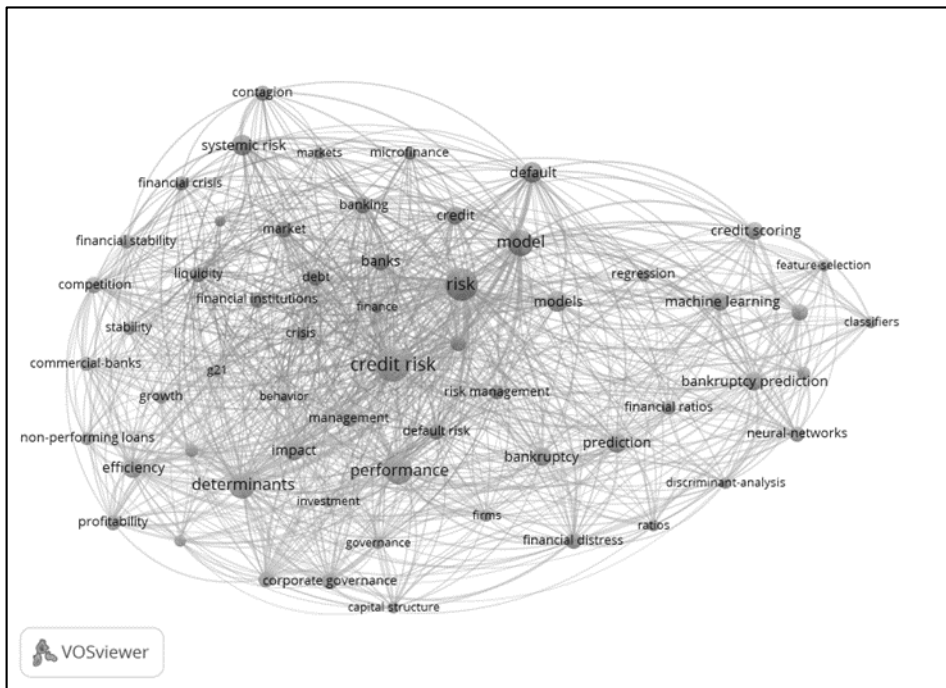


Figure 4: Bibliographic Coupling of Bankruptcy Prediction in Financial Institutions

The interconnectedness between the groups is dense, spanning financial ratios, default risk, and risk management, serving as a bridge between the managerial side (determinants/performance) and the methodological side (ML/credit scoring). This pattern implies a complete research flow, starting with the explanation of risk and performance drivers, then moving to the dynamics of systemic stability/transmission through liquidity and contagion, and finally to modeling and early warning based on statistics, then ML. In summary, the map depicts a research ecosystem that integrates governance, capital structure, NPLs, and market conditions with modern predictive techniques to comprehensively understand and manage credit risk.

The three clusters with the theme (cluster label), the number of publications, and Representative keywords in the Co-word analysis on Bankruptcy Prediction in Financial Institutions are summarized in Table 5. The first cluster (red) has 22 keywords, the second (green) and third (blue) clusters have 21 and 17 keywords, respectively. Each cluster is described in the following section.

3.3.1 Cluster 1 (Red)

The theme of this cluster is Commercial-bank behavior under corporate governance, capital structure, and competition, and its effects on efficiency, NPLs, profitability, and financial stability. Commercial banks essentially channel trust: pursuing growth while maintaining stability, so that governance, capital structure, and competition together shape efficiency, non-performing loans (NPLs), profits, and system resilience. Governance determines how risk appetite translates into credit and investment decisions. When shareholder impulses are stronger, risk-taking tends to rise, but the effect is highly dependent on the regulatory design and oversight that surrounds it (Laeven and Levine, 2009). The bank's capital structure is heavily influenced by ordinary corporate factors such as profitability, size, and tangible assets. Market discipline and managerial preference remain visible except when capital is close to the regulatory limit (Gropp and Heider, 2010). Competition drives efficiency, but if it is too tight, it can erode margins and trigger risk shifts without adequate capital buffers (Berger and Mester, 1997; Allen and Gale, 2004; Claessens and Laeven, 2004). NPLs triggered by macro conditions and bank characteristics, and strong earnings usually go hand in hand with lower NPLs (Louzis and Metaxas, 2012). Ultimately, a bank's margin and profit are the result of a combination of internal factors, macroeconomic cycles, financial structures, taxes, and regulations (Demirgüç-Kunt and Huizinga, 1999).

