

Enhancing Bankruptcy Prediction Accuracy: The Role of Financial and Non-Financial Indicators in the U.S. Capital Market

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Abstract: Corporate bankruptcy prediction is still a very important issue in the United States capital market because of its effects on investors, regulators, and even policymakers. Classical models of financial distress relying on financial ratios like Altman Z-score have presented a useful, but growingly inadequate, insight into the broad-based, multidimensional causes of financial distress in contemporary markets. The research objective is to improve the accuracy of the prediction of bankruptcy through combining financial and non-financial elements in hybrid and AI-oriented models. Among the objectives are the study of predictive model development, scrutiny of governance, Environmental, Social and Governance (ESG), and macroeconomic determinants, and research of best practices and failures in predicting bankruptcy. The case study of Ford Motor Company and Sears Holdings shows differing results: Ford was able to use governance and ESG-based strategies to remain afloat amidst times of crisis, but Sears failed to take advantage of and ignored non-financial indicators and used old financial models to demonstrate its downfall. The results indicate that hybrid models, which integrate quantitative ratios with qualitative and prospective indicators, have better predictive power, improve early warning systems, and mitigate systemic market risk. Finally, the study draws the conclusion that taking the step of combining financial, non-financial, and macroeconomic indicators by using AI-enhanced models is the future of bankruptcy prediction. These multidimensional strategies offer better, more transparent, policy-relevant tools to investors and regulators, to ensure financial stability and sustainable corporations within the United States capital market.

Keywords: Bankruptcy, Prediction Accuracy, Financial Indicators, Non-Financial Indicators, Capital Market.

INTRODUCTION

Corporate bankruptcy prediction is a delicate matter among investors, regulators, and policymakers within the capital market of the United States (Altman, *et al.*, 2019). Besides severe economic losses, bankruptcy destroys the motivation of investors, disorganizes the flow of capital, and makes the market unstable as well (Ghaleb & Kozimjonov, 2024). The literature on bankruptcy prediction has consistently been dominated by financial ratio-based models, the most prominent example of which is the Altman Z-score model, which was created in the late 60s (Laurila, 2020). Though these approaches became the foundation of the quantitative perspective of the distress analysis, they do not achieve the complexity of the corporate failure within the specific financial environment (Kanapickiene, *et al.*, 2023).

Over the last decade, the shortcomings of purely financial models have led researchers to incorporate non-financial indicators into bankruptcy prediction models (Kanapickiene *et al.*, 2023). Financial reporting metrics like leverage, liquidity, and profitability are still vital, and non-financial aspects, including corporate governance framework, management choices, Environmental, Social and Governance (ESG) actions, and industry-specific risks, have been demonstrated to hold incremental predictive strength (Nuraini, *et*

al., 2021). An example is a company that has bad governance and poor ESG, which will be prone to reputational risks, legal exposure, and inefficient operations that make it fast-tracked to financial distress despite reporting strong conventional ratios (Fernando, *et al.*, 2020).

Also, there is importance regarding macroeconomic conditions and the market-based signals. The existing literature emphasizes the importance of external shocks, including the COVID-19 pandemic, changes in interest rates, or a break in supply chains, which can have serious consequences on the solvency of a firm, despite a positive financial performance track record (Gavurova, *et al.*, 2022). This makes it possible to argue that the integration of forward-looking and qualitative signs leads to a better forecasting of bankruptcy in terms of timeliness and reliability.

Newly emerging methodologies play a role in supporting this trend. To process high volumes of data comprising financial statements and non-financial and macroeconomic data, machine learning and artificial intelligence-based models are deployed more frequently (Sharma & Mittal, 2024). This is because such models work better than the conventional statistical approaches in entailing nonlinear associations and dynamic interactions involving variables (Kuster, 2025). Especially the integrations of financial ratios, text-

based information, news sentiment, and governance metrics have proven to be particularly effective in raising prediction accuracy within the U.S. capital markets (Jones, 2017).

To conclude, financial indicators will always be an essential part of bankruptcy prediction, but when combining them with non-financial and macroeconomic effects, predicting accuracy will be significantly better (Knapickiene, *et al.*, 2023). This integrated strategy contention recognizes the intricacy of corporate medical health in modern markets as well as prepares investors, regulators, and policymakers to have a more comprehensive perspective of distress risk (Basiru, *et al.*, 2023). Therefore, the future state of bankruptcy prediction is a paradigm shift of moving past ratio-based procedures to multidimensional and data-driven models, which is representative of the dynamic nature of the U.S. capital market.

