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Predicting Firm Performance with Data Mining: A Systematic Review and Bibliometric Analysis

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Abstract

Firm performance is a critical driver of economic growth and investor confidence, impacting a wide range of stakeholders, including creditors, employees, managers, and governments. This study systematically examines the literature on predicting firms' performance using Data Mining (DM) techniques by combining a Systematic Literature Review (SLR) with bibliometric analysis. The review covers articles published between 2017 and 2024 across six major publishers. It identifies six key research themes: stock price prediction, customer-centric research, financial distress prediction, textual analysis, business cycle analysis, and ensemble boosting methods. Findings reveal that Saudi Arabia and the United Arab Emirates lead contributions within the Gulf Cooperation Council (GCC), while other GCC countries remain underrepresented, highlighting a regional research gap. The review also uncovers limited use of GCC datasets and underexplored dependent variables, such as profitability. A key limitation is reliance on the Web of Science database, which is partially mitigated by including 9 additional articles identified through website and citation searches. Overall, this study provides an updated, structured overview of DM applications in predicting firm performance, offers practical insights for researchers and business professionals, and identifies opportunities for future research in the GCC context.

Keywords: Bibliometric analysis, Data mining, Performance prediction, Systematic literature review.

1. Introduction

Firm performance is a critical factor that investors and stakeholders monitor closely, as it reflects both organizational success and long-term economic growth (Viera et al., 2019). It carries significant implications for creditors, employees, managers, and governments. Firm performance has been defined as the "economic outcomes resulting from the interaction of organizational characteristics, behavior, and environment" (Combs et al., 2005). Similarly, performance management is viewed as a philosophy underpinned by performance measurement (Lebas, 1995). In strategic management research, firm performance is commonly employed as a dependent variable. However, despite its frequent application, there is no universally accepted definition or standard measurement. Interpretations often vary across researchers' perspectives, leading to definitions that range from broad and abstract to highly specific and operationalized (Tudose et al., 2022).

The analysis and prediction of firm performance and financial situations are crucial for investors, creditors, and firm management, as they support business performance evaluation and the anticipation of potential failures. A firm's economic status reflects its financial health, often assessed through financial reports (Hantono, 2019). Firm performance has been modeled along four main dimensions: profitability, liquidity, growth, and stock market performance. The academic literature, however, demonstrates significant heterogeneity in the measurement of performance (dependent variables) and in the identification of its determinants (independent variables) as predictors (Hamann and Schiemann, 2021). The multidimensional frameworks theory suggests that specific non-financial indicators may act as leading indicators of financial outcomes (Wilcox and Bourne, 2003). Researchers have examined the relationships between causal variables arising from the environment, firm strategy, and organizational characteristics and performance measures (Hamann and Schiemann, 2021). Accordingly, different approaches have been developed to capture the drivers of financial performance (Hantono, 2015).

In recent years, predicting firms' performance using quantitative analysis techniques has gained increasing attention. The literature shows two main streams: studies applying technical analysis of stock prices and trading volumes (Kraus and Feuerriegel, 2017; Picaso et al., 2019; Weng et al., 2018; and Li et al., 2017) and studies employing fundamental indicators (Khalil et al., 2022; Ledhem, 2022; Saha et al., 2023; Son and Duong, 2024; Barboza, 2017; Wand and Wu, 2017; Halteh et al., 2018; Kim et al., 2018; Balasubramanian et al., 2019; Son et al., 2019; Smiti and Soui, 2020; Aljawaznedh et al., 2021; Jardin, 2021; Jabeur, 2021; Park et al., 2021; Arura and Saurabh, 2022; Garcia, 2022; Nguyen et al., 2023; Ainan et al., 2024; Mirza et al., 2020; Zhou et al., 2022; Al-Shammari et al., 2025; Chiadamrong and Wattanawarangkoon, 2022; Alanzi and Al-Shammari, 2025). The growing availability of Big Data has fueled this shift (Zhou et al., 2022), as has the advancement of Data Mining (DM) [Sharda et al., 2021].

This paper presents a Systematic Literature Review (SLR) of research on the prediction of firms' performance using DM techniques, guided by the approach outlined in Kitchenham and Charters (2007). To provide a broader context, a bibliometric analysis was first conducted on 457 articles published between 2017 and 2024 in the Web of Science (WoS) database, highlighting key themes, contributors, and trends that informed the SLR's focus. Building on this, 23 empirical studies were systematically analyzed, offering detailed insights into the prediction of firm performance using datasets, indicators, DM techniques, analytical tools, and evaluation metrics.

The paper is structured as follows: Section 2 reviews the evolution of research on predicting firm performance. Section 3 outlines the methodology and presents findings from both the bibliometric and systematic reviews. Section 4 concludes with key insights, limitations, and avenues for future research.

2. Theoretical Background

Firm performance has long been assessed through systematic financial analysis using accounting ratios and financial statements, with seminal studies establishing key indicators for predicting corporate failure (Wilcox and Bourne, 2003; Horrigan, 1968). Pioneering models include Beaver's univariate analysis (Beaver, 1966), Altman's Z-Score (Altman, 1968), Ohlson's logit (Ohlson, 1980), and Zmijewski's probit (Zmijewski, 1984). However, traditional statistical methods are limited by assumptions of linearity, independence, and fixed functional forms, thereby reducing their predictive power (Smiti and Soui, 2020).

To address these limitations, DM techniques have been increasingly applied. Early applications, such as neural networks for bankruptcy prediction (Martín-del-Brio and Carlos Serrano-Cinca, 1993), demonstrated their potential in handling complex financial data. The rise of Big Data, characterized by volume, velocity, variety, veracity, and value, has further underscored the need for advanced analytical methods capable of extracting meaningful patterns from large, heterogeneous datasets [35, Marshey, 1999; Laney, 2001; Wu et al., 2001).

DM integrates methods from statistics, machine learning, and data science to uncover trends for predictive analytics and business intelligence (Sarkar et al., 2018). In firm performance research, DM effectively processes financial and market data, with techniques such as Artificial Neural Networks (ANNs), Decision Trees (DTs), and Support Vector Machines (SVMs) widely used to model and predict outcomes (Horak et al., 2020).

3. Methodology

This study follows the SLR methodology of Kitchenham, B., and Charters (2007), aiming to identify, evaluate, and synthesize relevant research to answer the study's research questions. The review is structured into three chronological phases: planning, conducting, and reporting (Fig. 1). It systematically maps empirical studies on the use of DM for predicting firm performance, highlights research gaps, and provides a framework to guide future investigations. The review process adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021), ensuring transparent documentation of data collection and analysis at each stage (Fig. 2). To provide a broader context, a bibliometric analysis was first conducted on 457 articles retrieved from the WoS, addressing RQs 1–5 by examining publication trends, citation patterns, and author networks.

Figure 1. SLR phases (Kitchenham and Charters, 2007).

3.1. Planning

This study aims to explore the academic literature on firms' performance prediction using DM techniques. To achieve this, nine research questions (RQs) were formulated to investigate the intellectual structure and emerging trends in DM research within this domain.

