Integrative Analysis of Traditional and Cash Flow Financial Ratios: Insights from a Systematic Comparative Review

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Abstract: This systematic review analyzes and compares the predictive power between traditional financial ratios and cash flow-based ratios in estimating performance. Although traditional ratios of return on assets and debt to equity have received extensive application, cash flow ratios are increasingly valued by their dynamic insights into both liquidity and financial health. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, this review systematically analyzes 21 studies spread across various industries and regions. The results reveal that cash flow ratios usually dominate the traditional metrics during forecasting financial performance, especially in the presence of the use of machine learning models. Among the identified variables of the logistic regression model and gradient boosting model predictors, key indicators are those showing the return on investment, the current ratio, and the debt-to-asset ratio. The bottom line of the findings is that a combination of cash flow and traditional ratios gives a better understanding of a company's financial stability. These results may serve as a starting point for investors, regulators, and entrepreneurs and may further facilitate informed decisions with a reduced chance of miscalculations that enhance proactive financial planning. In addition, future prediction models should integrate non-financial factors such as governance quality and market conditions to enhance financial health assessments. Additionally, longitudinal studies examining the evolution of financial ratios over time, along with hybrid statistical and machine learning approaches, can improve forecasting accuracy. Integrating cutting-edge analytical tools with the strength of financial metrics gives this study actionable insights that allow stakeholders to understand financial performance in a more nuanced sense.

1. Introduction

Assessing a company's financial performance is critical for investors, policymakers, and corporate leaders as it determines strategic decision making and risk management. A comparison of financial performance requires the consideration of various indicators of finance. Key fields include liquidity, operating efficiency, profitability, and solvency (Abualrob and Maswadeh 2020; Dahiyat et al. 2021). Each field provides particular information to understand various aspects of a company's financial performance. Thus, a comprehensive analysis of such ratios can yield profound insights into a company's financial strengths and weaknesses (Barua and Saha 2015; Dahiyat et al. 2021; Rahman 2017).

The provision of cash flow information plays a crucial role in equipping users of financial statements with the necessary details regarding the utilization and acquisition of nearly all financial assets within a specific timeframe. Historically, financial performance has relied heavily on traditional ratios such as return on assets, return on equity, and net sales to assess profitability (Barua and Saha 2015). Cash flow ratios, such as cash to sales, cash to assets, and cash to equity, reflect the dynamic view of a company's financial performance as it captures the statement changes, whereas traditional ratios provide a static view of financial performance by measuring a single point in time. Cash flow ratios focus on what shareholders value the most, that is, the cash available for operation and investment (Atieh 2014). Traditional ratios only reflect cash availability at a specific date in the past (Agarwal and Taffler 2008; Yap et al. 2010). This enables a more accurate description of the financial position of a company.

This study compares traditional financial ratios with cash flow ratios in terms of their effectiveness in supporting the decision-making process by focusing on their ability to predict financial performance, enhance risk assessment, and predict the future financial performance of a business. The focus is on either traditional financial ratios or cash flow ratios in forecasting future business financial performance, as studied in the literature (Abualrob and Maswadeh 2020; Adnan Aziz and Dar 2006; Arlov et al. 2013; Biddle et al. 2022; Jones and Peat 2014). Consequently, it is uncommon to compare both approaches by using the same dataset (Bhandari et al. 2019).

Financial ratios play a pivotal role in assessing a firm's performance and presenting crucial metrics to stakeholders regarding profitability, liquidity, solvency, and operational efficiency (Rashid 2021). Traditionally, industry benchmarks have been set using traditional financial ratios, including return on assets (ROA) and debt-to-equity ratios, mainly because they are easy and widely understandable. These accrual-based accounting ratios are static in nature and provide a snapshot of the financial health of a company at a given point in time, thereby allowing the evaluation of firms and industries. They have become benchmarks by which decision making is carried out by investors, regulators, and corporate managers (Heikal et al. 2014).

In contrast, cash flow ratios have only recently attracted attention as they provide a dynamic view of a company's health. Unlike traditional ratios, cash flow ratios are derived from cash flow statements, capturing real-time liquidity and the company's ability to generate cash for operations, investments, and debt servicing. Furthermore, Tabot et al. (2016) provided empirical support for this assertion, demonstrating that cash flow ratios are particularly effective in predicting bankruptcy in environments where traditional financial disclosures may not provide complete transparency, such as unlisted and small-sized firms. This dynamic nature allows cash-flow ratios to reflect a company's adaptability to financial challenges and operational demands, which is particularly valuable in volatile economic environments (Das 2019).

For instance, cash-to-sales and cash flow-to-debt ratios are examples that highlight liquidity and solvency in a manner that cannot be achieved with traditional metrics because they account for the availability of cash resources and do not account for accruals (Laghari et al. 2023). This makes them more effective in assessing financial stability in an industry with irregular cash flows or when economic uncertainty has arisen. The application of cash flow ratios in combination with machine learning models has further enhanced their predictive power, offering more nuanced insights into future financial performance than traditional metrics. Although both ratios have specific strengths, there is a gap in the literature on direct comparisons (Dainelli et al. 2024). This necessitates a systematic comparison of their strengths and weaknesses to establish which is more effective in

helping stakeholders make decisions, especially when forecasting financial performance and mitigating risks.

2. Literature Review

Financial distress prediction has been a critical area of research, evolving from traditional statistical models to more dynamic and machine-learning-based approaches. Early studies focused on accrual-based financial ratios, with Beaver (1966) demonstrating that financial ratios, such as cash flow to total debt, could predict financial distress. Building on this, Altman (1968) introduced the Z-score model using multivariate discriminant analysis (MDA) to improve prediction accuracy. Ohlson (1980) later introduced logistic regression and refined probability-based bankruptcy predictions. Despite their widespread use, these models rely heavily on historical accounting data, making them less effective in dynamic financial environments (Taffler 1983; Zmijewski 1984).

Given the limitations of traditional ratios, researchers have increasingly adopted cash flow-based indicators that offer real-time insights into liquidity and solvency (Casey and Bartczak 1985; Deakin 1972; Lee 1986). Studies have found that cash flow-to-debt and operating cash flow ratios are superior predictors of financial distress (Bhandari and Iyer 2013; Jooste 2007), particularly in volatile industries, such as hospitality and telecommunications (Kirkham 2012; Ryu and Jang 2004). However, challenges such as limited historical data and inconsistent reporting standards have hindered their widespread adoption (Barua and Saha 2015).

Recent advancements in machine learning have significantly improved financial distress predictions by enabling more complex and nonlinear modeling (Chen et al. 2021; Gregova et al. 2020). Studies have shown that neural networks, random forests, and gradient boosting algorithms outperform traditional regression techniques (Gholampoor and Asadi 2024). Deep learning has revolutionized predictive modeling by allowing automated feature extraction and hierarchical representation learning, leading to state-of-the-art performance in various domains (LeCun et al. 2015). These methods have been instrumental in solving problems that were previously resistant to conventional machine learning approaches, making them highly applicable to financial risk prediction.

Random forests, as introduced by Breiman (2001), have proven to be particularly effective in classification tasks by leveraging an ensemble of decision trees to enhance predictive accuracy while mitigating overfitting issues. Their robust feature selection mechanism and ability to handle high-dimensional data make them well suited for financial distress prediction, especially when combined with other advanced models. However, despite their predictive power, concerns over interpretability, overfitting, and regulatory compliance remain significant challenges (Chen et al. 2021; Wasserbacher and Spindler 2022).

Although previous research has extensively examined traditional financial ratios, cash flow-based measures, and AI-driven models, few studies have compared these approaches within a unified framework. This study builds on past research by systematically comparing accrual-based and cash flow-based financial indicators in financial distress prediction. It evaluates their predictive effectiveness across industries by considering both traditional statistical approaches and machine learning techniques.

3. Methodology

This study used a systematic literature review (SLR) and a bibliography analysis approach to compare traditional financial ratios with cash flow ratios as tools for enhancing the quality of decision making and the prediction of financial performance. This study aimed to ensure proper and comprehensive research on this subject matter.

3.1. Research Questions

The questions in this study are as follows:

i.   What is the comparative effectiveness of traditional financial and cash flow ratios in predicting financial performance?

ii.   What statistical methods and datasets have been used in previous studies to compare the ratios?

iii. What are the trends and gaps in the research related to financial ratio analysis?

3.2. Search Strategy

The search strategy was conducted using two databases, Scopus and Google Scholar. These were chosen because of their extensive coverage of peer-reviewed and gray literature in finance and business research. Farooque et al. (2019) stated that Scopus is the world's largest database of abstracts and citations of peer-reviewed articles. Most scholarly papers are covered by Scopus, which helps open up future research prospects for scholars who plan to study a specific topic. Compared with other databases, Scopus offers a wider range of coverage (Farooque et al. 2019).

The search was carried out using Boolean operators and keywords, such as

("financial ratio*" OR "cash flow ratio*") AND ("decision-making" OR "comparison") AND ("forecast*" OR "predict*"). The use of wildcards (*) incorporates variations in key terms.

To ensure the relevance and quality of the selected literature, the search was restricted to articles published in English between 2000 and 2024 that covered contemporary research on the topic. The study focused on publications in the fields of "business, management, and accounting" and "economics, econometrics, and finance" to maintain subject-specific rigor. Furthermore, clearly defined inclusion and exclusion criteria were applied to refine the dataset, ensuring that only the most relevant and high-quality studies were incorporated into the analysis.

