"Hybrid bankruptcy forecasting for Indian firms: Integrating financial ratios, macroeconomic indicators, and random forest"

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HYBRID BANKRUPTCY FORECASTING FOR INDIAN FIRMS: INTEGRATING FINANCIAL RATIOS, MACROECONOMIC INDICATORS, AND RANDOM FOREST

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Abstract

Bankruptcy forecasting in emerging markets is complicated by macroeconomic and regulatory volatility. This study evaluates whether a hybrid model that integrates firm financial ratios, macro indicators, and a Random Forest classifier outperforms traditional ratio-only approaches for Indian firms. Each bankrupt company is analyzed over a five-year window preceding its actual failure date, resulting in ten bankrupt firms paired with ten matched healthy peers. Using these firm-specific five-year pre-bankruptcy panels, we estimate logistic regression and Random Forest models with stratified 5-fold cross-validation and derive a parsimonious four-factor risk score.

Relative to ratio-only baselines, the hybrid design improves accuracy from 0.76→0.80 (logit) and 0.82→0.86 (Random Forest), and lifts the Area Under the ROC Curve (AUC) from 0.70→0.78, indicating that the model correctly ranks a bankrupt firm as riskier than a healthy firm 78% of the time. Debt-to-Equity, Current Ratio, Net Profit Margin, and GDP Growth dominate feature importance, and rising risk scores typically cross ~0.40 two to three years before failure.

Robustness checks, including alternative class-balance weights, sector dummies, and rolling-window estimation, yield comparable gains and stable feature rankings. The resulting bankruptcy Early-Warning System (EWS) is transparent, portfolio-scalable, and easily embedded into bank risk dashboards. The evidence shows that multidimensional hybrid models provide earlier and more reliable warnings than ratio-based formulas, offering practical value to lenders, investors, and regulators in volatile settings.

Keywords bankruptcy, insolvency, random forest, risk, emerging markets

JEL Classification G33, C53

INTRODUCTION

Predicting corporate bankruptcy is a critical concern for emerging economies, where financial markets are often shaped by institutional volatility and regulatory fragmentation. India – one of the most dynamic yet turbulent emerging markets – has witnessed multiple high-profile corporate failures in recent years, ranging from financial institutions and airlines to infrastructure and steel firms. These events carry significant systemic implications, affecting investor confidence, employment, and credit allocation (Sengupta & Vardhan, 2020).

Traditional models of bankruptcy prediction, such as Altman's Z-score (1968), rely predominantly on static financial ratios. While these approaches proved effective in relatively stable environments, they struggle in economies characterized by policy shifts, currency volatility, and sectoral shocks. Their limitations become more ap-

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parent where governance transparency is inconsistent and qualitative indicators – such as auditor resignations or regulatory sanctions – signal deeper distress (Beaver, 1966; Dimitras et al., 1996; Jackson & Wood, 2013).

The global financial crisis of 2008 further exposed the shortcomings of conventional approaches, spurring the development of increasingly sophisticated tools (Shi & Li, 2019). Over the past two decades, research has expanded from statistical models to machine-learning and hybrid frameworks, each seeking to capture nonlinear dynamics and enhance predictive accuracy (Balcaen & Ooghe, 2006; Sun et al., 2014). Despite these advances, existing models often remain inadequate in volatile emerging-market settings, where macroeconomic instability, governance failures, and regulatory interventions play decisive roles in shaping financial fragility (Sengupta & Vardhan, 2020).

The scientific problem addressed here is that conventional, ratio-based models fail to capture the combined influence of firm-level deterioration, macroeconomic turbulence, and qualitative governance signals in emerging economies. This gap underscores the need for predictive frameworks that systematically integrate financial, macroeconomic, and institutional dimensions while maintaining interpretability.

1. LITERATURE REVIEW

Research on corporate failure spans finance, accounting, and data science, yet it lacks a single, consensual definition of "bankruptcy" or "financial distress." Legal perspectives emphasize insolvency proceedings, while empirical work often proxies distress with deteriorations in solvency, liquidity, profitability, or default events. An influential strand treats distress as a continuum rather than a binary state, complicating cross-study comparability (Beaver, 1966; Bruynseels & Willekens, 2012; Dimitras et al., 1996; Jackson & Wood, 2013; Ross et al., 1999; Sun et al., 2014). This definitional ambiguity motivates models that can flexibly accommodate multiple manifestations of distress across institutional settings.

Early analytical frameworks focused on firm-level ratios and linear classifiers. Altman's Z-score (1968) introduced multivariate discriminant analysis, employing logistic regression with size and transparency controls. Subsequent refinements included probit models, hazard functions, and modified MDA (Balcaen & Ooghe, 2006; Hillegeist et al., 2004). Logistic regression remains attractive for interpretability (Shi & Li, 2019), yet traditional ratio-based designs often struggle with multicollinearity, linearity constraints, and limited ability to model interactions.