LITERATURE REVIEW

Theoretical Framework

Conventional models used in the U.S. capital market to predict bankruptcy have always been centered on the use of financial ratios, but most recent research highlights the need to incorporate the use of non-financial predictors to enhance the prediction accuracy (Altman *et al.*, 2015). This theoretical framework is based on the classical models of financial distress, behavioral and governance models, and the new AI-based models to conceptualize the interaction of financial and non-financial variables in determining the outcomes of bankruptcy (Braunsberger & Aschauer, 2025).

Classical Financial Distress Models.

The basis of successful mechanisms of predicting bankruptcy rests in ratio-based models like the Z-score and O-score models created by Altman and Ohlson, respectively, based on liquidity ratios, profitability ratios, leverage ratios, and solvency ratios, to estimate the default risk. These models are based on financial statement analysis, which presupposes that the worsening of financial ratios is the phenomenon that leads to insolvency. Their simplicity and interpretability have failed to withstand their predictive ability in markets that are dynamic and technologically led. To take one such instance, Altman *et al.* (2017) returned to the Z-score and found that, despite remaining useful, it cannot manage the multidimensional nature of causes of failure in a modern context. In a similar vein, Rowlings (2016) points out that ratio-related models do not focus on future-oriented

information, non-financial signals, and system interdependencies. However, these models are still used extensively because they do not require substantial data and transparency, particularly in regulatory and credit risk settings (Bello, 2023). In such a way, although classical models offer a historical reference point when it comes to predicting distress, they are slowly being complemented by more intricate and sophisticated methods that employ wider information sources to enhance the predictive utility.

Non-Financial Indicators and Organizational Theories

Based on organizational and behavioral theories, non-financial indicators are now considered important indicators of bankruptcy. According to the corporate governance theory, board organization, management expertise, and ownership concentration adjust the firm's robustness to distress. Indicatively, Nugrahan, *et al.*, (2020) demonstrate that when the board is independent and there is a good governance approach, the firm has a low risk of bankruptcy. The institutional theory further introduces that the businesses that occupy weak regulatory environments or within rather corrupt institutions are vulnerable to a greater risk of financial distress, irrespective of financial ratios (Galeazzo, *et al.*, 2024). Still, according to the behavioral finance theory, managerial overconfidence, market sentiment, and consumer trust are also significant contributors to the solvency outcomes (Akin & Akin, 2024). Through non-financial indicators, these items reflect such qualitative elements as corporate culture, performance under ESG, and quality of leadership, which determine long-term sustainability (Esch, *et al.*, 2019). Combined, these organizational and behavioral theories show that numbers alone cannot be used to explain bankruptcies; instead, the reason behind the failure of a company rejects institutional contexts, the wrongful decisions made by managers, and related behavioral biases often play critical roles in corporate failure (Geulen, *et al.*, 2024).

Hybrid and AI-Enhanced Models

More recent developments incorporate both a hybrid and an AI-based approach to combine financial and non-financial metrics. Resource-based view (RBV) promotes the concept of intangible resources as those resources that can be relied upon to predict the long-term existence, including brand reputation, innovation capacity, and ESG performance (Mariani, *et al.*, 2025). Companies that have effective innovation pipelines

and ESG promise their resiliency even during downturns in the financial sector (Deng & Karia, 2025). These multifaceted inputs make researchers resort more to machine learning techniques, including neural networks, ensemble learning, and neuro-structural frameworks in operationalization. The paper by Mahbobi, *et al.*, (2023) shows that structural credit risk models are enhanced with neural networks to capture unobservable factors, such as asset volatility, which provide a better discriminatory factor than classical ratios. Such approaches are consistent with the concept of complexity theory, according to which bankruptcy can be viewed as a result of nonlinear interaction between financial and non-financial variables (Kanapickiene, *et al.*, 2023). Hybrid methods are also more accurate, but the problem is interpretability and transparency of the data (Kovari, 2024). However, as it stands, they are the regime of predictive modeling that allows stakeholders to envisage distress with more accuracy in an ever-evolving market environment.