- Inclusion criteria:

  - Publication year: studies published between 2000 and 2024.
  - Study design: peer-reviewed journal articles that included empirical research.
  - Comparative analysis: studies must directly compare traditional financial ratios and cash flow ratios.
  - Predictive analysis: studies that evaluate the effectiveness of these ratios in predicting financial performance, such as financial health or distress.
  - Statistical methods: inclusion of sophisticated statistical or machine learning methods, such as logistic regression, discriminant analysis, or neural networks.
  - Language: articles published in English

- Exclusion criteria:

  - Non-empirical studies: theoretical papers, reviews, or meta-analyses without new empirical results.
  - Single-ratio studies: studies that focus exclusively on either traditional financial ratios or cash flow ratios but do not compare them.
  - Non-peer-reviewed material: conference papers, books, book chapters, and gray literature.
  - Incomplete data: studies with incomplete data or those that did not provide a clear methodology and result analysis.
  - Non-comparative studies: research that does not provide a direct comparison between traditional and cash flow ratios.

3.3. Data Screening and Selection

Screening was conducted according to the PRISMA 2020 guidelines with searches in two databases: Scopus and Google Scholar. From these searches, 23,451 records were retrieved, including 7551 from Scopus and 15,900 from Google Scholar. After removing 7525 duplicate records, 15,926 articles were screened based on their titles and abstracts. This led to the exclusion of 11,167 studies because of their irrelevance to the research question.

A total of 4759 full-text studies were reviewed, of which 4702 were excluded due to irrelevance, the lack of statistical comparison, or irrelevance to the study question. Additionally, 36 documents listed for retrieval could not be accessed because they were either no longer available or had been removed by the original source. This limitation has been acknowledged to maintain transparency in the study methodology.

Ultimately, 21 studies met all inclusion criteria and were included in the final analysis. The selection process is illustrated in Figure 1, which provides a step-by-step depiction of the detailed screening and selection procedure.
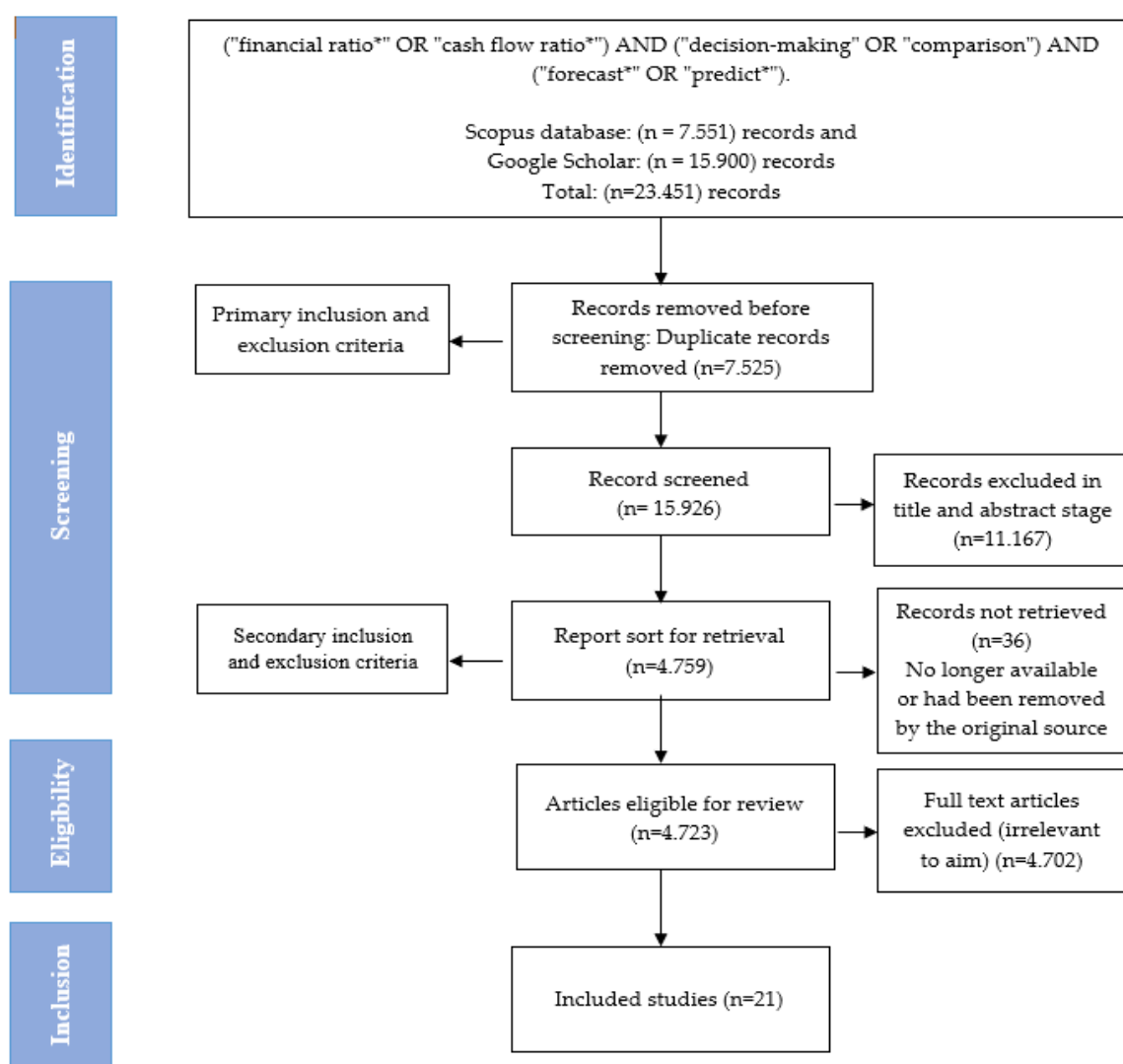
Figure 1. Flowchart of the process used to identify articles in the systematic review (Page et al. 2021).

3.4. Data Analysis

The included studies were analyzed using various bibliometric tools, namely Bibliometrix in R and VOSviewer. The analysis focused on the following aspects:

i. Yearly publication trends, influential authors, journals, and articles.

ii.   Citation analysis to identify highly cited studies.

iii.   Co-citation and keyword co-occurrence analyses were used to identify thematic clusters.

iv.   The statistical methods used in this research include logistic regression and discriminant analysis.

This systematic review focused on comparing methodologies (traditional financial ratios versus cash flow-based financial ratios) through a bibliometric and descriptive synthesis of empirical studies. The review did not include intervention studies or randomized controlled trials, and the primary goal was methodological comparison, rather than effectiveness evaluation. Thus, traditional risk-of-bias assessment tools designed to evaluate the internal validity of experimental interventions (such as the Cochrane Risk of Bias Tool or the Newcastle–Ottawa Scale) were not applicable or appropriate for this systematic review.

3.5. Statistical Analysis

To rigorously evaluate the predictive effectiveness of traditional financial ratios compared with cash flow ratios, we employed the Area Under Curve (AUC) derived from the Receiver Operating Characteristic (ROC) curve. The ROC curve serves as a fundamental tool in diagnostic testing and graphically depicts the performance of a binary classification system as its discrimination threshold varies (Malik et al. 2024). This method is especially appropriate for assessing how well financial ratios can distinguish between financially healthy and distressed firms.

The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity), offering an insightful visual representation of a model's trade-offs between sensitivity and specificity across various threshold settings (Metz 1978). The AUC, a summary measure derived from the ROC curve, quantifies a model's overall ability to discriminate between two predefined classes, such as firms that are financially stable versus those that are not.

The AUC value ranges from 0.5 to 1.0, where 1.0 indicates perfect discrimination (the model correctly classifies all cases without error), and 0.5 suggests a performance no better than random chance (Hanley and McNeil 1982). Thus, a higher AUC value indicates a more effective model in terms of predictive accuracy.

By applying the AUC metric, we conduct a comparative analysis of the effectiveness of traditional versus cash flow-based financial ratios. This analysis not only underscores which set of ratios provides a more reliable forecast of financial performance but also identifies potential areas for future research. The utilization of the AUC in this context provides a clear, quantifiable measure of each model's discriminative capability, facilitating a deeper understanding of the inherent predictive power embedded within these financial metrics.

Following the structured screening and analysis process outlined in the methodology, this study identified 21 relevant empirical studies that provide insights into financial distress prediction using traditional and cash flow ratios. The following section presents the key results, focusing on comparative accuracy, industry-specific applications, and the role of machine learning in financial forecasting.

4. Results

4.1. Bibliometric Analysis

This analysis provides an overview of the key insights derived from the bibliometric analysis of all references included in the systematic review of financial distress prediction and related themes.