From the 1990s onward, more flexible computational approaches broadened the toolkit: neural networks captured nonlinearities (Tam & Kiang, 1992; Fletcher & Goss, 1993; Wilson & Sharda, 1994; Lee et al., 1996; Kim, 2011), support vector machines offered margin-based classification and imbalance handling (Min & Lee, 2005; Chandra et al., 2010), and tree-based and ensemble techniques – including random forest models – provided robustness and feature-importance diagnostics (Lin et al., 2011; Wang & Wu, 2017). These methods typically improve accuracy but may trade off transparency and require larger, high-quality datasets, limiting adoption by practitioners and regulators.

To reconcile predictive performance with explainability, hybrid designs combine statistical models, computational learners, and richer covariate sets. Early work integrated case-based reasoning and data-mining approaches (Sun & Li, 2008). Later studies showed that adding macroeconomic factors improves stability under turbulence, with macro-augmented ensemble models reporting AUC values at or above ~0.80 (Mai et al., 2019; Mwachikoka et al., 2025). The literature increasingly favors parsimonious, interpretable hybrids that still capture key nonlinear dynamics.

Transferring such models to emerging markets is nontrivial. Structural volatility, regulatory shifts, and governance opacity alter distress pathways and weaken out-of-sample reliability. In India, reforms and shocks – such as the Real Estate (Regulation and Development) Act, the Insolvency and Bankruptcy Code, commodity cycles, and the IL&FS-linked NBFC liquidity stress – have shaped firm fragil-

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ity and model performance (Sengupta & Vardhan, 2020). Complementary evidence emphasizes the role of ownership structures, bank intermediation, and governance warning signals (Korol & Korodi, 2011). These findings argue for country-sensitive frameworks that integrate firm ratios, macro conditions, and institutional/governance flags.

Across five decades, the field has moved from ratio-based linear models to hybrid macro-financial architectures. Yet three gaps remain:

(1) limited contextualization for volatile, regulation-intensive environments;

(2) difficulty capturing interactions between firm fundamentals and macro shocks;

(3) lack of interpretable outputs suitable for decision-making in practice.

Addressing these gaps requires a hybrid, parsimonious, and transparent design that combines firm-level deterioration with macroeconomic conditions and observable governance warnings – particularly salient in India.

In sum, classical ratio-only models are interpretable but fragile under turbulence, whereas computational models increase discrimination at the expense of transparency. Hybrid approaches that fuse ratios with macroeconomic indicators – and, where feasible, governance signals – consistently outperform ratio-only baselines while remaining usable by practitioners (Sun & Li, 2008; Mai et al., 2019; Mwachikoka et al., 2025). In India's high-volatility context, such hybrids are theoretically and empirically warranted (Sengupta & Vardhan, 2020).

2. AIM

The present study, therefore, evaluates whether, in the Indian context, a hybrid model integrating firm financial ratios with macroeconomic indicators and random forest classifiers yields earlier and more reliable bankruptcy warnings than ratio-only baselines, while preserving interpretability for decision-makers. Distress risk is conceptualized as a function of leverage (positive association), liquidity (negative), and profitability (negative), moderated by macroeconomic pressures (GDP growth negative; inflation/interest-rate pressure positive) and accompanied by governance red flags (auditor resignations, abrupt board turnover) (Campbell et al., 2008).

The study formulates the following hypotheses to empirically test the proposed hybrid framework in the Indian context:

H1: *Leverage, liquidity, and profitability ratios are significant predictors of bankruptcy for Indian firms.*

H2: *Adding macroeconomic indicators to firm ratios improves predictive accuracy and discrimination.*

H3: *Incorporating governance warning signs (e.g., auditor resignations, board exits, regulatory sanctions) enhances predictive power.*

H4: *A hybrid specification (logit + random forest; ratios + macro [+ governance dummies]) outperforms ratio-only baselines on accuracy and AUC.*

3. METHODS

The study employs a matched-pair design that includes ten publicly listed Indian firms that filed for bankruptcy between 2012 and 2019, with each bankrupt firm observed over the five-year window immediately preceding its failure, and ten sector-matched healthy peers selected based on comparable revenue size, market exposure, and operational scope, yielding 20 firms and a total of 100 firm-year observations. Firms span housing finance, telecommunications, aviation, infrastructure, and steel. Financial data were collected from audited annual reports, Bloomberg, and the CMIE Prowess database. Macroeconomic indicators (GDP growth, inflation, and policy rates) were sourced from the International Monetary Fund (2022) and CEIC Data. Sector-specific disruptions such as regulatory shocks or major market entries were identified using archival news and policy reports. This ensures that the primary data for calculations derive directly from audited financial statements and reliable secondary databases, making the study replicable and transparent. To ensure reproducibility, the compiled dataset has been deposited in Mendeley Data (Bonelli, 2025).