Systemic Risk and Market Stability Theories

At a macro level, systemic risk theory underscores that the bankruptcies of companies can cause shocks in the capital market, especially in highly connected industries like finance, energy, and technology. Youvan (2024) emphasizes that collapsing major institutions may cause effects of contagion and increase risks throughout the whole financial ecosystem. This highlights the importance of predictive models being applied to protect firm-level solvency, as well as to maintain market stability. According to recent studies, systemic vulnerabilities are strongly correlated with firm-level distress, where regulatory weak signals will be elicited by predictive analytics in regulatory (or operational) early warning systems (Huang, *et al.*, 2024). According to the regulatory adaptation theory, regulators should incorporate state-of-the-art predictive instruments, including AI-driven models, into regulating structures as a way of forecasting risks as they occur (Beckley, 2025). As a method to create connections between firm-specific predictors and macro prudential surveillance, systemic risk models would enable the extension of the prediction of bankruptcy by micro-level managerial use up to financial stability on the level of an entire market, resilience to volatile economic conditions.

Integrated Conceptual Model

This model assumes that the effectiveness of bankruptcy forecasts gets much better in case financial ratios are supplemented with non-

financial indicators, including quality of governance, work of managers, ESGs, and macroeconomic shocks (Ali, *et al.*, 2025). The combination of such different types of data can be achieved with AI-enhanced hybrid models, which enable dynamic and adaptive predictions. As an example, Bork, *et al.*, (2023) show that hybrid systems of combining classic ratios with governance in the traditional capital markets, along with ESG information technologies, are better than single-indicator models. Combined, these aspects give the opportunity to have a multidimensional picture: the financial ratios will shed light on the quantitative indicators of the good financial position, qualitative weaknesses will be identified under the governance and behavioral indicators, and the systemic variables will illuminate how external pressure affects the subject (Hassan, 2023). These factors form a union of accuracy and practical relevance of prediction. Providing an applied perspective, the synthesized conceptual model implicates implications for investors in search of early warning indicators, regulators in the development of preventive frameworks, and firms in an aspiration of deepening resilience measures. The change of approach to a more integrative lens makes bankruptcy prediction no longer a confined accounting-based activity but rather a holistic method of prediction that is consistent with the challenges of modern markets (Celestin, *et al.*, 2025).

Financial Indicators in Bankruptcy Prediction

Bankruptcy predictors are still financially based, and classic ratio-based predictors like Z-score and O-score are the most used ones, being the foundation of the analytical systems. These models focus on profitability, liquidity, leverage, and efficiency ratios, which together indicate the short-term solvency and long-term financial sustainability of a firm. However, recent studies have shown that although such models can still be useful, they have been enhanced considerably by machine learning techniques. Sabek (2023) has found that neural networks using financial ratios obtained higher predictive accuracy than traditional logistic regression models since they apprehend nonlinear interactions among financial variables. On the same matter, Jones (2023) also discovered that cash flow ratios and leverage are the most prevalent predictors of bankruptcy risk among U.S firms.

There are two long-term outcomes of using financial indicators (Iacuzzi, 2022). On the one hand, they bring in standardized and measurable

metrics to the investors, regulators, and creditors, and hence enhance transparency in capital markets. Alternatively, excessive dependence on past financial information leads to the problem of underestimating systemic vulnerabilities, specifically in times of crisis when non-financial shocks cause insolvencies (Gowen, 2023). However, financial ratios keep influencing credit risk modeling, investment policy that remains stable in the capital markets, and promoting methodological new approaches to overcome predictive weaknesses (Francisca, 2025).

Non-Financial Indicators in Bankruptcy Prediction

Non-financial indicators in recent years have become a significant factor in the predictability of corporate bankruptcy. Prediction models are becoming increasingly intertwined with governance and executive compensation structures, ESG (Environmental, Social, and Governance) scores, and managerial quality (Fernando, *et al.*, 2020). Yahya, *et al.*, (2025) indicated that the quality of governance is positively correlated with bankruptcy risk, noting that the maintainability of firms in the lean periods is high when the quality of governance is transparent and there is an independent board. On the same note, Fernando, *et al.*, (2020) also identified ESG disclosures and environmental controversies as proactive indicators of financial distress. In addition to governance and ESG, news-based sentiment analysis and analyst reports, and social media have proven to be a strong distress signal, and, according to Hansen & Borch (2022), negative sentiment is a predictor of financial ruin.