- Citation network visualization

A structured citation analysis (Figure 2) was conducted using VOSviewer to identify the most influential studies on financial distress prediction. Altman (1968) emerged as the foundational work on financial ratios for financial distress prediction, with significant citations in later research. The analysis measured the "degree of connectivity" among the references, showing how some studies have significantly influenced further research.
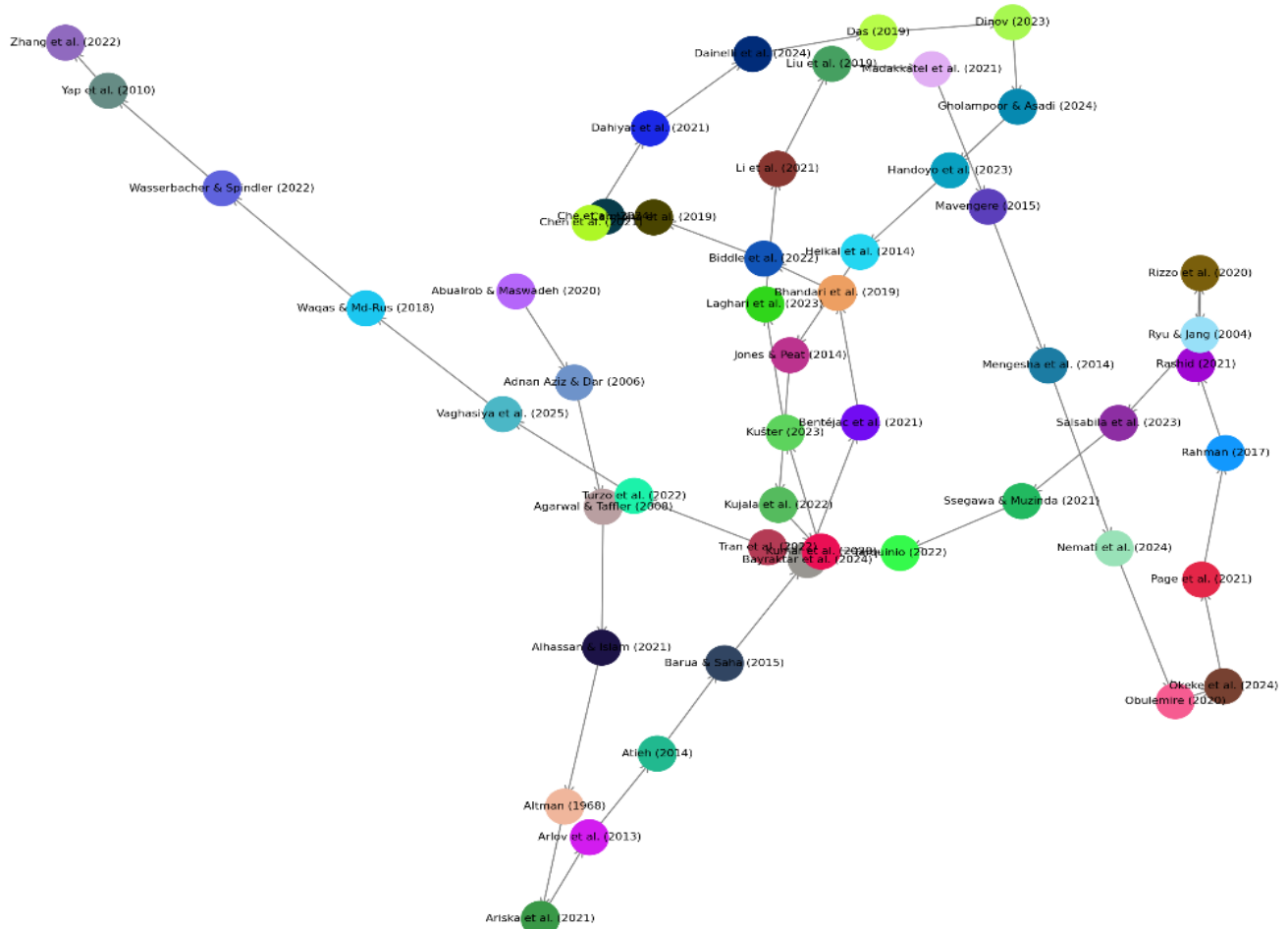
Figure 2. Citation network visualization highlights the connectivity among key articles in the domain of financial ratios, financial distress prediction, and financial performance.

Among the most cited articles, Altman (1968) is the most cited founding article as it provided the basis for later research on financial ratios and financial distress prediction. Other key contributions include Agarwal and Taffler (2008) and Adnan Adnan Aziz and Dar (2006), who discussed advanced models and frameworks that could be used to improve the accuracy of predictions. These studies highlight the significance of financial ratios in evaluating corporate health and predicting corporate distress. The citation network further reveals clusters of related research, with similarly colored nodes representing authors who work in very closely related areas, such as cash flow analysis and financial distress modeling. Cross-disciplinary collaborations are shown between nodes of different colors and indicate an increased integration of various methodologies and viewpoints in this area.

The comparative analysis of financial ratios across multiple empirical studies reveals key trends: cash flow-based ratios demonstrate higher predictive accuracy than traditional ratios, particularly when applied to machine learning models. However, industry-specific variations exist, highlighting the importance of tailored approaches to financial distress

prediction. The following discussion interprets these findings and contextualizes them within broader financial research and real-world applications.

- Author analysis

From the dataset, we identified the key contributors in the field. The production-over-time chart (Figure 3) shows that research output has significantly increased in recent years, with more authors actively publishing on topics such as financial distress prediction, machine learning, and bankruptcy analyses. However, the distribution indicates that many authors have contributed only once, suggesting a wide research interest, but fewer dominant contributors.
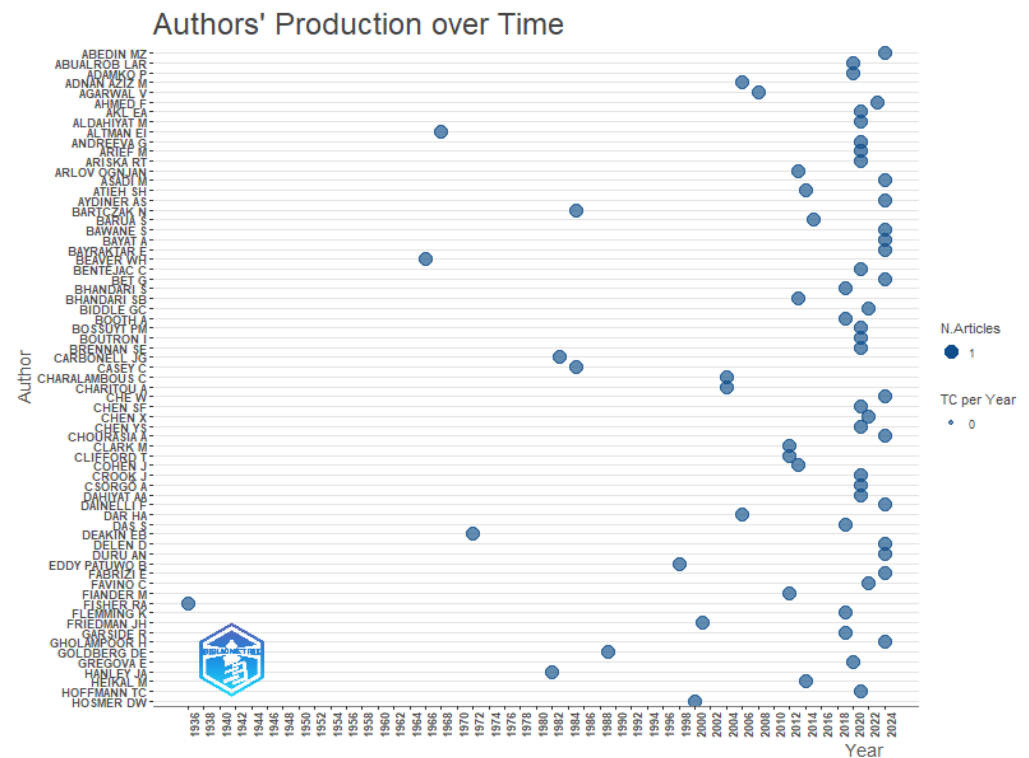

Figure 3. Authors' production over time.

Bibliographic coupling analysis indicates that authors sharing common references identified closely aligned researchers forming distinct clusters. The central authors, including Altman (1968), Beaver (1966), and LeCun et al. (2015), indicate strong coupling, demonstrating their influence in the financial distress prediction research field. Our analysis shows tight-knit groups, suggesting strong thematic coherence. The presence of machine learning and artificial intelligence researchers, such as LeCun et al. (2015), indicates the ongoing integration of advanced computational methodologies with traditional financial distress theories, notably represented by Altman and Beaver.

- Co-Citation patterns and theoretical foundations in financial distress research

Co-citation analysis (Figure 4) identifies influential cited works within the literature, illuminating foundational texts and core theoretical frameworks. Density visualization indicates highly co-cited foundational works by Altman (1968), Ohlson (1980), and Beaver (1966). These seminal texts remain central, underscoring their continued relevance in shaping contemporary research.
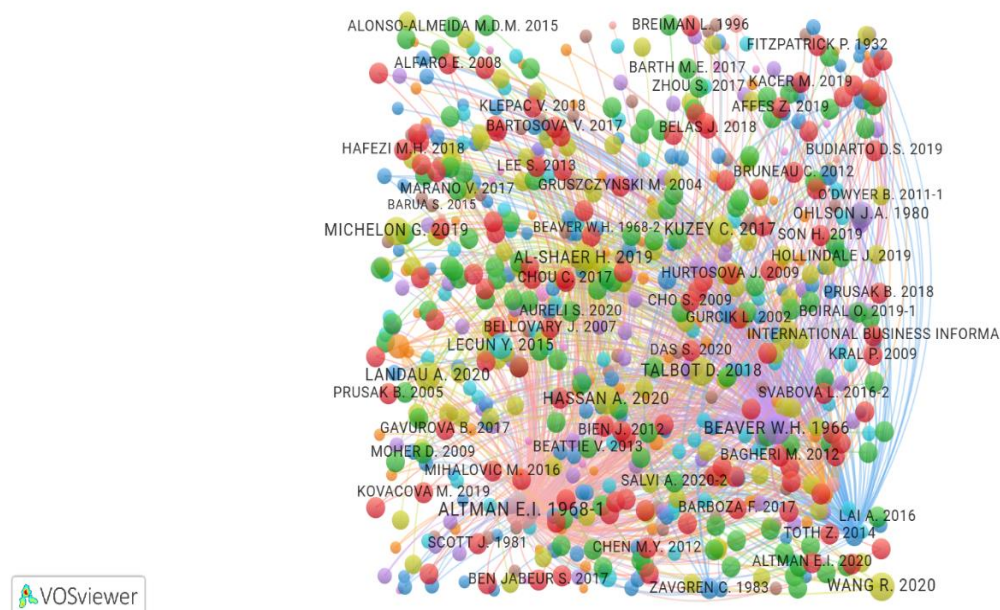
Figure 4. Network Co-Citation Analysis.