In addition to structured datasets, company disclosures and contemporaneous financial press were reviewed to flag governance warning signs such as auditor resignations, abrupt CEO or board-level departures, persistent stock price volatility, or governance failures. Because these archival items are not systematically curated, they are not cited individually and are used as corroborative evidence in the case analyses rather than as primary quantitative predictors.

Three families of predictors are incorporated. First, firm-level financial ratios capture liquidity, leverage, solvency, and profitability: Current Ratio, Quick Ratio, Debt-to-Equity, Interest Coverage, Return on Assets, Return on Equity, and Net Profit Margin (Beaver, 1966; Campbell et al., 2008). Second, macroeconomic indicators – annual GDP growth, inflation (CPI), and central bank policy rates – reflect the broader economic environment. Third, qualitative governance red flags provide contextual evidence of distress. Collectively, these variables operationalize the conceptual model in which bankruptcy risk is driven by leverage (positive association), liquidity (negative), profitability (negative), macroeconomic conditions (GDP growth negative; inflation/interest-rate pressure positive), and governance warnings (positive).

This workflow proceeds sequentially: (i) data ingestion from audited statements and databases; (ii) construction of matched bankrupt–healthy pairs; (iii) computation of financial ratios, extraction of macroeconomic series, and coding of governance warnings; (iv) descriptive longitudinal analysis of financial deterioration; (v) predictive modeling using logistic regression and random forest classification; and (vi) derivation and validation of an interpretable four-factor bankruptcy risk score through stratified five-fold cross-validation.

As an initial diagnostic step, we compare the average financial profiles of bankrupt and healthy firms over their five-year pre-bankruptcy windows.

The group means and t-tests are reported in Table 1 and confirm that bankrupt firms exhibit significantly higher leverage and lower liquidity and profitability (all $p < .05$).

Table 1. Group means and t-tests (five-year pre-bankruptcy window)

Variable	Bankrupt Firms	Healthy Firms	t-test (p-value)
DebttoEquity	3.42	1.85	< .01
Current Ratio	0.71	1.25	< .05
ROA (%)	–4.3	2.10	< .05
Profit Marg. (%)	–7.1	4.80	< .05
Interest Coverage	0.62	2.35	< .01

Note: Values are five-year averages prior to bankruptcy. t-tests show significant differences in leverage, liquidity, profitability, and solvency between bankrupt and healthy firms.

Logistic regression serves as the baseline, providing signs and significance of predictors, while a random forest captures nonlinearities, interactions, and feature importance. Neural networks were preliminarily explored but excluded from the final model due to marginal performance gains and reduced interpretability. Models are evaluated with accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC). The artificial-intelligence component of this study is limited to applying machine-learning algorithms for empirical modeling and validation; generative AI tools (ChatGPT) were used for language editing, with all data collection, modeling, and interpretation conducted by the author.

To translate model outputs into an actionable early-warning signal, the study introduces a continuous bankruptcy risk score derived from the four most influential predictors identified by the random forest: Debt-to-Equity (weight 0.35), Current Ratio (0.30), GDP Growth (0.20), and Net Profit Margin (0.15). Each metric is min–max normalized to [0, 1], where higher values indicate stronger financial health. To express risk directly, normalized values are inverted and aggregated by weights. The resulting score for firm *i* is calculated as follows:

$$\begin{aligned} Risk\ Score &= 0.35\cdot\left(1 - Norm\ Debt\text{-}to\text{-}Equity\right) \\ &+0.30\cdot\left(1 - Norm\ Current\ Ratio\right) \\ &+0.20\cdot\left(1 - Norm\ GDP\ Growth\right) \\ &+0.15\cdot\left(1 - Norm\ Net\ Profit\ Margin\right). \end{aligned} \tag{1}$$

or equivalently:

$$Risk\ Score = \sum\left(w_i\cdot\left(1 - Norm_i\right)\right). \tag{2}$$

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Scores near 1 indicate elevated bankruptcy risk, while values near 0 signal stability. In Eq. (1), each "Norm" term denotes min–max normalization to [0, 1] with higher values indicating stronger financial health; the inversion (*1 – Norm X*) converts each component into a risk contribution. These scores are computed for every firm-year to track the buildup of distress. Consistent with the aim defined at the end of the literature review, this methodological design operationalizes the four hypotheses and prepares the ground for empirical validation, reported in the next section on results.

4. RESULTS

This section reports firm-level evidence for ten companies, with detailed analyses for DHFL and RCom. For each firm, financial deterioration is examined across the five-year window immediately preceding its bankruptcy filing, consistent with the methodological framework.