RQs 1–5 are addressed through a bibliometric analysis of 457 articles to map the research landscape of DM techniques for firm performance prediction and to identify emerging trends and gaps guiding the empirical objectives of this paper. Two bibliometric techniques were employed: performance analysis, which evaluates productivity and impact, and science mapping, which examines the intellectual and bibliometric structure (Donthu et al., 2021). In this study, performance analysis addresses RQs 1 and 2, while science mapping addresses RQs 3–5:

- RQ1: What is the level of research? This question aims to identify the publication (productivity) trend in firms' performance prediction research using DM techniques to establish the time frame of the SLR by identifying periods of significant research activity and understanding how interest in this area has evolved.
- RQ2: What are the top-cited articles? This question aims to identify the most impactful (most cited) articles in the field of firms' performance prediction research, using DM techniques to identify foundational and highly influential research contributions. This question also serves as a benchmark for understanding the development and impact of DM techniques in the field.
- RQ3: What are the thematic clusters? This question aims to identify thematic clusters in the literature on firms' performance prediction using DM techniques, thereby aiding classification and mapping of the main research themes, providing insights into key areas of focus, and enabling a clearer understanding of various aspects of firm performance prediction.
- RQ4: What are the research trends? This question aims to identify trends in the literature on predicting firms' performance using DM techniques, thereby revealing shifts in research focus, emerging topics, and

technological advancements that are critical for understanding the field's future direction and identifying areas that require further exploration.

- RQ5: What are the countries of the collaborating authors? This question aims to identify the countries represented in the author affiliations involved in research on DM techniques for predicting firms' performance. This question helps map the global distribution of scholarly contributions and highlight active research areas. Such analysis also reveals patterns of international collaboration and knowledge exchange in the field.

The remaining RQs focus on more specific aspects of the literature:

- RQ6: Which datasets were primarily deployed in the literature? This question aims to determine the geographical distribution of datasets used in existing studies and identify gaps in the data sources employed for firm performance prediction.
- RQ7: Which variables were employed in the literature? Identifying the variables commonly used in predicting firm performance.
- RQ8: Which DM techniques and analytic tools were utilized? This question aims to explore the DM techniques and analytic tools used in existing research, evaluate their effectiveness and popularity, and identify research gaps in underutilized DM techniques or tools.
- RQ9: Which metrics are most commonly used? Exploring preprocessing methods in the literature to enhance the accuracy of predictive models.

To address RQs 6–9, relevant journal articles were selected based on predefined inclusion and exclusion criteria (Table 1) to ensure alignment with the study's objectives. Review articles (Li and Bastos, 2020; Lu et al., 2020) focused on technical analysis, such as stock prices or trading volumes, and purely statistical studies were excluded. Only empirical studies applying DM techniques to firm-level financial performance using fundamental indicators were included. A quality assessment (Table 2) further ensured methodological rigor, retaining studies that clearly stated objectives, reported financial variables and DM methods transparently, and provided well-defined evaluation metrics and results. This process ensured that the final analysis included only robust, relevant studies.

Table 1. Inclusion/ Exclusion Criteria.

Inclusion criteria	Exclusion criteria
Studies focused on fundamental analysis (Balance sheet and income statement variables).	Studies focused on technical analysis (close price, volume, etc.).
Studies used DM techniques.	Studies used statistical methods.
Studies used economic indicators.	Studies used sentiment analysis and text analysis.
Studies focused on financial performance.	Studies focused on daily/weekly stock returns.

Table 2. Quality Criteria.

Description
Are the objectives of the article clearly stated?
Is the methodology adequately presented?
Are financial variables clearly presented?
Are the data mining techniques clearly explained?
Are the evaluation metrics clearly defined, explained, and presented?
Are the results of the research study clearly explained?

3.2. Conducting

The second stage focuses on identifying and selecting publications for the systematic review using predefined inclusion and exclusion criteria. The study selection process followed the PRISMA framework proposed by Page et al. (2021) and is illustrated in Fig. 2. The initial bibliometric search, conducted on April 14, 2024, using the WoS database, yielded 4,025 records. At the time, access was limited to WoS, which was chosen for its strict indexing criteria and broad coverage of peer-reviewed journals. The search string was:

(Firm OR Corporat OR Compan* OR Enterprise OR Business) AND (Financial OR Performance OR Efficiency OR Profit* OR growth) AND (Predict OR Forecast) AND ("Artificial Intelligence" OR "Data Mining" OR "Machine Learning" OR "Deep Learning" OR "Ensemble").*

Applying the practical inclusion criteria outlined in the PRISMA identification stage (Fig. 2), which considered language, document type, publisher, subject area, and time span, 3,568 records were excluded, leaving 457 for screening.

Screening was conducted in two stages. First, titles and abstracts were reviewed for relevance using the inclusion and exclusion criteria (Table 1). Second, full-text screening was conducted according to the predefined quality and eligibility criteria (Table 2), yielding 14 eligible studies. To mitigate the limitation of using a single database, manual reference screening and citation tracking were applied, identifying an additional nine relevant studies. The final dataset comprised 23 studies for in-depth analysis and data extraction.

A descriptive (narrative) synthesis was used to summarize and interpret the findings. Although the search was limited to WoS due to access constraints, complementary search methods helped reduce publication bias and enhance the review's robustness. Nevertheless, studies indexed exclusively in other databases, such as Scopus, may not have been captured, which remains a limitation of this review.