Density visualization (Figure 5) further highlights influential methodological contributions from authors such as Breiman (2001) and LeCun et al. (2015), reflecting a robust methodological evolution driven by machine learning and artificial intelligence in the recent literature. The prominence of these authors confirms a strong methodological underpinning in current financial distress prediction research, merging classical financial metrics with advanced predictive modeling techniques.
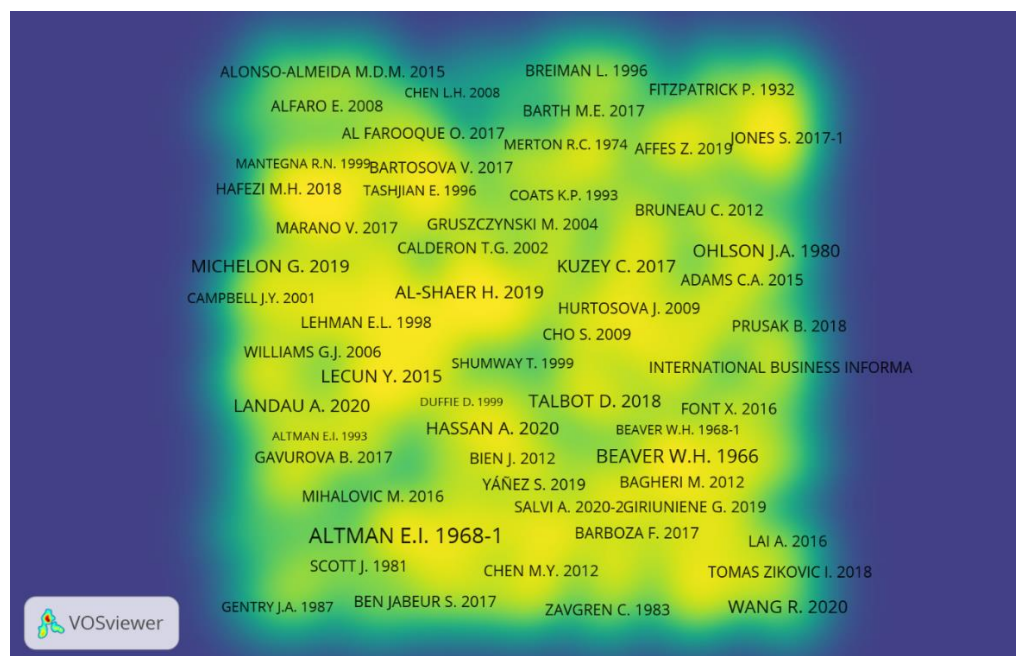
Figure 5. Density co-citation visualization.

- Top journals

The *Journal of Accounting Research* is the most prolific journal in this domain, publishing significantly more articles (five) than all the others. Other notable journals include *Artificial Intelligence Review* and *Information Processing & Management*, indicating a growing intersection between financial distress prediction and AI-driven methodologies (Figure 6).
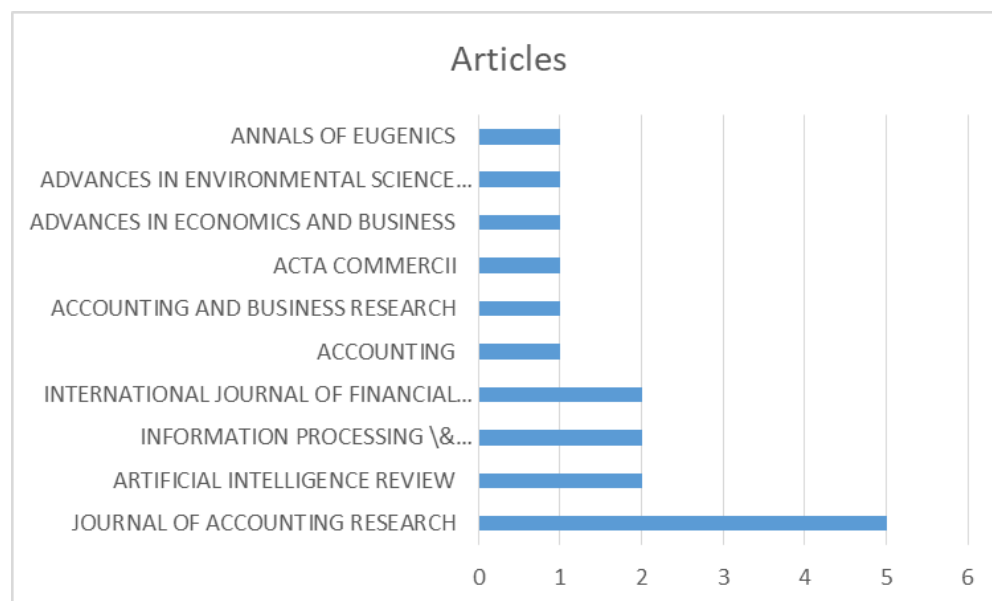
Figure 6. Top journals visualization.

- Keyword co-occurrence network and density visualization

The visualization of keyword relationships (Figure 7), reveals financial ratios, machine learning, artificial intelligence, and credit risk as central themes. These keywords frequently co-occur, highlighting the field's focus on predictive analytics and risk assessment. Cash flow, bankruptcy prediction, and discriminant analysis also appear strongly, reinforcing traditional financial distress modeling approaches.
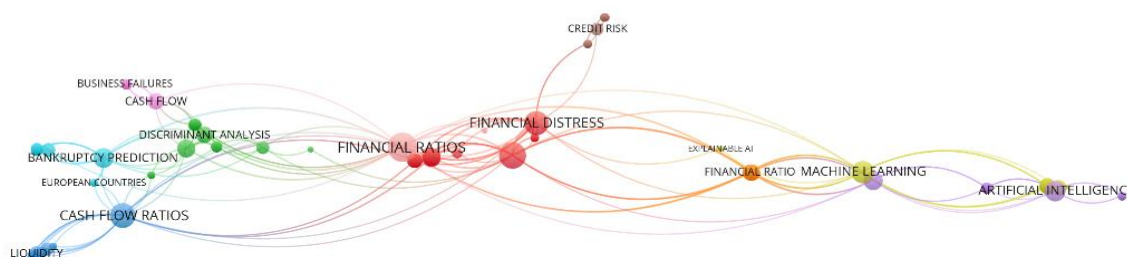
Figure 7. Keyword co-occurrence network visualization.

Density mapping (Figure 8) shows that financial ratios and machine learning are the most researched topics, followed by bankruptcy prediction and credit risk analysis. This indicates a blend of traditional financial metrics and modern AI-driven forecasting models. Emerging trends, such as explainable AI, suggest a move towards more interpretable financial distress models.
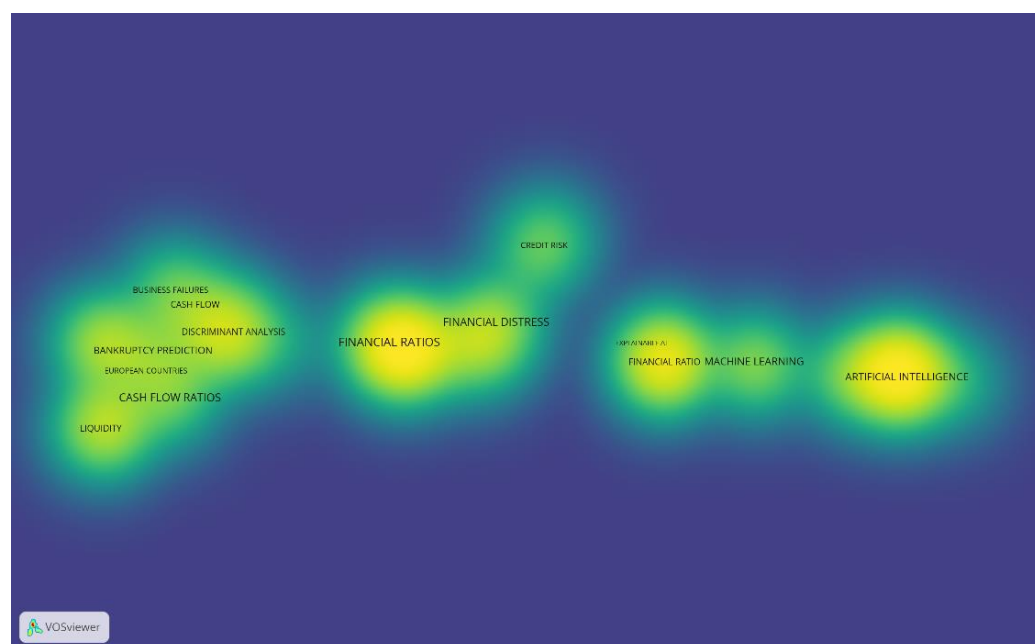
Figure 8. Keyword co-occurrence density visualization.

- Thematic evolution and future directions

Our thematic map (Figure 9) positions financial distress, bankruptcy, and emerging markets as motor themes that are highly relevant and well developed. Niche themes, such as liquidity and traditional ratios, show focused but less central importance. Declining or emerging themes include credit risk and financial distress prediction, suggesting potential areas for future research.