Table 5: Summary of co-word analysis on Bankruptcy Prediction in Financial Institutions

Cluster No and color	Cluster label	No. of keywords	Representative Keywords
1 (red)	Commercial-bank behavior under corporate governance, capital structure, and competition, and its effects on efficiency, NPLs, profitability, and financial stability	22	Behavior, capital structure, commercial banks, competition, corporate governance, profitability, financial stability, non-performing loans, stability, performance, efficiency.
2 (green)	Microfinance and Banking Stability: Credit Risk, Liquidity, and Governance.	21	Microfinance, banking, banking stability, credit risk, liquidity, governance
3 (blue)	From Financial Ratios to Machine Learning for Bankruptcy Prediction.	17	financial ratios, financial distress, machine learning, bankruptcy prediction, regression models, feature selection, classifiers, discriminant analysis, neural networks, support vector machine, classification, ratios, prediction, credit scoring

3.3.2 Cluster 2 (Green)

The theme of cluster 2 is Microfinance and Banking Stability: Credit Risk, Liquidity, and Governance. This cluster highlights how microfinance and banking are intertwined in maintaining banking stability: small-scale financial services can expand access to credit while demanding careful governance to keep risk measurable (Laeven and Levine, 2009). In essence, credit risk control necessitates the careful selection of debtors and disciplined portfolio monitoring, as macroeconomic shocks and bank characteristics quickly impact asset quality (Louzis and Metaxas, 2012). At the same time, liquidity management, a cash buffer, a funding structure, and product price are key to dampening volatility in fund flows (Demirgüç-Kunt and Huizinga, 1999). All of this rests on governance that encourages incentives right between credit growth and prudence (Laeven and Levine, 2009).

3.3.3 Cluster 3 (Blue)

The theme of the blue cluster is From Financial Ratios to Machine Learning for Bankruptcy Prediction. This cluster traces the evolution from financial ratios as an early marker of financial distress to high-accuracy machine learning for bankruptcy prediction. Initially, single ratios and multivariate scores distinguish healthy and troubled companies (Beaver, 1966; Altman, 1968). Then, logit regression formulates the probability of default directly and is more calibrated (Ohlson, 1980). Time-based modeling approach enriches predictions with risk per period (Shumway, 2001). Entering the data era, feature selection and classifier design, ranging from discriminant analysis, neural networks, to support vector machines, generally increase the accuracy of unbalanced data (Kumar and Ravi, 2007; Kimura and Altman, 2017). As a result, the hybrid classification pipeline from ratios to prediction became the practical standard in modern credit scoring (Kumar and Ravi, 2007).

4. Conclusion

This study addresses the need to examine a map of science and practice regarding bankruptcy prediction and banking risk in a more structured manner. Using bibliometrics and science mapping, we trace the evolution of core ideas from ratio- and econometric models to computational and network approaches, and how those findings shifted in response to market and regulatory dynamics.

Key findings summarize four interrelated themes: (1) the surge in the use of ensemble/machine learning for credit risk and bankruptcy prediction; (2) the relationship between the sovereign–bank nexus, capital, and credit risk premiums; (3) the role of governance–competition–capital in shaping bank behavior and asset quality; and (4) the network-based systemic risk and tail-connectedness perspective that explains crisis transmission. Recurring subthemes include handling class imbalances, temporal/out-of-time validation, contextual feature selection, and the need for explainability in models to enable auditing and adoption.