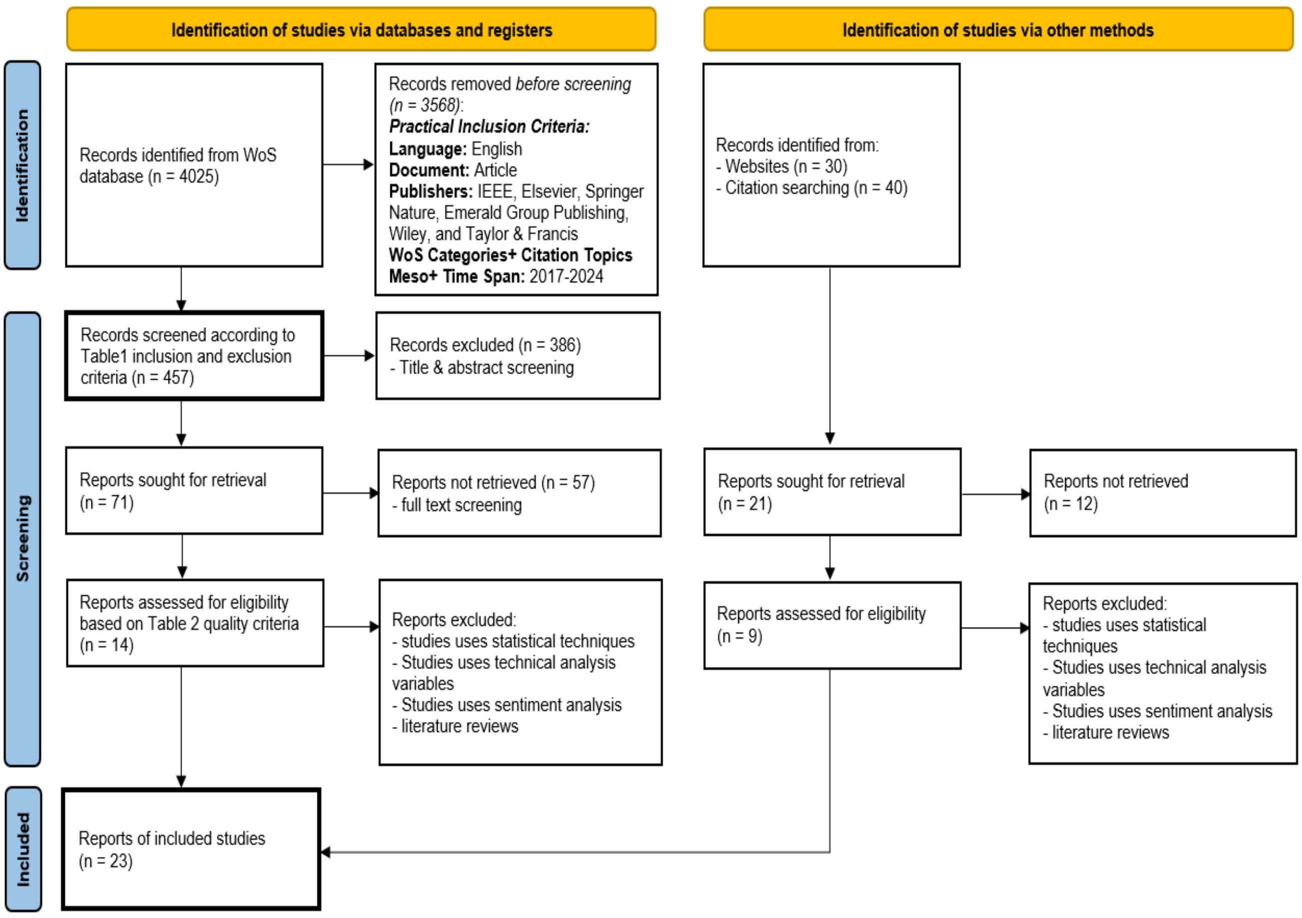

Figure 2. The Study Review Process, according to the PRISMA guidelines.

3.3. Reporting the Bibliometric Analysis

Two recognized bibliometric tools, RStudio 2023.12.1+402 "Ocean Storm" Bibliometrix Package (Aria and Cuccurullo, 2017) and VOSviewer 1.6.20, were used to analyze the bibliometric data from 457 articles retrieved from WoS.

3.3.1. Evolution of Firm Performance Prediction Using DM

Figure 3 presents the evolution of annual article production in the field of firms' performance prediction using DM techniques. Early articles used the Artificial Intelligence (AI) knowledge base to predict financial firms' performance conducted by Abramson and Finizza in 1991 to predict oil prices using belief networks (Abramson and Finizza, 1991), followed by Martin-del-Brio and Serrano-Cinca (1993) who applied Self-organizing Neural Networks to analyze the financial state of Spanish companies and make an assessment of bankruptcy risk by clustering the bankrupt and solvent regions together.

Research on DM techniques for predicting firms' performance began to attract more attention in 2017, with 28 published articles, and gradually increased to 103 and 112 in 2022 and 2023, respectively. In 2024, 31 articles were produced, increasing the production rate. Since this research area began to gain significant attention in 2017, the time frame for the SLR studies has been defined accordingly, covering the period from 2017 to 2024.

It is essential to recognize that the evolution of ratio analysis in assessing firm performance has followed distinct trajectories, driven by the purposes of creditors and managers. Credit analysis primarily evaluates an entity's ability to meet its financial obligations, with a focus on bankruptcy prediction models. In contrast, managerial analysis focuses on profitability, using performance prediction models to estimate potential earnings. Although both approaches employ similar components of financial ratios, their applications and objectives differ significantly. Credit analysis is crucial in informing decision-making applications (Zhao et al., 2024).

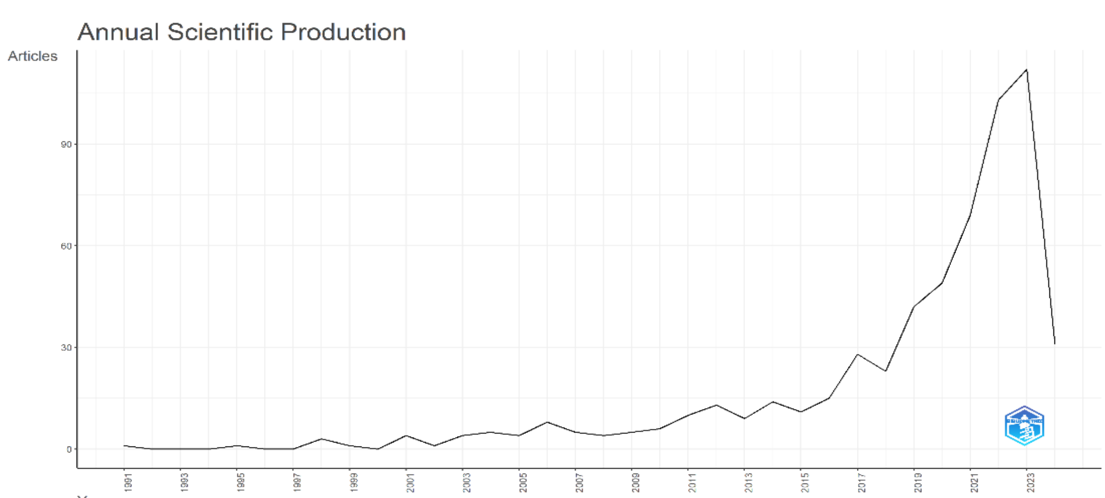

Figure 3. Annual Scientific Production of DM research in the field of firm performance prediction plotted using R-bibliometrix (Aria et al., 2017).

3.3.2. Most Cited Articles in Literature

The top five globally cited publications in DM research on financial performance prediction are presented in Table 3. Barboza et al. (2017) published the most impactful article, with 342 citations in WoS, followed by Lu et al. (2020) with 228 citations. Barboza et al. (2017) significantly improved bankruptcy prediction accuracy using single and ensemble DM techniques for American and Canadian companies from 1985 to 2013, whereas Lu et al. (2020) conducted a systematic review of the business literature to assess the impact of service robots on customers and employees. Further analysis of the top-cited publications reveals that studies focusing on DM applications in fundamental and technical approaches to performance prediction as well as in customer-centric research (Steinhoff, 2019; Wamba-Taguimdje, 2020) are particularly influential and impactful in advancing the field.

Table 3. Top 5 cited Publications in Performance using DM Techniques.