Figure 9. Thematic evolution and future directions.
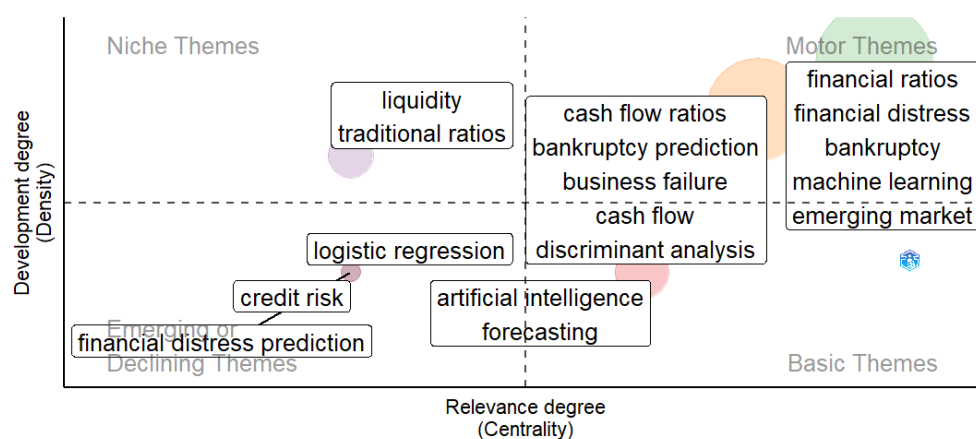
4.2. Review of Empirical Studies on Financial Distress Prediction

This review of empirical studies spanning various regions and industries consistently illustrates the superior predictive power of cash flow ratios over traditional financial ratios in assessing financial distress (Barua and Saha 2015). Ariska et al. (2021) conducted an empirical study to determine the relationship between financial ratios and financial distress in 94 manufacturing firms listed on the Indonesian Stock Exchange from 2014 to 2018. Using logistic regression analysis, the study found that return on assets exhibited a significant negative association with financial distress, indicating that higher profitability reduces the likelihood of financial difficulties. Conversely, the ratio of working capital to total assets had a significant positive effect, suggesting that an increased proportion of working capital

relative to total assets heightens the risk of financial distress. These two variables were identified as key predictors, whereas other financial ratios, including the debt ratio, were not statistically significant in forecasting financial distress.

Ryu and Jang (2004) demonstrated that, in the hospitality sector, cash flow ratios reflect liquidity more accurately than traditional ratios, particularly highlighting the financial robustness of casino hotels over commercial hotels. Expanding the scope to different sectors, Atieh (2014) later examined liquidity assessment methods in Jordan's pharmaceutical industry by comparing traditional financial ratios with cash flow-based measures. The study found that while traditional ratios offer a static view of liquidity based on balance sheet data, cash flow ratios provide a more dynamic and informative perspective. Relying solely on traditional ratios may lead to misleading conclusions, making cash flow-based measures essential for comprehensive liquidity analysis.

Kirkham (2012), presented a comprehensive comparison between the traditional ratios and cash flow ratios of twenty-five companies in the same industry over a five-year period. This analysis revealed distinct discrepancies between the two ratios. For instance, while traditional ratios occasionally suggest adequate liquidity, cash flow ratios often paint a more nuanced picture, indicating potential cash flow issues that are not captured by traditional metrics. This divergence highlights the limitations of traditional liquidity measures in reflecting a firm's dynamic cash flow status accurately.

In terms of analytical methods, Kušter (2023) analyzed financial data from 74 Serbian companies using discriminant analysis to create a financial distress prediction model. The study achieved a classification accuracy of 71.6%, with the Altman Z-score variables (Altman 1968) as significant predictors. Similarly, Kumar et al. (2020) analyzed financial distress in Indian companies using logistic regression and achieved an overall accuracy of 96.8%. Their study, based on financial data from 51 listed companies on the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE), identified the interest coverage ratio, net profit margin, and working capital as the most significant predictors of insolvency. The findings highlight the importance of these financial indicators in forecasting corporate distress and guiding risk-assessment strategies.

Barua and Saha (2015) demonstrated that cash flow-based indicators provide better predictive power across different industries. Waqas and Md-Rus (2018b) used logistic regression to forecast financial distress in Pakistani firms using financial data from 290 non-financial firms over 10 years. The results showed that profitability, liquidity, and leverage ratios were significant predictors of distress. Looking ahead, Okeke et al. (2024) continued this line of investigation in the Nigerian healthcare industry, where they discovered that operating cash flow and cash flow-to-debt ratios were significant predictors of business failure. This highlights the variability in the results depending on the industrial context.

Gregova et al. (2020) took a more technologically advanced approach by comparing logistic regression, random forest, and neural network models to predict financial distress among Slovak industrial enterprises, with neural networks providing the highest accuracy. Similarly, Tabot et al. (2016) explored the predictive power of cash flow components in bankruptcy determination among small, unlisted firms in Spain. Using logistic regression analysis, their study highlighted that cash flow ratios, particularly cash flow from operations relative to total liabilities and current liabilities, offer a more accurate prediction of bankruptcy than traditional financial metrics. This study reinforced the notion that cash flow ratios can provide critical insights into financial distress, especially in smaller and less transparent market segments.

Further reinforcing the role of cash flow ratios, Ryu and Jang (2004) analyzed the reliability of cash flow ratios vis à vis traditional ratios in the hospitality industry. An independent t-test of the financial data of hotel companies found that cash flow ratios were

a better indicator of liquidity position. Finally, they showed that cash flow ratios were better than others at predicting liquidity and financial distress across industries.

On the topic of liquidity, Mavengere (2015) examined liquidity in Zimbabwe's retail sector by comparing traditional financial ratios with cash flow-based measures. The study found that while traditional ratios, such as the current ratio, provide a static view of liquidity, cash flow ratios offer a more dynamic and accurate assessment. The findings emphasized that relying solely on traditional ratios can be misleading, reinforcing the need to incorporate cash flow-based measures for a more comprehensive evaluation of financial health. Barua and Saha (2015) echoed this argument, highlighting how traditional ratios can overestimate liquidity and profitability because of accrual-based distortions.

The predictive power of cash flow ratios has been further validated by extensive empirical research. For instance, Bhandari et al. (2019) examined the effectiveness of accrual-based and cash flow-based financial measures in predicting business failures. Their logistic regression analysis of financial data from various U.S. industries revealed that cash flow ratios were significantly more reliable, achieving a high accuracy of 96.8%. Charitou et al. (2004) provide compelling evidence of the predictive power of operating cash flow ratios. Their research demonstrated that a model incorporating the cash flow ratio, profitability ratio, and financial leverage ratio could achieve an overall classification accuracy of 83% one year prior to failure. This high level of accuracy underscores the significant potential of cash flow information to enhance the predictability of financial distress models for industrial firms in the UK. Further research by Jooste (2007) provided compelling evidence of the predictive value of cash flow ratios in indicating financial distress. By focusing on various cash flow ratios, Jooste identified the cash flow to total debt ratio as the most effective indicator of financial distress, with predictive capabilities up to three years prior to failure.

In the realm of machine learning, Chen et al. (2021) developed hybrid models integrating traditional financial ratios with advanced techniques, such as K-Nearest Neighbors and decision trees, to predict bankruptcy in Taiwan's electronics industry, achieving a high prediction accuracy of 92%. This integration of machine learning underscores the significant role of these technologies in enhancing financial risk assessment.

Similarly, Gholampoor and Asadi (2024) assessed bankruptcy risks in the U.S. healthcare industry using machine learning models. Their analysis of financial data from 1265 firms found that gradient boosting, with an accuracy exceeding 90%, effectively predicted financial distress. Key predictors included return on investment (ROI), return on assets (ROA), and Enterprise Value to Earnings Before Interest and Taxes (EV/EBIT), reinforcing the importance of machine learning in financial risk assessment.

Building on the theme of the effectiveness of cash flow measures, the study conducted by Bhandari and Iyer (2013) further validated the utility of these ratios through a discriminant analysis model that achieved 83.3% accuracy in classifying original grouped cases and 79.5% in cross-validation. This model, which utilized a set of seven cash flow-based financial ratios, was not only effective but also demonstrated statistical significance with a robust Wilks' lambda test ($p < 0.001$), underscoring the model's performance in differentiating between failed and non-failed firms. The high classification accuracy of this study highlights the potential of cash flow measures in predicting business failures, reinforcing the findings from various sectors that cash flow ratios provide more dynamic and accurate financial assessments than traditional ratios do.

In terms of fraud detection, Nemati et al. (2024) applied machine learning algorithms to detect fraud in financial statements from 180 Iranian firms. Among the tested models, the bagging algorithm proved to be the most effective, achieving an 81.7% accuracy with optimized financial ratios. Similarly, Rizzo et al. (2020) investigated financial distress

predictions across five European countries using genetic algorithms and fuzzy logic. Their analysis of financial data from 719,124 companies revealed a strong predictive performance, with notable variations across different national economies. The findings underscore the effectiveness of genetic algorithms in assessing bankruptcy risks and financial distress in diverse financial environments.

Table 1 summarizes the studies derived from the systematic review, outlining each study's ID, aim, methodology, and results. This table offers a concise overview that helps readers quickly grasp the scope and primary conclusions of each study, facilitating a deeper understanding of the various approaches to financial data analysis within the contexts of the industries studied.

Table 2 presents a detailed financial ratio analysis of the studies. It includes specific details, such as the study number, study ID, region, industry, time period, sample size, financial ratios analyzed, models used, accuracy percentages, AUC values, and key predictors. This table focuses on the quantitative aspects of financial ratios used in the studies and their efficacy in predicting financial performance and distress, highlighting the relevance of these ratios in different regional and industrial contexts.

Table 1. Summary of systematic review studies.

	Study ID	Aim	Methodology	Results
1	(Ariska et al. 2021)	To examine gender diversity and financial ratios on financial distress in manufacturing firms.	Logistic regression analysis of 94 companies from 2014 to 2018.	Return on assets negatively impacts distress; working capital to total assets positively impacts distress.
2	(Atieh 2014)	To compare cash flow ratios and traditional ratios in assessing liquidity in Jordan's pharmaceutical sector.	Statistical Package for the Social Sciences (SPSS) analysis of financial data from 7 companies between 2007 and 2012.	Cash flow ratios provide more insight into liquidity than traditional ratios.
3	(Barua and Saha 2015)	The main focus of this study is exploring the potential of traditional and cash flow ratios in the prediction of forthcoming cash flows in Bangladeshi companies.	The study analyzed financial data from non-manufacturing companies listed on the Dhaka Stock Exchange from 2001 to 2010. It used both traditional ratios derived from balance sheets and income statements and cash flow-based ratios derived from cash flow statements.	Based on empirical evidence, it has been established that the cash flow and accrual components of earnings are reliable indicators for forecasting future cash flows of Bangladeshi companies listed on the stock market. It has also been concluded that cash flow ratios are more effective in predicting future cash flows than traditional ratios. Nevertheless, it should be noted that the accuracy of the financial picture offered by cash flow ratios is sometimes superior and may vary.