The study's main contribution lies in three things: first, a concise taxonomy that brings together a stream of methods and thematic domains; second, cluster maps that connect theoretical foundations with the forefront of computational and systemic research; Third, an operational research agenda and implementation guide, ranging from evaluation standards to model governance, so that research results are better prepared for use by regulators, banks, and micro-institutions in accurate, transparent, and resilient decision-making across market regimes.

4.1 Limitations of the Study

This study has some limitations. First, the Publication Base is limited to Web of Science, English-language articles, and the period 1970–2025, with a download date of April 21, 2025, so publications outside of WoS (e.g., Scopus), non-articles (proceedings/books/working papers), and non-English may not be covered. Second, bibliometric results are sensitive to query strategies (keywords, synonyms, Boolean operators/wildcards), so it is still possible to miss relevant articles or less relevant articles. Third, the citation metric has a time lag, and 2025 is not yet complete because the data were downloaded in April; hence, interpreting the most recent trends should be cautious. Fourth, mapping using VOSviewer (bibliographic coupling and co-word) captures bibliographic/thematic proximity, but does not replace evaluating the methodological quality of each study or benchmarking the model's performance on the same dataset.

4.2 Implication of the Study

4.2.1 To the Subject of Concern

The roadmap for regulators/banks/micro-institutions is derived from the study's purpose of mapping the "research map" and identifying research gaps and agendas, enabling policies to link macro-micro indicators and predictive approaches in an integrated manner. The emphasis on the approach's contextualization of regulation, macro dynamics, and systemic linkages reinforces the rationale for buffer setting, alert thresholds, and proportionate surveillance responses. The capital, governance, and risk cluster reference links directly to policy consequences at the banking level.

4.2.2 To the Body of Knowledge

The taxonomy and positioning of scientific contributions rely on the bibliometric methodological aspects (bibliographic coupling, co-word analysis) and the reasons why they are objective, replicable, and scalable, serving as the basis for constructing the "intellectual foundation" and "research frontline" in an evidentiary manner, rather than merely relying on narrative. The emphasis in the previous literature on performance analysis justifies the need for science mapping to uncover knowledge architectures and methodological gaps specific to the financial sector.

4.2.3 To Researchers

This study provides a compass map for designing research that is both relevant and replicable. First, use the taxonomy of findings as a hypothesis framework, a bridge test between classical models (ratios, logits, hazards) and modern algorithms (ensembles, networks, SVMs) with temporal/out-of-time validation, so that findings can withstand regime change. Second, design open benchmarks: curated datasets, consistent label definitions, cost-sensitive metrics, and challenge splits (imbalanced, cold-start, crisis) to ensure fair cross-study comparisons. Third, prioritize interpretability and governance models, reporting key features, coefficient stability (SHAP), and predictive uncertainty. Fourth, incorporate the institutional context, including cross-border tests, bank/microfinance types, and economic cycles, to ensure the findings are visible. Finally, provide a replication package (including code, data dictionary, and model cards) so that the community can update the results as data or policies change.

Future research requires governance-conscious credit assessment, combining capital structure and competition intensity into a machine learning model that can be explained using Shapley's additive values to set credit limits and prices transparently. Default risk should be modeled as a time-to-event process that evolves under liquidity pressures. At the same time, the network connectivity is downsized to micro-features that enhance predictions beyond the sample. The path from individual scores to portfolio losses, and then to network-based resilience testing, allows for counterfactual policy evaluation.