The capital market in the US is greatly affected in the long run by the implementation of non-financial indicators (Ombai, *et al.*, 2024). The broadening of quantitative financial metrics into reputational risks, ethical conduct, and trust aspects of the institution inherent in markets will make them ideal elements for capturing and attracting sustainable investment (Emma, 2024). Additionally, the focus on ESG is consistent with the global trends of responsible finance, moving capital flows towards companies that have sustainable practices. This not only increases predictive accuracy but also leads to a state of market stability because corporations are more motivated to be accountable and tolerant of risks associated with environmental, social, and governance.

Integrated Approaches

Integrated methods are the innovation in bankruptcy prediction through more complex integration of both financial and non-financial metrics in the framework of sophisticated machine learning algorithms (Kuster, 2025). Sun, *et al.*, (2024) have shown that hybrid models that use financial ratios, data on governance, and macroeconomic indicator data will do much better than single-dimensional ones. The algorithms used in such methods include random forests, support vector machines, and ensemble methods that represent complex nonlinear relationships among various variables (Kyriazos & Poga, 2024). With integration, it is also possible to include real-time data streams such as macroeconomic shocks and market sentiment and make early warning systems timelier (Kovari, 2024).

Integrated models have a transformational long-term impact on capital markets (Oyeyipo, *et al.*, 2023). These models promote a certain level of confidence in the investors, decrease the existence of asymmetric information, and enable regulatory actions taken by the regulators before the point of distress transitions into systemic crises (Dugbartey, 2025). In addition, holistic solutions facilitate the multidimensional perspective of firm health that pays an equal amount of attention to the quantitative financial solvency and the qualitative aspects of governance and ESG (Deng & Karia, 2025). This broader framework will make the capital allocation more effective, as it will allocate funds to more resilient companies and avoid tension in terms of exposure to their weak counterparts. In the long term, the predictive systems could deepen the resilience of the U.S. capital market, ensure sustainable growth, and minimize systemic volatility with the prevalence of integrated predictive systems (Francisca, 2025).

Transformation of AI and Machine Learning

The use of Artificial Intelligence and Machine Learning transformed the predictability of bankruptcies as it allows more data-driven insights, which exceed the drawbacks offered by the conventional financial models (Olubusola, *et al.*, 2024). Technology can use bulk amounts of structured and unstructured data, such as financial reports, trends on the market, and social media sentiment, along with macroeconomic indicators, to identify subtle patterns and correlations that could indicate financial distress (Amin, *et al.*, 2024). Neural networks, support vector machines, and ensemble learning, among other approaches, have been proven to be superior in detecting early

warning features of bankruptcy that also capture nonlinear behavior characteristics that conventional models are unable to identify (Zhao, *et al.*, 2024). Literature findings showed that machine learning models are constantly being improved as new data is fed to the models, increasing the model's prediction accuracy in the long run. This not only enhances risk management to investors and regulators but also provides tools for companies to be proactive in dealing with potential weaknesses before they become critical (Oko-Odion & Angela, 2025).

Predictive methods for assessing bankruptcy safety

Models that mix financial ratios with statistical techniques have been developed to boost the prediction of bankruptcy.

Altman's Z-Score Model

Bankruptcy prediction is a popular and well-known area in the finance field. In 1968, Altman created the Z-score, which has become popular to determine a company's risk. This model anticipates the risk of an enterprise going bankrupt within two years through five financial ratios. Ratios used are working capital to total assets, retained earnings to total assets, earnings before interest and tax (EBIT) to total assets, market value of equity to total liabilities, and sales to total assets. For instance, banks will flag a company as at high risk for bankruptcy if its Z-score is below -1.8, and scores above 3 are considered safe. While it was very useful, the standard model was created for manufacturing firms only, so alternative versions such as Altman's Z-Score were introduced for more general use (Martins, 2024).

Ohlson's O-Score Model

In 1980, the O-score was created through logistic regression, as opposed to the Z-score, which uses the regression model. Besides using financial measures, this approach also includes a company's size and liquidity, giving a more approximate than zero-definite view of possible bankruptcy (Lisin, *et al.*, 2022).