	Study ID	Aim	Methodology	Results
4	(Bhandari and Iyer 2013)	To develop a new model for predicting business failure using primarily cash flow statement-based measures.	The study analyzed data from 100 firms (50 failed and 50 non-failed) using discriminant analysis. The predictor variables included operating cash flow divided by current liabilities, cash flow coverage of interest, operating cash flow margin, operating cash flow return on total assets, earning quality, quick ratio, and three-year sales growth. Data were sourced from COMPUSTAT and analyzed using IBM SPSS Statistic, Version 19.0 software.	The discriminant analysis model correctly classified 83.3% of the original grouped cases. The cross-validated method correctly classified 79.5% of cases. The model performed exceptionally well at distinguishing between failed and non-failed firms, with statistical significance achieved at the Wilks' lambda test ($p < 0.001$).
5	(Bhandari et al. 2019)	To compare accrual vs. cash flow-based financial measures for predicting business failure.	Logistic regression to compare financial measures in predicting failure.	Cash flow-based measures outperform accrual measures for predicting business failures.
6	(Charitou et al. 2004)	To investigate the incremental information content of operating cash flows over traditional accounting measures in predicting financial distress using neural networks and logit analysis.	The study used a dataset of fifty-one matched pairs of failed and non-failed UK public industrial firms from 1988 to 1997. Neural networks and logit methodologies were applied to assess the predictive power of cash flow-based and traditional accrual-based financial ratios. Validation was performed using the out-of-sample ex-ante test and the Lachenbruch jackknife procedure.	The study found that models incorporating cash flow ratios, along with profitability and financial leverage ratios, provided a high classification accuracy of 83% one year prior to failure, demonstrating significant predictive power in assessing financial distress.
7	(Chen et al. 2021)	To develop hybrid models for financial distress prediction in Taiwan's electronics industry.	Hybrid models combining machine learning and traditional methods.	Hybrid models achieved high accuracy, with liquidity and debt ratios as key predictors.

Table 1. *Cont.*

	Study ID	Aim	Methodology	Results
8	(Gregova et al. 2020)	To compare the effectiveness of logistic regression, random forest, and neural network models in predicting financial distress among industrial enterprises in Slovakia, aiming to identify the most accurate prediction model for this specific environment.	The study utilized a dataset of approximately 50,000 Slovak industrial enterprises from 2016 to 2018, evaluating the prediction accuracy of three different models (logistic regression, random forest, neural network) in the context of new legislation impacting financial crisis definitions.	All models showed high discrimination accuracy, with neural network models demonstrating superior performance across all evaluated metrics. This highlights the potential of machine learning techniques in enhancing the predictability of financial distress in specific national contexts
9	(Jooste 2007)	To evaluate the effectiveness of various cash flow ratios in predicting financial distress and potential bankruptcy, highlighting the potential of these ratios to serve as early warning indicators.	The study analyzed eight cash flow ratios across ten failed entities and compared them to similar non-failed entities in the same sectors for five years prior to failure. Mean values for each ratio were calculated annually to compare the financial states of the failed and non-failed entities.	The study found that cash flow ratios, particularly the cash flow to total debt ratio, effectively predicted financial failure up to three years in advance. Failed entities consistently showed poorer cash flow ratios compared to non-failed entities, indicating their inability to meet debt obligations and higher tendencies to incur debt.
10	(Kirkham 2012)	To examine the value of analyzing company liquidity using traditional ratios compared to the more recently devised cash flow ratios.	The study compared traditional liquidity ratios (current ratio, quick ratio, interest coverage ratio) with cash flow ratios (cash flow ratio, critical needs cash coverage ratio, cash interest coverage ratio) for twenty-five companies in the telecommunications sector in Australia over a five-year period. Data were sourced from the FinAnalysis database.	The study revealed that there were significant differences between traditional liquidity ratios and cash flow ratios. It found that decisions based solely on traditional ratios could lead to incorrect conclusions about a company's liquidity, either overestimating or underestimating the true cash flow position of the companies.
11	(Kušter 2023)	To create a financial distress prediction model for Serbian companies using discriminant analysis.	Discriminant analysis on financial data from 74 companies.	Model achieved 71.6% classification accuracy; Altman Z-score variables were key predictors.
12	(Gholampoor and Asadi 2024)	To assess bankruptcy risks in U.S. healthcare industries using machine learning models.	Gradient boosting on financial data from 1265 firms using 40 financial ratios.	Gradient boosting achieved over 90% accuracy; ROI and ROA were key predictors.

Table 1. *Cont.*

	Study ID	Aim	Methodology	Results
13	(Kumar et al. 2020)	To predict corporate financial distress in Indian companies using logistic regression.	Logistic regression on financial data from 51 companies listed on BSE/NSE.	Interest coverage ratio, net profit margin, and working capital were significant predictors of insolvency.
14	(Mavengere 2015)	To analyze liquidity in Zimbabwean retail companies using traditional and cash flow ratios.	Comparison of liquidity ratios using company financial statements.	Cash flow ratios revealed insights missed by traditional ratios.
15	(Nemati et al. 2024)	To identify fraud risk detection methods in financial statements using classification algorithms.	Machine learning algorithms (Support Vector Machines (SVM), bagging, K-Nearest Neighbors (K-NN)) applied to financial data of 180 firms.	Bagging performed best, achieving an accuracy of 81.7%.
16	(Okeke et al. 2024)	To analyze cash flow ratios as predictors of business failure in Nigerian healthcare firms.	Multiple regression analysis of healthcare firms (2013–2022).	Operating cash flow and cash flow-to-debt ratios had non-significant effects on Altman Z-scores.
17	(Rizzo et al. 2020)	To test cash flow ratios in financial distress prediction using genetic algorithms and fuzzy logic.	Analysis of 719,124 companies across five European countries using machine learning models.	Model showed strong performance in predicting bankruptcy; country-level variations in performance noted.
18	(Ryu and Jang 2004)	To compare cash flow and traditional financial ratios in hospitality companies.	Independent *t*-tests of financial data from hotel companies.	Cash flow ratios were more reliable indicators of liquidity than traditional ratios.
19	(Tabot et al. 2016)	To evaluate the effectiveness of cash flow components in predicting bankruptcy among small, unlisted firms.	Logistic regression analysis of cash flows.	Cash flow components provided a superior prediction of bankruptcy compared to financial ratios. The study highlighted the particular effectiveness of certain cash flow ratios over traditional financial metrics in forecasting firm distress, emphasizing their utility in financial distress models for small firms.
20	(Waqas and Md-Rus 2018b)	To predict financial distress using accounting and market variables in Pakistani firms.	Logit regression analysis on financial data from 290 non-financial firms over 10 years.	Profitability, liquidity, and leverage ratios were significant predictors of financial distress.
21	(Waqas and Md-Rus 2018a)	Compare O-score model and logit model in predicting financial distress in Pakistani firms.	Empirical analysis of 290 firms (2006–2016) using financial ratios.	Logit model outperformed O-score model in predictive accuracy; cash flow ratios enhanced distress prediction.

Table 2. Financial ratios analysis across studies.

Num.	Study ID	Region	Industry	Time Period	Sample Size	Financial Ratios Analyzed	Model(s) Used	Accuracy (%)	AUC	Key Predictors
1	(Ariska et al. 2021)	Indonesia	Manufacturing	2014–2018	94 companies	Return on assets, net profit margin, current ratio, debt ratio	Logistic regression	85	0.88	Return on assets, working capital, debt ratio
2	(Atieh 2014)	Jordan	Pharmaceutical	2007–2012	7 companies	Cash flow ratios, current ratio, quick ratio, operating cash margin	SPSS analysis	NA	NA	Current ratio, quick ratio, cash flow ratios
3	(Barua and Saha 2015)	Bangladesh	Non-manufacturing	2001–2010	95 companies	Traditional financial ratios (e.g., ROA, ROE) and cash flow-based ratios (e.g., operating cash flow to total debt, free cash flow)	Comparative financial ratio analysis	NA	NA	Cash flow ratios were identified as better predictors of financial performance and future cash flows compared to traditional financial ratios
4	(Bhandari and Iyer 2013)	USA	Various industries	2008–2010	100 firms (50 failed, 50 non-failed)	Operating cash flow divided by current liabilities, cash flow coverage of interest, operating cash flow margin, operating cash flow return on total assets, earning quality, quick ratio, three-year sales growth	Discriminant analysis (DA)	83.3% (original grouped cases), 79.5% (cross-validated)	NA	Operating cash flow/current abilities, cash flow coverage of interest, operating cash flow margin, operating cash flow return on total assets, earning quality, quick ratio, three-year sales growth
5	(Bhandari et al. 2019)	USA	Mixed industries	NA	NA	Cash flow ratios vs. accrual measures	Binary logistic regression	96.8	NA	Cash flow ratios vs. accrual measures
6	(Charitou et al. 2004)	United Kingdom	Industrial (public firms)	1988–1997	102 firms (51 matched pairs of failed and non-failed firms)	Cash flow ratios, profitability ratios, financial leverage ratios	Neural networks, Logit analysis	83%	NA	Cash flow ratio, profitability ratio, financial leverage ratio
7	(Chen et al. 2021)	Taiwan	Electronics	2000–2019	8 industries	Liquidity ratio, debt ratio, fixed assets turnover ratio	Hybrid intelligent models (logistic, K-Nearest Neighbors, decision trees (DT)	92%	NA	Liquidity ratio, debt ratio, fixed assets turnover
8	(Gholampoor and Asadi 2024)	USA	Healthcare	2022	1.265 companies	ROI, ROA, EV/EBIT	Machine learning (gradient boosting)	90%	0.92	ROI, ROA, EV/EBIT