Study	Publication Year	Study Title	Total Citations
[Barboza et al.]	2017	Machine Learning (ML) models and bankruptcy prediction	342
[Lu et al.]	2020	Service robots, customers, and service employees: what can we learn from academic literature, and where are the gaps?	228
[Kraus]	2017	Decision support from financial disclosures with deep neural networks and transfer learning	175
[Stienhoff et al.]	2019	Online relationship marketing	173
[Wamba et al.]	2020	Influence of AI on firm performance: The business value of AI-based transformation projects	164

3.3.3. Thematic Clusters of Literature

This review further examines knowledge related to DM research in the context of firms' performance prediction using bibliographic coupling. Bibliographic coupling relies on citing publications to explain the extant knowledge in the field (Kessler, 1968). It describes the connection between two articles that cite the same third work in their reference lists. When two articles have more references in common, their bibliographic coupling becomes stronger. This process helps to group thematically similar documents into clusters. Using VOSviewer, 457 articles published between 2017 and 2024 were grouped into six clusters in the field of DM research on firm performance prediction. Fig. 4 presents the bibliographic coupling analysis of the documents with the full-counting method. Below is a summary of the clusters.

The first cluster, shown in red, stock price prediction, highlights influential studies that leverage technical indicators within prediction models. Notable contributions include Kraus and Feuerriegel (2017) with 175 citations, Picaso et al. (2019) with 138, and Weng et al. (2018) with 114. This theme emphasizes the critical role of DM techniques in predicting stock prices, illustrating the significance of market-driven predictive models. Specifically, [8] explored the use of deep neural networks for financial decision support, aiming to predict stock price movements based on insights from financial disclosures. The prominence of this cluster suggests that predictive modeling for market behavior remains a core application of DM, reflecting the continued demand for tools that can support real-time investment decisions.

The second cluster, in green, customer-centric research, comprises 87 articles centered on the application of DM in customer service, collectively cited 1,516 times in WoS. The most highly cited articles in this cluster include Lu et al. (2020) with 228 citations, Steinhoff et al. (2019) with 173 citations, and Wamba-Taguimdje et al. (2020) with 164 citations. Lu et al. (2020) conducted a comprehensive literature review in 2017, examining the deployment of service robots in business contexts, encompassing publications from the Financial Times top 50 journals and a broad range of additional journals. Their analysis delved into the impact of service robots on customers and employees, providing critical insights into this evolving field. This cluster indicates a growing shift toward integrating DM with customer experience strategies, highlighting the strategic importance of technology in enhancing service quality and operational efficiency.

The third cluster, in blue, bankruptcy and financial distress prediction, contains 77 articles cited 1,619 times based on WoS data. The leading contributions in this area are Barboza et al. (2017) with 342 citations, Mai et al. (2019) with 143 citations, and Li et al. (2017) with 66 citations. Barboza et al. (2017) introduced novel predictive variables, including operating margin, changes in return-on-equity and price-to-book ratios, and growth indicators for assets, sales, and employee numbers, to forecast bankruptcy 1 year before its occurrence. Their findings demonstrated that ensemble methods, including bagging, boosting, and random forests, significantly outperformed other prediction techniques, providing a more reliable approach to forecasting financial distress. The continued dominance of bankruptcy prediction research underscores the field's focus on risk management. At the same time, the shift toward ensemble methods reflects the need for higher accuracy and robustness in forecasting financial distress.

The fourth cluster, in yellow, DM in business-cycle analysis, comprises 65 articles that were cited 1,094 times in WoS. The most cited articles in this category are Amin et al. (2017) with 103 citations, Bussmann et al. (2021) with 100 citations, and Hoornaert et al. (2017) with 89 citations. These studies applied ML techniques to address and analyze business challenges, including customer churn prediction, credit risk assessment, and the identification of innovative product concepts, showcasing the versatility of ML in optimizing business operations and informing strategic decision-making. This cluster reflects DM's versatility in analyzing complex business processes and indicates an increasing integration of predictive analytics into strategic decision-making across industries.

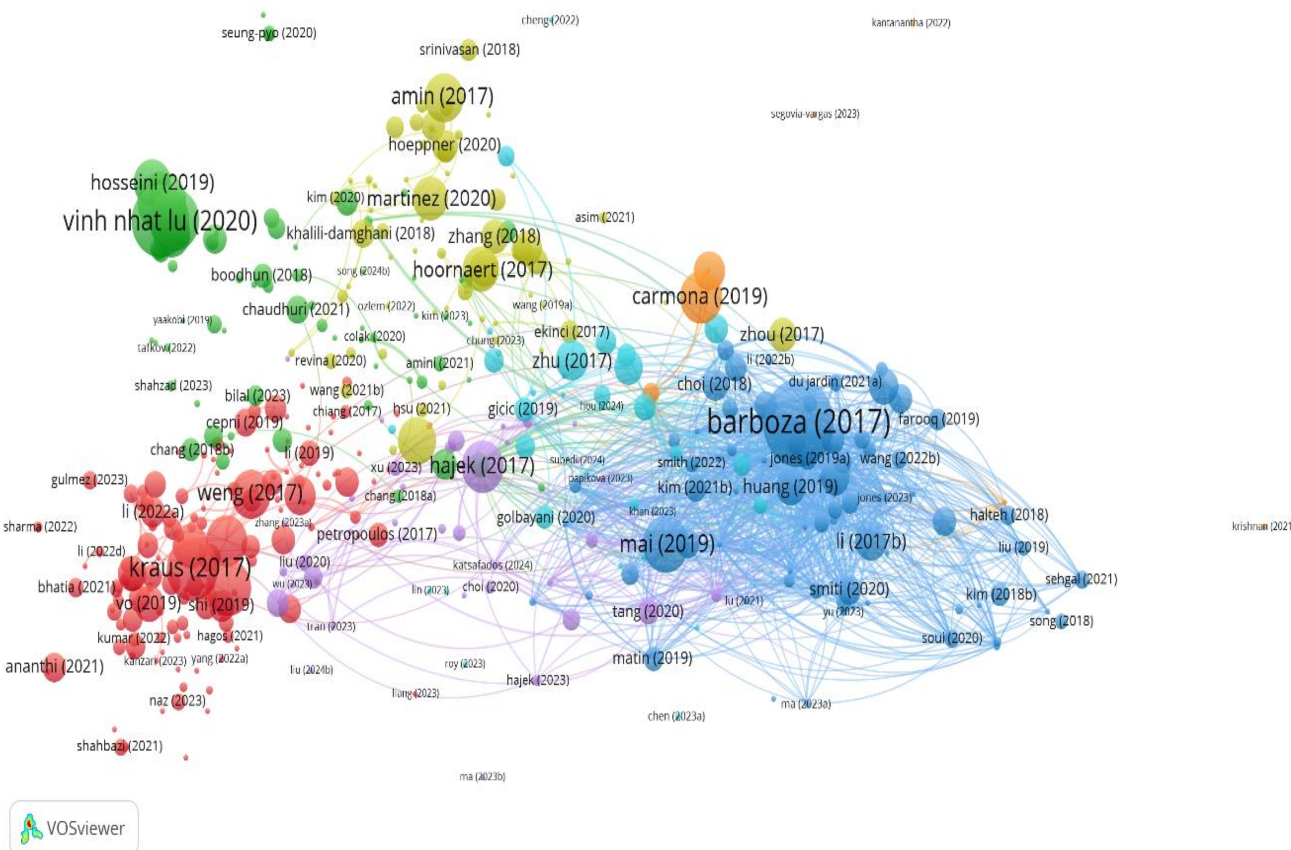

Figure 3. Bibliographic coupling network.