References

- Abelián & Castellano, J. G., J. (2017). A comparative study on base classifiers in ensemble methods for credit scoring. *Expert Systems With Applications*, 73, 1–10.
- Acharya, D. I., & Schnabl, P., V. (2014). A Pyrrhic Victory? Bank Bailouts and Sovereign Credit Risk. *Journal of Finance*, 69(6), 2689–2739.
- Aggarwal & Jacques, K. T., R. (2001). The impact of FDICIA and prompt corrective action on bank capital and risk: Estimates using a simultaneous equations model. *Journal of Banking & Finance*, 25(6), 1139–1160.
- Ahmed Alshater, M. M., Ammari, A. El, & Hammami, H., S. (2022). Artificial intelligence and machine learning in finance: A bibliometric review. *Research in International Business and*

- Finance*, 61, 101646.
- Ala'Raj & Abbod, M. F., M. (2016). Classifiers consensus system approach for credit scoring. *Knowledge-Based Systems*, 104, 89–105.
- Allen & Gale, D., F. (2004). Competition and financial stability. *Journal of Money, Credit and Banking*, 36(3), 453–480.
- Altman Iwanicz-Drozdzowska, M., Laitinen, E. K., & Suvas, A., E. I. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-Score Model. *Journal of International Financial Management & Accounting*, 28(2), 131–171.
- Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589–609.
- Amini, C. R., & Minca, A., H. (2016). Resilience to contagion in financial networks. *Mathematical Finance*, 26(2), 329–365.
- Ando, T. (2022). Quantile connectedness: Modeling tail behavior in the topology of financial networks. *Management Science*, 68(4), 2401–2431.
- Anginer & Demirguc-Kunt, A., D. (2014). Has the global banking system become more fragile over time? *Journal of Financial Stability*, 13, 202–213.
- Aria & Cuccurullo, C., M. (2017). Bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, 11(4), 959–975.
- Bangia, D. F. X., Kronimus, A., Schagen, C., & Schuermann, T., A. (2002). Ratings migration and the business cycle, with application to credit portfolio stress testing. *Journal of Banking & Finance*, 26(2–3), 445–474.
- Bardoscia, B. S., Caccioli, F., & Caldarelli, G., M. (2017). Pathways towards instability in financial networks. *Nature Communications*, 8.
- Barry, L. L., & Tarazi, A., T. A. (2011). Ownership structure and risk in publicly held and privately owned banks. *Journal of Banking & Finance*, 35(5), 1327–1340.
- Beaver, W. H. (1966). Financial Ratios as Predictors of Failure. *Journal of Accounting Research*, 4.
- Berger & Mester, L. J., A. N. (1997). Inside the black box: What explains differences in the efficiencies of financial institutions? *Journal of Banking & Finance*, 21(7), 895–947.
- Betz, O. S., Peltonen, T. A., & Sarlin, P., F. (2014). Predicting distress in European banks. *Journal of Banking & Finance*, 45, 225–241.
- Beutel List, S., & von Schweinitz, G., J. (2019). Does machine learning help us predict banking crises? *Journal of Financial Stability*, 45, 100693.
- Carmona, C. F., & Momparler, A., P. (2019). Predicting failure in the US banking sector: An extreme gradient boosting approach. *International Review of Economics & Finance*, 61, 304–323.
- Chang, C. K. H., & Wu, G. J., Y. C. (2018). Application of eXtreme gradient boosting trees in the construction of credit risk assessment models for financial institutions. *Applied Soft Computing*, 73, 914–920.
- Chava, S. (2014). Environmental Externalities and Cost of Capital. *Management Science*, 60(9), 2223–2247.
- Chohan, L. T., Ramakrishnan, S., & Sheraz, M., M. A. (2025). Artificial Intelligence in Financial Risk Early Warning Systems: A Bibliometric and Thematic Analysis of Emerging Trends and Insights. *International Journal of Advanced Computer Science & Applications*, 16(1).
- Cihák & Hesse, H., M. (2010). Islamic Banks and Financial Stability: An Empirical Analysis. *Journal of Financial Services Research*, 38(2–3), 95–113.
- Claessens & Laeven, L., S. (2004). What drives bank competition? Some international evidence. *Journal of Money, Credit and Banking*, 36(3), 563–583.
- Demirgüç-Kunt & Huizinga, H., A. (1999). Determinants of commercial bank interest margins and profitability: Some international evidence. *The World Bank Economic Review*, 13(2), 379–408.
- Diamond & Rajan, R. G., D. W. (2000). A theory of bank capital. *Journal of Finance*, 55(6), 2431–

2465.