Table 2. *Cont.*

Num.	Study ID	Region	Industry	Time Period	Sample Size	Financial Ratios Analyzed	Model(s) Used	Accuracy (%)	AUC	Key Predictors
9	(Gregova et al. 2020)	Slovakia	Industrial	2016–2018	Approximately 50,000 enterprises	Return on capital (net), return on capital (gross), return on corporate revenues (net), asset turnover, current assets turnover, cash ratio, quick ratio, current ratio, net working capital ratio, RE–TA ratio retained, earnings/total assets, debt ratio, current debt ratio, financial debt ratio, debt–equity ratio.	Logistic regression, random forest, neural networks	The study mentions high discrimination accuracy with neural networks outperforming other models.	NA	NA. Involved a broad set of financial ratios used to feed the predictive models.
10	(Jooste 2007)	South Africa	Multiple sectors, excluding public utilities, transportation, investment, insurance, and financial institutions due to their unique financial structures	2000–2004	10 failed entities compared with 14 non-failed entities (after excluding 6 non-financially sound entities from an initial group of 20)	Cash flow to sales, cash flow to assets, reinvestment ratio, cash flow to total debt, critical needs coverage, cash interest coverage, dividend coverage, cash flow to income	Comparative financial analysis using cash flow ratios	NA	NA	Cash flow to total debt, which was identified as the best indicator of failure among the studied ratios
11	(Kirkham 2012)	Australia	Telecommunications	2007–2011	25 companies	Traditional ratios (current ratio, quick ratio, interest coverage ratio), cash flow ratios (cash flow ratio, critical needs cash coverage ratio, cash interest coverage ratio)	Comparative financial ratio analysis	NA	NA	The study did not specifically identify 'key predictors' as it was not predictive modeling but did highlight the comparative effectiveness of cash flow ratios versus traditional ratios in liquidity analysis.
12	(Kušter 2023)	Serbia	General businesses	Pre-bankruptcy	74 companies	Common financial ratios (Altman Z-Score variables)	Discriminant analysis, logistic models	71.6	NA	Financial Ratios (Altman Z-Score variables)

Table 2. *Cont.*

| Num.	Study ID	Region	Industry	Time Period	Sample Size	Financial Ratios Analyzed	Model(s) Used	Accuracy (%)	AUC	Key Predictors
13	(Kumar et al. 2020)	India	Mixed sectors	NA	51 companies	Net profit margin, interest coverage ratio, working capital ratio	Binary logistic regression	96.8	0.94	Net profit margin, interest coverage ratio
14	(Mavengere 2015)	Zimbabwe	Retail	2010–2014	Multiple	Current ratio, quick ratio, cash flow ratios	Comparative analysis	NA	NA	Current ratio, quick ratio, cash flow ratios
15	(Nemati et al. 2024)	Iran	Various sectors	2014–2021	180 companies	Nine key financial ratios (post optimization)	Machine learning (bagging, SVM, etc.)	81.7	NA	Nine optimized financial ratios
16	(Okeke et al. 2024)	Nigeria	Healthcare	2013–2022	Multiple	Operating cash flow ratio, cash flow-to-debt ratio, price-to-cash flow ratio	Multiple Regression	NA	NA	Operating Cash flow, cash-flow-to-debt ratio
17	(Rizzo et al. 2020)	Europe	Multiple sectors	2015–2018	719,124 companies	Cash flow ratios, genetic algorithms, and fuzzy logic	Genetic algorithms, fuzzy logic	NA	NA	Profitability, liquidity, leverage, cash flow ratios
18	(Ryu and Jang 2004)	USA	Hospitality	5 years	Multiple	Liquidity, solvency, and operational efficiency ratios	T-test analysis	NA	0.85	Operating cash flow, debt ratios
19	(Tabot et al. 2016)	Spain	Various	2008–2009	534 firms	Cash flow from operations/total liabilities, cash flow from operations/current liabilities, net liquid balance	Logistic regression	NA	NA	Cash flow from operations to total liabilities, cash flow from operations to current liabilities, net liquid balance
20	(Waqas and Md-Rus 2018b)	Pakistan	Various sectors	2007–2016	290 firms	Profitability, liquidity, leverage, cash flow ratios, market factors	Logit regression	NA	NA	Liquidity, solvency, operational efficiency ratios
21	(Waqas and Md-Rus 2018a)	Pakistan	Various (Pakistan Stock Exchange)	2006–2016	290 firms (45 distressed, 245 healthy)	Profitability, liquidity, leverage, cash flow ratios	Logit model, O-score model	Logit model had higher accuracy	Not explicitly reported	Cash flow ratios, leverage, profitability, liquidity

The conceptual framework adopted for financial distress prediction matches, to a great extent, the purposes and approach of the research at hand; thus, a framework in structured analysis has been found to compare traditional financial ratios with cash flow ratios. The input variables contain essential financial metrics, including return on assets (ROA), return on investment (ROI), the debt-to-asset ratio, and the current ratio (CR), as

well as industry-related data. These variables reflect a host of factors driving financial health and offer a rich dataset for prediction analysis.

This methodology combines statistical and machine learning techniques, reflecting the approaches used in this study. Logistic regression is used as the primary statistical method for identifying binary outcomes such as financial distress because of its simplicity and interpretability. Moreover, more sophisticated machine learning techniques, such as gradient boosting, are employed to enhance the precision of predictions by uncovering nonlinear relationships and interactions between variables. This ensures robustness and adaptability across industries and datasets.

Outcomes based on the framework are developed such that ROA and the debt-to-asset ratio are key predictors of financial distress. This has been validated through the application of performance metrics such as accuracy, AUC, and feature importance. These form part of the criteria that can be employed in evaluating the performance of traditional and cash flow ratios, as considered in this study.

The applications of the framework are directed toward risk assessment and strategic decision making, which is the thrust of the study. To that effect, this type of framework shall provide actionable insight that would allow stakeholders in financial forecasting to perform risk assessment and make informed decisions with support (Figure 10).
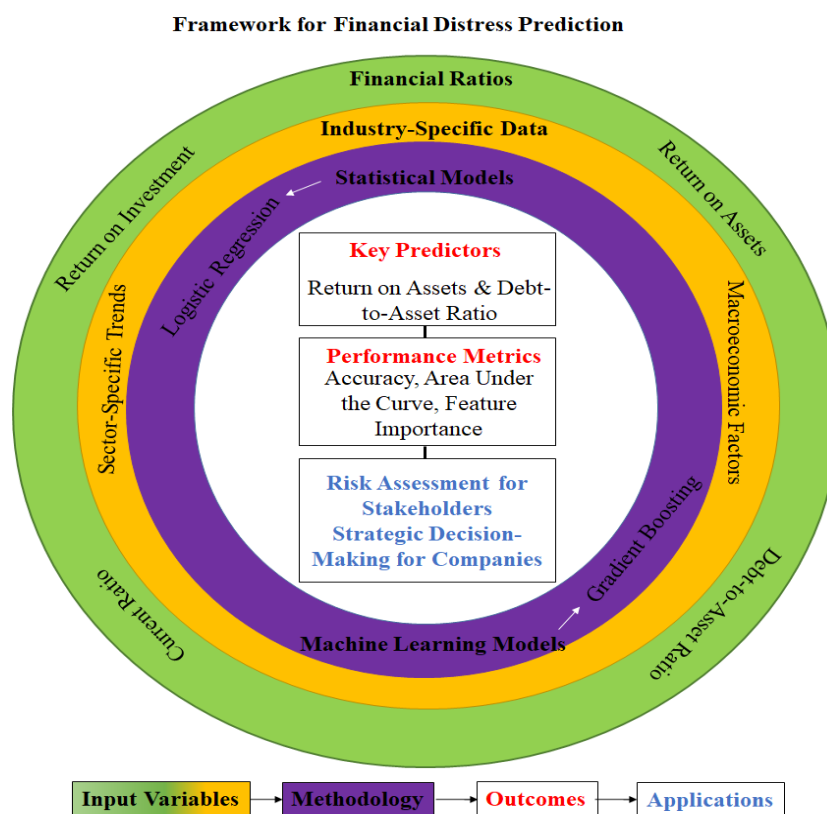
Figure 10. Conceptual framework for financial distress prediction.

5. Discussion

The use of financial ratios to evaluate a company's financial health and predict financial distress has significantly evolved in recent years. This study confirms that cash flow-based financial ratios offer a more accurate measure of financial stability than traditional accrual-based ratios do. Unlike traditional ratios such as return on assets (ROA) and return on equity (ROE), which provide static snapshots of financial performance, cash flow ratios offer a more dynamic perspective on liquidity and solvency. This distinction is particularly

relevant in industries with fluctuating cash flows, where traditional ratios may paint an overly optimistic picture of financial stability (Bhandari and Iyer 2013; Jooste 2007; Kirkham 2012).

Empirical studies consistently show that cash flow ratios are better predictors of financial distress. For example, Bhandari and Iyer (2013) found that cash flow-based measures achieved a 96.8% accuracy rate in predicting business failures, outperforming accrual-based metrics. Similarly, Jooste (2007) demonstrated that the cash flow-to-total debt ratio could provide early warning signals of financial distress up to three years in advance. Further industry-specific studies have reinforced these findings. Ryu and Jang (2004) showed that cash flow ratios assess liquidity in the hospitality industry more accurately than traditional financial ratios. In the telecommunications sector, Kirkham (2012) found that, while traditional financial ratios often overestimate financial stability, cash flow-based measures provide a more realistic assessment.