The fifth cluster, in purple, textual analysis, comprises 38 articles on DM applications in textual analysis, totaling 374 WoS citations. The leading articles are Hajek, P., and Henriques (2017) with 124 citations, Hajek (2018) with 36 citations, and Tang et al. (2020) with 31 citations. These studies employed textual analysis to address issues such as fraud detection, stock return prediction, and early identification of firm distress. This theme highlights the significance of analyzing unstructured textual data to extract actionable financial and business insights. The emergence of textual analysis highlights the growing importance of unstructured data, signaling that integrating textual insights with traditional financial metrics can provide a more comprehensive view of firm performance.

The sixth cluster, in orange, the ensemble DM approach in credit risk and firms' default predictions, includes 37 articles cited a total of 682 times, based on WoS data. The top contributions in this field are Carmona et al. (2019) with 122 citations, Zhou et al. (2017) with 72, and Climent et al. (2019) with 66 citations. These studies focus on applying ensemble ML techniques, such as bagging and boosting, to enhance credit risk evaluation accuracy and predict firm defaults, emphasizing the effectiveness of ensemble methods in managing financial risk and improving predictive reliability. The prominence of this cluster underscores the field's preference for ensemble methods in financial prediction, reflecting the need for highly reliable, generalizable models to support risk management and regulatory compliance.

3.3.4. Literature Trends

Figure 5 shows the keyword evolution map generated using overlay visualization in VOSviewer, illustrating the progression of research themes in DM for firm performance prediction from 2017 to 2024. This map was created through a co-occurrence analysis of all terms using the "All Keywords" approach, which combines author keywords with KeyWords Plus. The analysis aims to uncover the thematic evolution of topics related to predicting financial performance, as reflected in at least five articles in the review. A complete counting method was applied in VOSviewer, with the minimum number of occurrences for a term set to 5 out of 2,325 terms; 162 met this threshold. The closeness between terms reflects the strength of their relationship, while co-occurrence in documents establishes relatedness. Node size indicates the frequency of occurrence. Among the most prominent terms in this field are "machine learning," "model," "bankruptcy prediction," "prediction," "performance," "classification," "deep learning," "models," "neural networks," and "impact."

The research trend of DM in firms' performance prediction shows that, before 2021, studies primarily focused on "bankruptcy prediction," "financial distress," "churn prediction," "business failure prediction," and "credit risk," using methods such as "classification," "support vector machine," "neural networks," and traditional "data mining" techniques. Around 2021, the emphasis shifted toward "financial ratios," "firms," "information," and "determinants," accompanied by methods including "machine learning," "deep learning," "models," "forecasting," "regression," "neural networks," "ensemble learning," and "XGBoost." By 2022, research increasingly concentrated on "behavior," "finance," "impact," "corporate governance," and "firm performance."

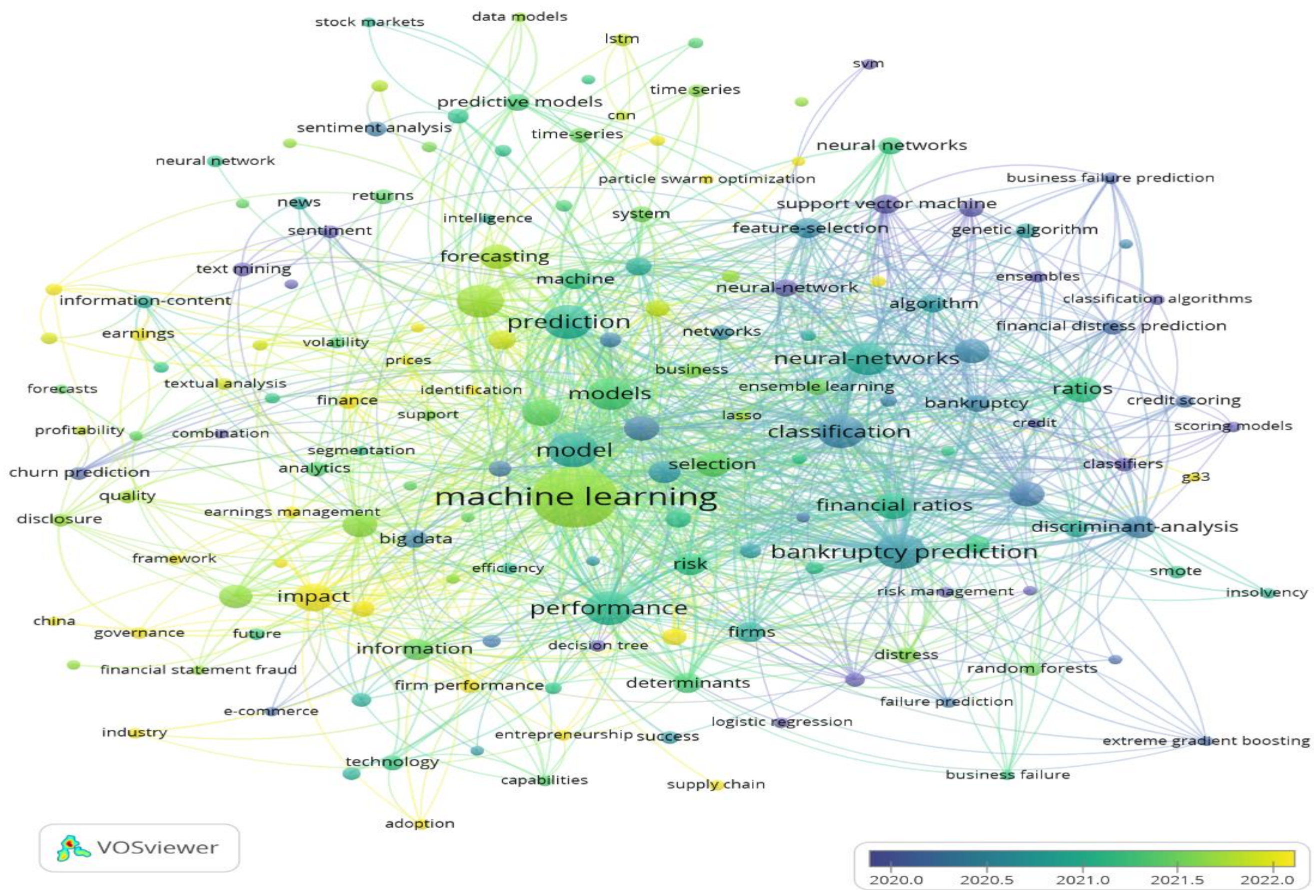

Figure 5. Keyword evolution of DM research in firms' performance prediction.