Logit and Probit Models

Applications for logit and probit models have also appeared in bankruptcy prediction. By studying financial information, companies estimate the risk of failure by considering several factors together. These traditional models are efficient and are unable to fully account for the relationships that occur among financial variables (Jones, *et al.*, 2017).

The business of financial forecasting in the U.S. has witnessed a phenomenal transformation from traditional to the use of Artificial Intelligence and Machine Learning. This shift reflects a more general trend towards digitization and progress in the financial world, which has transformed the way everybody makes financial decisions and analyzes finance (Shetty, *et al.*, 2022). Financial prediction has been mainly based on qualitative judgment, a limited amount of data, and expert judgment. Analysts have, in most cases, used fundamental and technical analyses, which review financial statements and market trends to try to predict future financial performance. But, since the dawn of artificial intelligence and machine learning, there has been a fundamental shift in the field. Such technologies enable us to process huge datasets and to use advanced algorithms to see deeper into the subject and discover complex patterns (Bhatt & Singh, 2023).

TYPES OF U.S. CORPORATE BANKRUPTCY LAWS AND PROCESSES

Liquidation Bankruptcy

The U.S. Chapter 7 liquidation bankruptcy consists of the sale of assets of a firm to pay creditors in case of the impossibility of reorganization (Yu & He, 2018). Although it guarantees payments to creditors, it can frequently result in loss of employment and economic recession of the region (Wang, 2021).

Reorganization Bankruptcy

Under Chapter 11, reorganization bankruptcy allows companies to readjust debts with continued operations (Bradley, 2020). This is a process that maintains business value, keeps down the number of layoffs, and ensures economic stability (Broude, 2025).

Pre-Packaged Bankruptcy

The pre-packaged bankruptcy consists of an out-of-court creditor agreement with official filing; this saves time and expenses (Gurrea-Martinez, 2023). It has become popular, particularly in industries that are capital-intensive, because the method is efficient (Hampson & Katz, 2024).

Cross-Border Bankruptcy

Chapter 15 of the U.S. regulates cross-border bankruptcy, which coordinates with the aim of avoiding conflicting cases (Das, 2020). It has become more crucial because international corporations are in financial distress in various jurisdictions (Cavallini & Gaboardi, 2023).

Current Application of Corporate Bankruptcy Laws.

The bankruptcy laws in the United States have been adjusted in a manner to provide balance to repayment of creditors, recovery of debtors, and systemic stability (Hampson & Katz, 2024). The new legislation, like the Small Business Reorganization Act of 2019, draws attention to utilizing reorganization frameworks to become more current (Broude, 2025).

Moreover, the US laws on bankruptcy have given a methodical legal system that regulates the way individuals and corporations are treated concerning insolvency and financial distress. The United States Bankruptcy Code under Title 11 of the United States Code is the leading law that governs corporate bankruptcy, which is presided over by the federal bankruptcy courts. The two most relevant chapters to corporate entities are Chapter 7 (liquidation) and Chapter 11 (reorganization) (Skeel & Triantis, 2018).

Chapter 7 bankruptcy is the liquidation of the assets of a firm to settle the creditors, which usually ends the existence of the firm. It is an ongoing process that is regulated by a court-appointed trustee who sells the non-exempt assets and allocates the proceeds to secured and unsecured creditors in line with priority regulations established by law (Seymour, 2022). Conversely, Chapter 11 bankruptcy permits companies to reorganize the debt but continue operations. Under the form of a debtor in possession, the debtor can remain in control of the company but will be required to consult with sound advice with the court regarding significant financial decisions such as restructuring efforts and asset sales (Triantis, 2020).

The recent reforms and interpretations of the law have transformed the practice of bankruptcy in the U.S. An example of this is the Small Business Reorganization Act (SBRA) of 2019, which created Subchapter V of Chapter 11 to streamline the processes of small businesses (Hotchkiss, *et al.*, 2023). Similarly, temporary proposals provided by the CARES Act (i.e., under new Subchapter V) to address the COVID-19 pandemic demonstrate how regulations can be modified, depending on the situation (Casey, 2021). These changes demonstrate how bankruptcy laws try to adapt to economic crises and systemic risks.