Despite their high predictive accuracy in many industries, cash flow ratios are not universally superior. In capital-intensive sectors with stable revenue streams, such as utilities and insurance, traditional financial ratios remain reliable indicators of financial health. Meanwhile, in industries where research and development (R&D) and intellectual property investments are critical to financial performance, such as technology and pharmaceuticals, alternative indicators, such as innovation investment and intangible asset valuation, may offer stronger predictive power than either traditional or cash flow-based ratios alone (Dainelli et al. 2024).

A major development in financial distress prediction has been the increasing use of machine learning techniques, which have significantly improved predictive accuracy. Chen et al. (2021) applied hybrid AI models in Taiwan's electronics industry and achieved a 92% prediction accuracy, while Gholampoor and Asadi (2024) reported similarly high accuracy levels in the U.S. healthcare sector using gradient boosting algorithms. Machine learning models are particularly effective in identifying complex, nonlinear relationships among financial variables that traditional statistical models such as logistic regression and discriminant analysis may overlook. In particular, neural networks have demonstrated superior performance in financial forecasting by leveraging intricate data patterns to enhance prediction accuracy (Gregova et al. 2020).

Despite these advantages, machine learning models also present challenges, particularly in terms of transparency and interpretability. Unlike traditional financial models, AI-driven financial distress models often function as "black boxes", which makes it difficult for investors, auditors, and regulators to understand how predictions are made (Chen et al. 2021). This lack of explainability raises ethical concerns, as decision makers may struggle to trust AI-generated financial risk assessments, especially when regulatory oversight is required (Wasserbacher and Spindler 2022). One potential solution to these concerns is the development of hybrid models that combine machine learning with traditional statistical techniques, allowing for enhanced predictive accuracy while maintaining the interpretability required for decision making (Tran et al. 2022; Zhang et al. 2022).

The increasing reliance on AI-driven financial modeling also raises ethical and regulatory concerns. Many AI models rely on historical financial data, which can reinforce systemic biases and disproportionately impact certain industries or firm sizes (Wasserbacher and Spindler 2022). Additionally, the lack of transparency in AI-based financial distress models complicates regulatory oversight, making it difficult for policymakers to ensure fair and unbiased financial risk assessments (Che et al. 2024). In response to these challenges, regulatory frameworks are evolving to address the ethical implications of AI in financial risk assessments. Explainable AI (XAI) frameworks have been developed to improve model transparency while maintaining predictive accuracy (Che et al. 2024).

Regulators also advocate mandatory AI auditing practices to enhance accountability in financial modeling (Li et al. 2021). Future research should focus on integrating ethical AI principles into financial distress models to ensure continued reliability and fairness (Wasserbacher and Spindler 2022).

While firm-level financial indicators remain central to financial distress prediction, macroeconomic factors, such as inflation, interest rates, and broader economic conditions, also play a crucial role. Recent studies indicate that economic downturns significantly increase financial distress risk, particularly for highly leveraged firms (Bayraktar et al. 2024; Che et al. 2024). However, most financial distress models focus primarily on company-specific financial metrics, often neglecting external economic influences. Incorporating macroeconomic indicators into financial distress models could enhance forecasting accuracy because variables such as interest rate fluctuations and inflationary pressures directly impact a firm's ability to meet financial obligations (Li et al. 2021). Given the growing complexity of financial markets, integrating macroeconomic indicators into predictive models is essential to create a more holistic approach to financial distress forecasting.

The effectiveness of financial distress prediction models also varies across industries, emphasizing the need for tailored approaches. Cash flow ratios have been shown to be particularly effective in industries with seasonal cash flow fluctuations, such as hospitality, retail, and healthcare (Ryu and Jang 2004). In contrast, traditional financial ratios remain more applicable in sectors with stable cash flows, such as utilities and insurance. Research suggests that industry-specific factors must be considered when developing financial distress models, as a one-size-fits-all approach may fail to capture the nuances of different business environments (Dainelli et al. 2024).

These findings have important implications for investors, regulators, and corporate decision makers. Investors who rely solely on traditional financial ratios may misjudge a company's financial risk, particularly in industries with volatile cash flow. To improve investment decisions, financial distress models should integrate cash flow-based indicators with traditional valuation techniques (Bhandari and Iyer 2013; Jooste 2007). Regulators should also consider updating financial reporting requirements to ensure that real-time liquidity measures, rather than balance sheet metrics alone, are incorporated into financial health assessments (Li et al. 2021). Regulatory bodies, such as the SEC and financial stability oversight councils, may benefit from mandating the disclosure of cash flow-based financial ratios, particularly for firms operating in high-risk industries (Che et al. 2024). For business leaders, maintaining strong operating cash flows is critical for financial solvency, especially in industries that are vulnerable to economic fluctuations (Bayraktar et al. 2024). The adoption of AI-powered financial risk assessment tools could further enhance decision making by providing early warning signals of financial distress (Wasserbacher and Spindler 2022).

In conclusion, this study confirms that cash flow ratios generally outperform traditional financial ratios in predicting financial distress, particularly when integrated with AI-driven models. However, ethical concerns, macroeconomic factors, and industry-specific variations must be considered to ensure the development of robust and transparent frameworks for predicting financial distress. Future research should focus on refining hybrid models, incorporating macroeconomic indicators, and ensuring AI interpretability to create more effective and reliable financial risk assessment tools for an increasingly complex financial landscape.

6. Conclusions, Limitations, and Future Research

This systematic review evaluates the predictive effectiveness of traditional financial ratios versus cash flow-based ratios, emphasizing their significant role in predicting financial distress. Our analysis synthesizes evidence from various industries and methodologies,

revealing that cash flow-based ratios, such as return on investment (ROI), the current ratio (CR), and the debt-to-asset ratio, consistently demonstrate stronger predictive capabilities. Machine learning methods, notably gradient boosting models, have further enhanced these capabilities by effectively capturing complex, nonlinear relationships between financial variables across diverse industries and datasets, compared to traditional statistical models.

This study underscores the necessity of developing sector-specific financial distress prediction models that acknowledge unique industry characteristics, thus enhancing accuracy and practical utility in risk assessment. Moreover, our findings support the integration of cash flow-based ratios into decision-making processes, particularly in industries characterized by volatile financial conditions and irregular cash flows, such as hospitality, retail, and telecommunications.

Although these findings offer valuable insights into financial distress prediction, it is essential to acknowledge certain limitations to ensure a balanced interpretation. One key constraint is the reliance solely on Scopus and Google Scholar for literature retrieval. Although these databases are widely recognized for their extensive coverage, they do not encompass all relevant studies in the field. Important financial distress research may be indexed in other repositories, such as Web of Science, Social Science Research Network (SSRN), EconLit, and ProQuest, which host high-impact journal articles, working papers, and gray literature that could provide deeper insights. The exclusion of these sources may limit the comprehensiveness of the review and introduce selection bias (Page et al. 2021). Additionally, restricting the review to English-language publications may introduce a selection bias, potentially underrepresenting findings from non-English-speaking economies and emerging markets (Morrison et al. 2012).

Another key limitation is the exclusion of qualitative factors such as corporate governance, macroeconomic indicators, and regulatory frameworks, which prior research has shown to significantly influence financial stability (Bayraktar et al. 2024). Moreover, the inherent nature of systematic literature reviews relying on secondary data limits the quality and current relevance of the findings, constrained by the methodologies and sample sizes of the included studies (Tarquinio 2022). Finally, despite their accuracy, machine learning models pose interpretability challenges and the risk of overfitting, especially with smaller or imbalanced datasets (Bentéjac et al. 2021; Wasserbacher and Spindler 2022).

Building on these limitations, future research should address these gaps by incorporating comprehensive multilingual and gray literature sources, thus mitigating potential biases and increasing global relevance (Booth et al. 2019; Morrison et al. 2012). Future research should consider incorporating a broader range of databases to enhance literature diversity and ensure a more holistic and representative synthesis of financial distress prediction studies. Additionally, expanding predictive models to include qualitative indicators such as corporate governance metrics, macroeconomic trends, and regulatory influences would provide a more holistic framework for predicting financial distress (Che et al. 2024).

A promising avenue for future exploration lies in the development of hybrid models that combine traditional statistical methods (e.g., logistic regression and discriminant analysis) with advanced machine learning techniques (e.g., gradient boosting and deep learning). Such models should leverage explainable AI (XAI) techniques to maintain transparency and enhance interpretability and trustworthiness for stakeholders (Tran et al. 2022; Zhang et al. 2022).

Moreover, future research should emphasize longitudinal studies employing time-series and survival analysis methods to better understand the evolving nature of financial distress indicators over time and capture the impacts of dynamic market conditions and corporate governance changes (Gregova et al. 2020). Industry-specific customization of

predictive models is another promising avenue for addressing sector-specific differences in financial structures and enhancing model relevance and accuracy (Dainelli et al. 2024).

Additionally, there is a significant need to explore the regulatory and policy implications of predicting financial distress. Given the increasing reliance on financial ratios for credit risk assessments, regulatory compliance, and capital market supervision, it is critical to understand how frameworks such as the Basel Accords, IFRS standards, and SEC regulations influence model effectiveness (Li et al. 2021). Policymakers could benefit greatly from integrating predictive financial distress models into regulatory frameworks as proactive early warning systems for financial instability.

Future research should also explicitly explore ethical considerations related to predictive modeling practices, particularly addressing biases inherent in historical financial data and the ethical implications of AI-based financial decision-making tools (Wasserbacher and Spindler 2022). The ethical evaluations of predictive modeling can significantly enhance transparency, accountability, and stakeholder confidence.

Addressing these research avenues will substantially improve the robustness, interpretability, and practical application of financial distress prediction models, ultimately benefiting investors, corporate managers, regulators, and policymakers by equipping them with reliable tools for strategic financial decision making and risk management.

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