This evolution indicates a clear shift from traditional bankruptcy and distress prediction toward broader financial performance and profitability modeling. It reflects a growing preference for regression-based and ensemble approaches over single-model classification techniques, highlighting the field's emphasis on developing more accurate, robust, and generalizable predictive frameworks. The increasing adoption of ensemble methods underscores their effectiveness in improving prediction reliability, managing complex financial data, and supporting strategic decision-making for firms. Overall, the evolution of keywords demonstrates that DM research on financial performance is maturing, moving from simple predictive classification to integrated, high-performing models that address multiple dimensions of firm performance.

3.3.5. Countries of the Collaborating Authors

The co-authorship network reflects collaboration among authors, organizations, and countries, fostering novel scientific output and higher-quality research papers. Fig. 6 and Table 4 present the co-authorship network of countries affiliated with authors who published at least 5 papers between 2017 and 2024. In setting the threshold, the minimum number of citations per country was set to 0, resulting in 36 of 70 countries being included. In the network, node size represents the number of published articles, while links indicate co-authorship connections between countries.

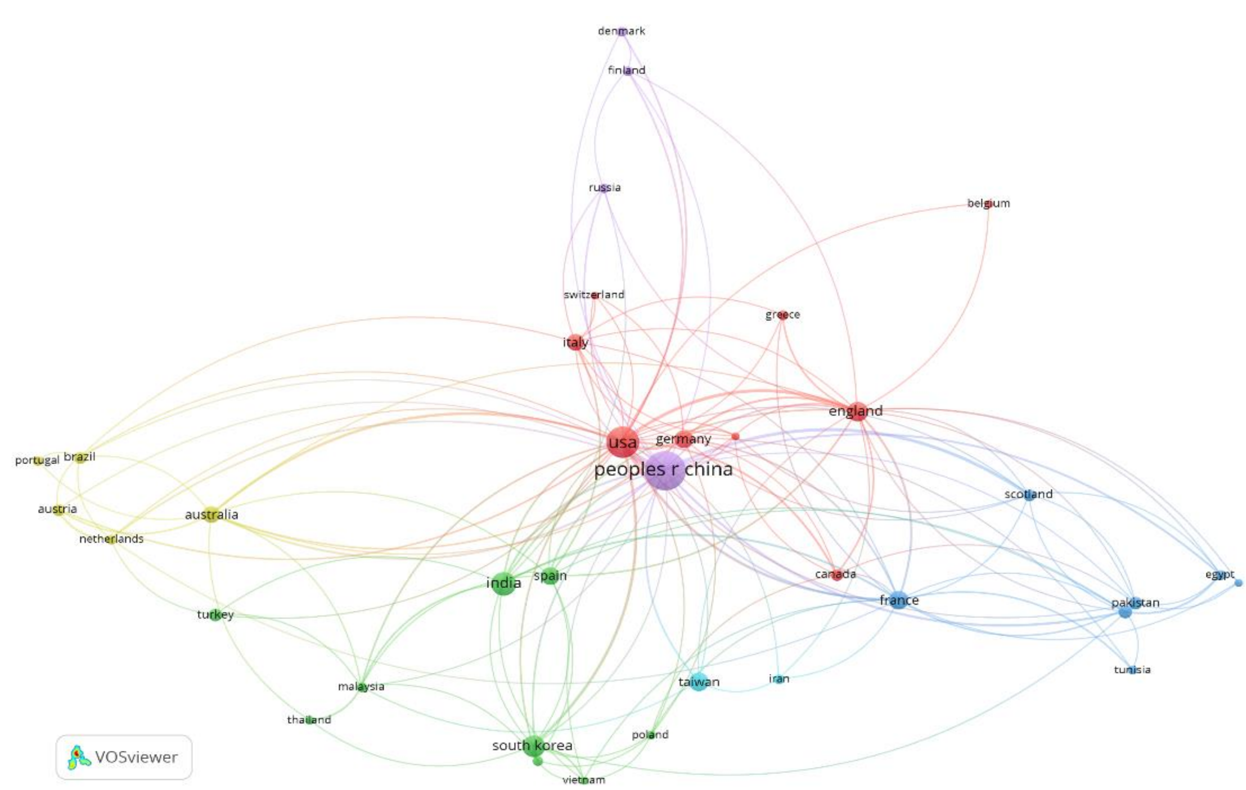

Figure 4. Co-Authorship Network of Authors' Affiliated Countries.

Five main clusters of country collaborations emerge. The strongest linkages are observed between the USA, England, Germany, Italy, Canada, Singapore, Greece, Switzerland, and Belgium, reflecting collaboration among leading research economies with established expertise in DM and financial analysis. The second cluster, France, Saudi Arabia, Scotland, Pakistan, Egypt, Tunisia, and the UAE, suggests regional partnerships influenced by geographic proximity, shared language, or similar research priorities in emerging markets. The third cluster, India, South Korea, Spain, Malaysia, Japan, Poland, Vietnam, Thailand, and Turkey, demonstrates cross-continental collaborations driven by growing academic and industrial interest in applying DM to firm performance in both developing and developed economies. The fourth cluster, China, Finland, Russia, and Denmark, represents collaborations among countries with strong technological capabilities and an emphasis on AI and ML research. The fifth cluster, Australia, Austria, the Netherlands, Brazil, and Portugal, shows transnational partnerships facilitated by international research funding programs and thematic alignment in business and finance studies. Additional linkages exist among other countries, such as Taiwan and Iran, reflecting niche collaborations and emerging contributions from less-represented regions.

Table 4. Co-authorship between countries

Cluster		Country	Total link strength	Articles	Citations
1 (Red)	1	USA	64	73	1987
	2	England	36	29	619
	3	Germany	20	24	947
	4	Italy	12	21	484
	5	Canada	10	11	106
	6	Singapore	9	5	419
	7	Greece	5	8	99
	8	Switzerland	4	5	196
	9	Belgium	2	5	159
		Total	162	181	5016
2 (Blue)	1	France	29	25	476
	2	Saudi Arabia	17	12	305
	3	Scotland	15	10	206
	4	Pakistan	14	12	222
	5	Egypt	10	7	45
	6	Tunisia	4	6	101
	7	UAE	4	5	78
		Total	93	77	1433
3 (Green)	1	India	18	40	370
	2	South Korea	14	34	395
	3	Spain	13	24	456
	4	Malaysia	12	7	55
	5	Japan	9	8	190
	6	Poland	7	6	98
	7	Vietnam	7	5	56
	8	Thailand	4	6	29
	9	Turkey	4	12	141
		Total	88	142	1790
4 (Yellow)	1	Australia	19	20	605
	2	Austria	9	10	126
	3	Netherlands	9	8	125
	4	Brazil	7	11	394
	5	Portugal	2	7	190
		Total	46	56	1440
5 (Purple)	1	China	53	108	1289
	2	Finland	6	8	26
	3	Russia	6	7	90
	4	Denmark	4	7	81
		Total	69	130	1486
6 (Sky Blue)	1	Taiwan	6	26	366
	2	Iran	4	7	58
		Total	10	33	424

Overall, these patterns suggest that collaborations are influenced not only by geographic proximity and shared language but also by complementary expertise, access to research resources, and participation in international networks. Countries with strong prior research output in data mining and financial performance tend to form hubs, attracting collaborations that enhance both scientific quality and global impact.