The procedure starts with the voluntary filing of a bankruptcy petition by a debtor or, in some rare

instances, begins with the filing of an involuntary petition by the creditors. In its occurrence, the filing means that most forms of collection efforts are automatically stayed, and assets of the debtor are safeguarded, which also enables discussion of reorganization proceedings (Hunter & Shannon, 2020; Kraemer, 2024). Chapter 11 has a reorganization plan proposed by the debtor, which must go through the creditors and be confirmed by the court. Without ensuring that a good plan can be made, they could be converted to Chapter 7 liquidation (Shekhar, 2025).

The United States is remarkable with its debtor-supportive dynamics, especially the goal of flexibility under Chapter 11 that ensures the going-concern value and job protection (Gurrea-Martinez, 2023). Criticisms are, however, that high costs and complexity of the procedure favor the larger companies, which prompts questions of efficiency and equity (Alle, 2021). Despite these struggles, the U.S. bankruptcy system helps ensure stability in the capital markets, whether this is through a predictable way of solving debts and reallocating resources (Francisca, 2025).

CHALLENGES AND FUTURE TRENDS

Challenges

A major concern in predicting bankruptcy is the tradeoff between the accuracy and interpretability of models and the availability of data. Conventional financial models involving the use of financial ratios will still be encircled within dynamic markets where intangible assets and macro-economic shocks are the dominant drivers of insolvency risks (Altman, *et al.*, 2017). Incorporating non-financial metrics like ESG reports, quality of governance, and sentiment data is rather prospective and made difficult by inconsistent disclosures and standards (Dimitropoulos & Chatzigianni, 2022). Furthermore, even with powerful machine learning models, they have black box problems that decrease transparency among regulators and investors (Hassija, *et al.*, 2024). These issues highlight the multi-faceted nature of creating resilient, trustworthy, and extensively deployable systems for predicting bankruptcy in the U.S. capital market.

Future Trends

Further developments of bankruptcy prediction can be highlighted with the implementation of a hybrid model that combines financial ratios, non-financial indicators, and AI-based analytics. Such sophisticated machine learning algorithms as deep

learning or ensemble models will likely be able to handle nonlinear interactions and increase the accuracy of prediction (Alvi, *et al.*, 2024). Increased significance of ESG data and governance data will influence comprehensive risk models, which will associate corporate sustainability with default risks (Dimitropoulos & Chatzigianni, 2022). Also, the authorities engaged in controlling risk, like the Federal Reserve, are studying predictive analytics to improve the monitoring of systemic risks (Dugbartey, 2025). The above developments have indicated a future in which bankruptcy prediction becomes a multidimensional, transparent, and policy-relevant instrument to investors and regulators.

CASE STUDIES

Best Practice: Ford Motor Company (2019–2021)

Ford Motor Company presents a good example of how effective managing bankruptcy risks can be achieved by considering both financial and non-financial indicators. Although Ford had a liquidity crisis during the COVID-19 crisis, the company used its good ESG performance, proactive governance frameworks, and vital refinancing to sustain its solvency (Kurtz, *et al.*, 2023; Shem & Mupa, 2024). Analysts observed that timeliness in restructuring decisions, clear objectives and disclosures, plus confidence of markets towards sustainability initiatives raised by Ford greatly decreased the likelihood of default relative to that of peers (Bremser, *et al.*, 2022). The case will present how the hybrid models that use financial ratios in addition to governance and ESG measures can be used to determine strategic considerations at a company level and investor trust (Prencipe, 2024).

Failed Practice: Sears Holdings (2015–2018)

Instead, Sears Holdings signifies the drawback of the high reliance on the conventional models of financial ratios and the neglect of the non-financial indicators (Harris, *et al.*, 2019). Despite indicators of financial distress due to reduced sales and worsening liquidity ratios, the company underestimated the consequences of the lack of proper corporate governance, ineffective innovation strategy, and negative brand reputation development (Manodamrongsat, *et al.*, 2019; Jouali, *et al.*, 2024). In 2018, the bankruptcies of companies revealed that predictive models based solely on balance-sheet indicators could not identify the non-financial vulnerability of the system in other parts that caused accelerated

collapse (Taskinsoy, 2020; Breuer & Mersmann, 2025). The Sears case underscores the fact that integrated models that incorporate tangible and intangible drivers of corporate distress are needed.