- Diebold & Yilmaz, K., F. X. (2015). *Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring*. Oxford University Press.
- Donthu, K. S., Mukherjee, D., Pandey, N., & Lim, W. M., N. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, 133, 285–296.
- Duan, S. J., & Wang, T., J. C. (2012). Multiperiod corporate default prediction-A forward intensity approach. *Journal of Econometrics*, 170(1), 191–209.
- Fakhar, M. K. F., Tabash, M. I., Ahmad, G., Akhter, J., & Al-Absy, M. S. M., S. (2023). Financial distress in the banking industry: A bibliometric synthesis and exploration. *Cogent Economics and Finance*, 11(2), 2253076.
- Flannery & Rangan, K. P., M. J. (2008). What caused the bank capital build-up of the 1990s? *Review of Finance*, 12(2), 391–430.
- Gennaioli, M. A., & Rossi, S., N. (2014). Sovereign default, domestic banks, and financial institutions. *Journal of Finance*, 69(2), 819–866.
- Glasserman & Young, B. P., P. (2015). How likely is contagion in financial networks? *Journal of Banking & Finance*, 50, 383–399.
- Gropp & Heider, F., R. (2010). The determinants of bank capital structure. *Review of Finance*, 14(4), 587–622.
- Huang, Z. H., & Zhu, H. B., X. (2009). A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance*, 33(11), 2036–2049.
- Huang, Z. H., & Zhu, H. B., X. (2012). Assessing the systemic risk of a heterogeneous portfolio of banks during the recent financial crisis. *Journal of Financial Stability*, 8(3), 193–205.
- Imbierowicz & Rauch, C., B. (2014). The relationship between liquidity risk and credit risk in banks. *Journal of Banking & Finance*, 40, 242–256.
- Iturriaga & Sanz, I. P., F. J. L. (2015). Bankruptcy visualization and prediction using neural networks: A study of US commercial banks. *Expert Systems With Applications*, 42(6), 2857–2869.
- Jorion & Zhang, G. Y., P. (2009). Credit contagion from counterparty risk. *Journal of Finance*, 64(5), 2053–2087.
- Khandani, K. A. J., & Lo, A. W., A. E. (2010). Consumer credit-risk models via machine-learning algorithms. *Journal of Banking & Finance*, 34(11), 2767–2787.
- Kim, W. T. H., & Manganelli, S., H. (2015). VAR for VaR: Measuring tail dependence using multivariate regression quantiles. *Journal of Econometrics*, 187(1), 169–188.
- Kimura, B. H., & Altman, E., F. (2017). Machine learning models and bankruptcy prediction. *Expert Systems with Applications*, 83, 405–417.
- Kumar, P. R., & Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques -- A review. *European Journal of Operational Research*, 180(1), 1–28.
- Kwan & Eisenbeis, R. A., S. (1997). Bank risk, capitalization, and operating efficiency. *Journal of Financial Services Research*, 12(2–3), 117–131.
- Laeven & Levine, R., L. (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics*, 93(2), 259–275.
- Li Ding, S., Chen, Y., Wang, H., & Yang, S. L., W. (2019). Transfer learning-based default prediction model for consumer credit in China. *Journal of Supercomputing*, 75(2), 862–884.
- Li, H. (2021). Embedded microprocessor wireless communication data collection aids in early warning of default risk for internet finance bank customers. *Journal of Sensors*, 2021.
- Liang, L. C. C., Tsai, C. F., & Shih, G. A., D. (2016). Financial ratios and corporate governance indicators in bankruptcy prediction: A comprehensive study. *European Journal of Operational Research*, 252(2), 561–572.
- Louzis, V. A. T., & Metaxas, V. L., D. P. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan

- portfolios. *Journal of Banking & Finance*, 36(4), 1012–1027.
- Ma Z. X., Zhou, Z. L., & Liu, Y. Y., L. (2018). A new aspect on P2P online lending default prediction using meta-level phone usage data in China. *Decision Support Systems*, 111, 60–71.
- Malhotra & Malhotra, D. K., R. (2003). Evaluating consumer loans using neural networks. *Omega-International Journal of Management Science*, 31(2), 83–96.
- Milevsky, M. A., & Promislow, S. D. (2001). Mortality derivatives and the option to annuitise. *Insurance Mathematics & Economics*, 29(Annual Conference of Insurance: Mathematics and Economics), 299–318.
- Mishkin, F. S. (2011). Over the Cliff: From the subprime to the global financial crisis. *Journal of Economic Perspectives*, 25(1), 49–70.
- Muñoz, M. H.-V. E., Santisteban-Espejo, A., & Cobo, M. J., J. A. (2020). Software tools for conducting bibliometric analysis in science: An up-to-date review. *El Profesional de La Información*, 29(1), e290103.
- Muravyev, A., Talavera, O., & Schäfer, D. (2009). Entrepreneurs' gender and financial constraints: Evidence from international data. *Journal of Comparative Economics*, 37(2), 270–286.
- Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 18(1), 109–131.
- Palvia, V. E., & Vähämaa, S., A. (2015). Are Female CEOs and Chairwomen More Conservative and Risk Averse? Evidence from the Banking Industry During the Financial Crisis. *Journal of Business Ethics*, 131(3), 577–594.
- Papouskova & Hajek, P., M. (2019). Two-stage consumer credit risk modelling using heterogeneous ensemble learning. *Decision Support Systems*, 118, 33–45.
- Perianes-Rodríguez W. L., & van Eck, N. J., A. (2016). Constructing bibliometric networks: A comparison between full and fractional counting. *Journal of Informetrics*, 10(4), 1178–1195.
- Petropoulos, S. V., Stavroulakis, E., & Vlachogiannakis, N. E., A. (2020). Predicting bank insolvencies using machine learning techniques. *International Journal of Forecasting*, 36(3), 1092–1113.
- Serrano-Cinca, G.-N. B., & López-Palacios, L., C. (2015). Determinants of Default in P2P Lending. *PLOS ONE*, 10(10).
- Shi & Li, X., Y. (2019). A bibliometric study on intelligent techniques of bankruptcy prediction for corporate firms. *Heliyon*, 5(12).
- Shumway, T. (2001). Forecasting Bankruptcy More Accurately: A Simple Hazard Model. *Journal of Business*, 74(1), 101–124.
- Umar, J. X. F., Mirza, N., & Naqvi, B., M. (2021). Carbon neutrality, bank lending, and credit risk: Evidence from the Eurozone. *Journal of Environmental Management*, 296.
- Veronesi & Zingales, L., P. (2010). Paulson's gift. *Journal of Financial Economics*, 97(3), 339–368.
- Wahlen, J. M. (1994). The nature of information in commercial bank loan loss disclosures. *Accounting Review*, 69(3), 455–478.
- Wheelock & Wilson, P. W., D. C. (2000). Why do banks disappear? The determinants of US bank failures and acquisitions. *Review of Economics And Statistics*, 82(1), 127–138.
- Xia L. C. Z., Da, B. W., & Xie, F. M., Y. F. (2018). A novel heterogeneous ensemble credit scoring model based on bstacking approach. *Expert Systems With Applications*, 93, 182–199.
- Zhao, O. J., & De Smedt, J., J. X. (2024). Survey, classification and critical analysis of the literature on corporate bankruptcy and financial distress prediction. *Machine Learning With Applications*, 15, 100527.
- Župič & Čater, T., I. (2015). Bibliometric Methods in Management and Organization. *Organizational Research Methods*, 18(3), 429–472.