3.4. Reporting the Analyzed Articles (Synthesis)

The final stage of the SLR synthesizes the findings of 23 targeted empirical studies, as summarized in Table 5, which employ DM techniques to predict firm performance. These findings are elaborated upon in the subsequent sections.

Table 5. Studies of firm performance prediction using DM techniques*

DM Task	Study	Independent Variable(s)	Dependent Variable(s)	DM Techniques
Regression	[Assous]	17 financial ratios	Efficiency ratio	SVM, CHAID, LR, ANN
	[Khalil et al.]	21 financial ratios	solvency ratio	SVR, RF, ensemble models (bagging and boosting)
	[Ledhem]	3 financial ratios and variables	ROA	LASSO regression, RF, ANN, kNN
	[Saha et al.]	14 variables of firm size measures	WPI and PBDITA	RT, Bootstrap Forests, Boosted Trees, BART
	[Son and Duong]	14 financial variables	ROA	RF, GBR, XGBoost, KNN, SVR, Lasso, RR, MLP
	[Barboza et al.]	11 financial indicators	Failed, non-failed	Bagging, Boosting, RF, SVM, ANN, LoR, MDA
	[Wang and Wu]	24 financial indicators	Failed, non-failed	FSOM, FSVM, ANN
	[Halteh et al.]	18 financial ratios and variables	Success, Failure	DT-CART, SGB, RF
	[Kim et al.]	53 financial ratios	Failed, non-failed	Logit, MDA, ANN, data depth (DD-SVM)
	[Balasubramanian et al.]	9 financial and 4 non-financial variables	sick, healthy	LoR
	[Son et al.]	108 financial ratios + 22 variables represent firm size	Normal, bankrupt	LoR, RF, Gradient Boosting (XGBoost, LightGBM), ANN
	[Li et al.]	51 Financial variables	Credit Rating (7 classes)	ANN, SVM, RF, CHAID, CART
	[Smiti and Sui]	64 financial ratios	Bankrupt, non-bankrupt	A novel approach called BSM-SAES with kNN, DT, SVM, ANN, and C5.0
	[Aljawazned et al.]	95 attributes	Bankrupt, Solvent	DBN, LSTM, and MLP, RF, SVM, kNN, AdaBoost, XGBoost
	[Jardin et al.]	30 financial ratios	Failed, non-failed	LoR, DT-CART, k-NN, BBNNs, SVM, ELM, bagging, AdaBoost, ensemble SONNs, RF, and XGBoost
	[Jabeur et al.]	18 financial ratios	Bankrupt, non-bankrupt	CatBoost, XGBoost, GBM, SVM, RF, NN, DNN, DA, LoR
	[Park et al.]	111 financial ratios	Bankrupt, non-bankrupt	XGB, LightGBM, RF
	[Arora and Saurabh]	18 firm-level financial ratios	Financial distress, not distress	LoR, lasso regression, DT, RF bagging, XGBoost, SVM
	[Gracia]	6 financial ratios and market variables	Bankrupt, non-bankrupt	LoR, Boosted LoR, LDA, PLS-DA, NB, kNN, NN, SVM, XGBoost, RF, RF ensemble
	[Zhou et al.]	36 financial indicators	Performance rating (5 classes)	SOM-CNN, LSTM-CNN, Gaussian, Linear, Quadratic SVM
	[Chiadamrong]	6 financial ratios	ROA+ROE+ROS (3 classes)	MLR, LoR
	[Nguyen et al.]	24 financial ratios	Failed, non-failed	LR, DA, SVM, ANN, RF, LightGBM, XGBoost, NGBoost
	[Ainan et al.]	64 financial attributes	Bankrupt, successful	RF, XGBoost, SVM, hybrid XGBoost +ANN

Note: * ROA: Return on Assets, ROE: Return on Equity, ROS: Return on Sales, WPI: Wholesale Price Index, PBDITA: Profits before depreciation, interest, tax, and amortization. ANN: Neural Networks, SVM: Support Vector Machine, k-NN: k-Nearest Neighbor, MDA: Multivariate Discriminant Analysis, LoR: Logistic Regression, LR: Linear Regression, CLR: Cost-sensitive variation of Logistic Regression, AD: AdaBoost, AC: Ada Cost, SVM: Support Vector Machines, CSVM: Cost-sensitive Support Vector Machines, RF: Random Forest, XGBoost: Extreme Gradient Boosting, RT: Regression Tree, DBN: Deep Belief Network, BART: Bayesian Additive Regression Trees, CART: Classification and Regression Trees, CHAID: Chi-squared Automatic Interaction Detection, C4.5: classification tree, CatBoost: Categorical Boosting, XGBoost: Extreme Gradient Boosting, GBM: Gradient Boosting Machine, RF: Random Forest, DNN: Deep neural networks, DA: Discriminant Analysis, LDA: Linear discriminant analysis, BSM: Borderline Synthetic Minority oversampling technique, SAE: Stacked Auto Encoder, MLP: Multi-layer Perceptron, LSTM: Long Short-term Memory, CNN: Convolutional Neural Networks, CITs: Conditional Inference Trees, CRT: Cubist Regression Tree, MLR: Multiple Linear Regression, FSVM: Fuzzy Support Vector Machine, KFSOM: Kernel-based Fuzzy Self-Organizing Map, GBR: Gradient Boosting Regressor, SVR: Support Vector Regression, RR: Ridge Regression, SMOTE: Synthetic Minority Over-sampling Technique, ENN: Edited Nearest Neighbors, NGBoost: Natural Gradient Boosting. RMSE: Root Mean Square Error, MSE: Mean Squared Error, MAE: Mean Absolute Error, MAPE: Mean Absolute Percentage Error, MBE: Mean Bias Error, RAE: Relative Absolute Error, RSE: Relative Squared Error, AUC: Area under the ROC (Receiver Operating Characteristic) curve.

3.4.1. Geographical Datasets in Literature

Table 6 highlights the geographical distribution of datasets used in firm performance prediction studies, as reported in 23 studies. It reveals that datasets from countries such as France, India, and Korea are most used, reflecting their strong presence in this field of DM research. These countries have contributed multiple studies that indicate greater data availability or a greater focus on firm performance prediction in these regions. For example, India is represented by three studies, and Korea and the USA each have several papers utilizing their respective datasets.

On the other hand, countries such as Canada, Egypt, Kuwait, and Poland have only one or two studies each, indicating less frequent use of datasets from these regions. In addition, some articles focus exclusively on the banking sector, exploring and comparing banks in the GCC region and highlighting niche research areas within specific financial sectors (Assous, 2022).