RESEARCH GAPS

Despite the body of work studied on bankruptcy prediction, there are still important gaps in the combination of financial and non-financial metrics. The conventional ratio-based models are good at providing benchmarks that are reliable but do not capture qualitative variables like the quality of governance, competence of the managers, and the performance of ESP (Altman, *et al.*, 2017; Fernando, *et al.*, 2020). In contrast to that, non-financial-based literature emphasizes the importance of organization-focused and behavior-based characteristics but is not adequately validated by industries and economic cycles (Galeazzo, *et al.*, 2024). Even though new hybrid and AI-based models have higher accuracy, there are still difficulties in the transparency of data, understanding of information, and inter-firm generalization (Mahbobi, *et al.*, 2023; Kovari, 2024). Besides, most of the literature addresses the issue of individual firm-level distress without adequate consideration of systemic risk, as well as macroeconomic shocks, which gain growing importance as drivers of insolvencies in globalized markets (Youvan, 2024). Case studies also present less empirical testing of common models in successful and unsuccessful practices, as well as gaps in comparative evidence to apply the policies and regulations.

DISCUSSION & FINDINGS

As pointed out in the review, financial ratios like liquidity, leverage, or profitability are still important in bankruptcy prediction, but need to be framed in larger non-financial and macroeconomic contexts. Results show that corporate governance framework, ESG commitments, and managerial behavior have a strong impact on corporate resilience, and firms with more institutionalized governance and sustainable business conduct are less prone to default (Nugrahanti, *et al.*, 2020; Zhou, *et al.*, 2022) (Table 1). Classical models are worse in performance than hybrids and AI-driven models since the models offer insight into nonlinear interactions and include the current data, like sentiment and shocks in the marketplace (Sharma and Mittal, 2024). Analysis of the case further substantiates these results: the strategic application of governance and ESG performance allowed Ford to reduce the risk of bankruptcy,

whereas Sears was unable to maintain stability due to the disregard of the non-financial role (Bremser,

et al., 2022; Harris, et al., 2019).

Table 1: Types of nonfinancial information included in the study

TABLE 1 Types of Nonfinancial Information Included in the Study		
Economic Performance and Sustainability	Governance	Social
Market Share	Independence Standards	Workforce Retention
Quality Rankings	Board Selection Processes	Diversity Information
Customer Satisfaction Survey Data	Executive Compensation	Health and Safety Record/ Industry Metrics
Employee Satisfaction Data Metrics	Employee Training/Human Capital Development	Supply Chain Practices
Turnover Data	Change of Control Procedures	Human Rights Information
Innovation Data	Audit Processes	Humanitarian Initiatives
Other	Ethics Guidelines	Customer Satisfaction or Product Safety Information
	Management Systems	Community Relations Information
	Adoption of Balanced Scorecard/JIT/TQM	Political Giving/Lobbying/ Related
	Other	Environmental Ratings
		Environmental Programs
		Other

Source: Cohen, et al., (2011).

This conveyed the conclusion that integrated prediction models are more comprehensive in terms of giving early-warning systems and actionable information to investors and regulators. Moreover, the concept of systemic risk argues that predictive instruments must be modified to more interconnected markets rather than become limited to the firm level in estimating their effects on the market (Huang et al., 2024). Overall, the results indicate that multidimensional, data-driven models would increase the level of accuracy, enhance market stability, and perform well, keeping pace with the changing dynamics of the capital markets in the United States.

CONCLUSION

It is concluded that to improve the predictive powers of bankruptcy, a new paradigm shift is necessary where traditional ratio-based methods will be replaced by multidimensional models. Financial indicators are still relevant, but they are deficient by themselves to reflect the complexity of contemporary corporate failures. The inclusion of non-finance variables, such as the quality of governance, decisions made by the managers, and the performance of ESG, is also predictive with great success, especially when connected to the

macroeconomic and market-based signals. This conclusion is supported by case studies of Ford and Sears, which show that integrated frameworks help reduce risk, and old-fashioned, purely financial models cannot stop a collapse. Aggregating AI-promising hybrid models, which are the future of bankruptcy prediction, provide powerful computational tools to detect early symptoms of distress and facilitate corporate strategy and regulatory supervision. Through holistic solutions, the stakeholders will be able to enhance financial stability, investor confidence, and sustainability in the U.S. capital market and, as a result, increase resilience to systemic and firm-level shocks.

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