It is important to note that the studies were selected based on inclusion criteria that focus on the use of fundamental analysis variables to measure firm performance. Fundamental analysis provides a more reliable prediction than technical analysis, as it evaluates a firm's financial health over time by analyzing its financial statements, such as income statements, balance sheets, and cash flows, rather than relying on daily stock price movements. This approach offers deeper insights into a company's performance, making it a preferred method for predicting firm performance (Barak et al., 2017).

The table also illustrates various countries, including emerging markets such as Vietnam, Thailand, and Indonesia, where firm performance prediction models are applied. These variations in dataset origin contribute to a broader understanding of how firm performance prediction models operate across diverse financial environments and regulatory frameworks.

3.4.2. Associated Variables in Prediction Models

Table 4 shows that the dependent variables used in the literature to predict firm performance using DM are categorized into two main types: classification and regression models, based on the prediction model task. Furthermore, the independent variables are categorized into fundamental, macroeconomic, and non-financial factors. This categorization highlights the multidimensional nature of firm performance prediction, where both internal financial conditions and external economic environments are jointly considered.

Table 6. Studies Based on the Dataset Region.

Studies	Country-related dataset
[Son and Duong, 2024]	Vietnam
[Barboza et al., 2017; Garcia, 2022]	USA
[Chiadamrong and Wattanawarangkoon, 2023]	Thailand
[Aljawazneh, 2021]	Spain, Taiwan, Poland
[Assous, 2022]	Saudi Banks
[Smiti and Soui, 2020, Ainan et al., 2024]	Poland
[Kim et al., 2023; Son et al., 2019; Park et al., 2021]	Korea
[Halthe et al., 2018]	Islamic Banks
[Ledhem, 2022]	Indonesia
[Saha et al., 2023; Balasubramanian et al.; Arora and Saurabh, 2022]	India
[Li et al., 2020]	GCC Banks
[Jardin, 2021; Jabeur, 2021; Nguyen, 2023]	France
[Khalil et al., 2022]	Egypt
[Wang and Wu, 2017; Zhou et al., 2022]	China
[Barboza, 2017]	Canada

Furthermore, regarding the prediction tasks, the literature encompasses various categories based on the type of dependent variable. Regression analysis is commonly employed to predict financial metrics such as Solvency Ratio, Return on Assets, Wholesale Price Index, and Profit Before Depreciation, Interest, Taxes, and Amortization. Binary classification has been widely used to distinguish between failed and non-failed firms or between bankrupt and non-bankrupt firms. This dominance of classification models reflects the strong practical importance of failure prediction for risk management, credit assessment, and early warning systems. Multi-class classification, though less common, has been applied to predict complex outcomes such as credit ratings, performance ratings, and rates of return across multiple classes. The limited use of multi-class models suggests that predicting nuanced performance levels remains more challenging and less explored than predicting binary outcomes.

3.4.3. Utilization of DM Techniques and Analytic Tools

Ensemble methods, particularly bagging and boosting, were the most frequently employed DM techniques, reflecting their robustness in handling complex financial datasets and their ability to improve predictive accuracy through model aggregation. Individual methods such as ANN, SVM, LR, and DT were also widely used, demonstrating the continued relevance of traditional ML approaches. NB was the least utilized technique, likely because it performs less well at capturing nonlinear relationships and interactions in financial data. The most used analytic tools were R and Python packages, which provide versatile, accessible platforms for efficiently implementing these advanced DM models.

3.4.4. Evaluation Metrics of Prediction Models

The studies reviewed employed a range of evaluation metrics to evaluate DM models in firm performance prediction tasks. For classification models, accuracy and AUC were the most used metrics, providing measures of overall predictive power. Type I and Type II errors were also frequently reported, reflecting the practical importance of understanding false positives and false negatives in financial decision-making. For regression tasks, error-based metrics such as RMSE, MAE, and R-squared were predominantly used to evaluate the models' ability to predict continuous variables, including profitability, solvency, and firm performance.

The consistent use of both classification and regression metrics indicates careful consideration of model reliability and practical relevance. By combining overall predictive accuracy with error-specific measures, researchers ensure that DM models are not only statistically robust but also actionable for decision-making in high-stakes financial contexts. This emphasis on rigorous evaluation reflects a maturing methodological standard in the field, in which predictive performance is systematically linked to real-world implications.

4. Conclusion

This research makes a novel contribution by investigating DM techniques for predicting firm performance using SLR and by integrating bibliometric analysis to assess pre-screened articles. By addressing several key research questions, the study provides both an overview of existing work and a foundation for future investigations.

The findings indicate a steady increase in research activity within this field, accompanied by growing collaboration among scholars across countries, with publications appearing in top-tier journals. Interest in this area accelerated in 2017, as evidenced by 28 publications, highlighting the relatively recent emergence and rapid growth of this research domain. The most influential contribution came from [16], who predicted firm bankruptcy and garnered 342 citations in the WoS database. Since 2021, the research focus has shifted toward regression-based ML tasks and ensemble techniques. Regional contributions remain limited, with only Saudi Arabia and the UAE from the GCC included in the second-strongest global co-authorship networks, suggesting a geographic imbalance in research coverage.

Using scientific mapping, six thematic clusters were identified: stock price prediction, customer-centric research, bankruptcy prediction, business-cycle evaluation, textual analysis, and ensemble-boosting methods. While the literature has focused on technical analysis for stock price forecasting and on fundamental analysis for predicting financial distress, significant gaps remain in the examination of profitability metrics using regression-based DM techniques.

Synthesizing the reviewed articles reveals several significant gaps in the literature as follows:

- Regional focus: Few studies investigate GCC firms, and their related articles are limited to the banking sector. This gap is important because the GCC represents a rapidly developing economic region with unique market characteristics, and insights from this region may differ from global trends.
- Dependent variables: Return on Investment (ROI), a comprehensive indicator of profitability and investment efficiency is underutilized relative to traditional ratios such as ROA, solvency, and credit ratings. Incorporating ROI can provide a more holistic understanding of firm performance (Lipták et al., 2022),.
- Independent variables: Prior studies have predominantly relied on financial ratios, with limited use of market-based, macroeconomic, or non-financial indicators. Including a broader set of predictors could enhance model accuracy and generalizability.
- Techniques: Although boosting methods such as XGBoost, AdaBoost, RF, and LightGBM are widely used, CatBoost has been used infrequently for firm performance prediction. Exploring underutilized techniques may further improve predictive power and model robustness.

Addressing these gaps is critical for advancing the field. Future research should adopt a comprehensive, region-specific approach, integrating regression-based DM techniques to analyze ROI as a dependent variable, incorporating a broader range of financial, market, and non-financial predictors, and exploring advanced ensemble methods such as CatBoost. By doing so, future studies can generate more accurate, actionable insights, enhance predictive performance, and provide regionally relevant evidence for both academics and practitioners.

Acknowledging limitations, this study relied primarily on the WoS database, which may have excluded some relevant publications. However, this was partly mitigated by incorporating nine additional articles identified through website searches and citation analysis. Future research could expand coverage by systematically incorporating multiple databases, such as Scopus, to gain a more comprehensive perspective.

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