DHFL's leverage increased substantially, with the Debt-to-Equity Ratio rising from 6.1 in 2015 to 10.5 in 2019 (Author's calculations from Bloomberg and DHFL Annual Reports). Liquidity deteriorated as the Current Ratio fell from 1.2 to 0.7 over the same period (Author's calculations from Bloomberg and DHFL Annual Reports). Profitability weakened: ROA declined from 1.5% to –0.3%, while Net Profit Margin dropped from 12.3% to –2.1% (Author's calculations from CMIE Prowess). Solvency risk intensified as the Interest Coverage Ratio fell below 1.0 (Author's calculations from Bloomberg). Between 2015 and 2019, India's GDP growth declined from 8.0% to 3.9%, and the 2018 IL&FS crisis increased liquidity pressures across the non-banking financial sector (Sengupta & Vardhan, 2020). Several qualitative warning signs were observed, including auditor resignations, public allegations of fund diversion, and reports of operational issues (Author's compilation). In peer comparison, HDFC Ltd. maintained a Debt-to-Equity Ratio below 5.0, a Current Ratio above 1.2, and Net Profit Margins exceeding 15% throughout the observation period (HDFC Ltd. Annual Reports; Author's calculations). The random forest model achieved 87% accuracy, 85% precision, 88% recall, and an F1-score of 86.4%; the most influential predictors included the Debt-to-Equity Ratio, Current Ratio, and GDP Growth Rate (Author's computation). The predicted probabilities and classification outcomes for DHFL are reported in Table 2.

Table 2. DHFL bankruptcy probability (2015–2019)

Year	Status	Probability	Outcome
2015	Going Concern	0.42	Low Risk
2016	Going Concern	0.55	Moderate Risk
2017	Going Concern	0.71	High Risk
2018	Distress	0.89	High Risk
2019	Bankrupt	0.94	High Risk

Note: Predicted probabilities and outcomes from the random forest model with stratified 5-fold cross-validation; firm-level and macroeconomic predictors as specified in the methodology.

Using the risk score methodology described in the Methods, DHFL's bankruptcy risk score rose from 0.36 in 2016 to 0.40 in 2017, calculated from the weighted normalized scores of the four key predictors (Debt-to-Equity increased from 0.63 to 0.66; Current Ratio declined from 0.71 to 0.68; GDP Growth slowed from 0.59 to 0.58; Net Profit Margin moved from 0.62 to 0.61).

For Reliance Communications (RCom), Debt-to-Equity rose from 1.7 in 2015 to 3.0 by 2018, before collapsing to –0.8 in 2019 (Author's calculations from Bloomberg and RCom Annual Reports). The Current Ratio declined from 0.8 to 0.5 (CMIE Prowess). ROA fell from 0.8% to –4.6%, and Net Profit Margin from –0.7% to –17.1% by 2018, with a temporary rebound to 3.5% in 2019 due to one-off asset sales (Author's calculations from Bloomberg). Interest Coverage turned negative (CMIE Prowess). The 2016 entry of Reliance Jio triggered an industry-wide tariff adjustment with broad revenue impacts (Sengupta & Vardhan, 2020; Author's compilation from TRAI and CEIC Data). Escalating legal disputes, asset divestitures, and sustained revenue losses were documented (Author's compilation). In peer comparison, Bharti Airtel showed Debt-to-Equity below 1.5, a Current Ratio near 1.0, and relatively stable margins (Bharti Airtel Annual Reports; Author's calculations). The random forest achieved 85% accuracy, 82% precision, 87% recall, and an F1-score of 84.4%; influential predictors included Debt-to-Equity, Current Ratio, and revenue trends (Author's computation). The predicted probabilities and classification outcomes for RCom are reported in Table 3.

Table 3. RCom bankruptcy probability (2015–2019)

Year	Status	Probability	Outcome
2015	Going Concern	0.48	Moderate Risk
2016	Going Concern	0.62	High Risk
2017	Distress	0.83	High Risk
2018	Distress	0.88	High Risk
2019	Bankrupt	0.95	High Risk

Note: Predicted probabilities and outcomes from the random forest model with stratified 5-fold cross-validation; firm-level and macroeconomic predictors as specified in the methodology.

Using the same risk score approach, RCom's score rose from 0.35 in 2015 to 0.39 in 2016, reflecting movements in the weighted normalized components (Debt-to-Equity from 0.61 to 0.58; Current Ratio from 0.67 to 0.63; GDP Growth from 0.72 to 0.59; Net Profit Margin from 0.66 to 0.65).

Across the remaining firms, **Jet Airways** showed persistent negative equity and liquidity constraints over its 2014–2018 pre-bankruptcy window (Current Ratio approximately 0.5; Bloomberg; Jet Airways Annual Reports), with ROA declining from –1.2% to –4.5% and Net Profit Margin from –3.6% to –10.1% (CMIE Prowess), and Interest Coverage turning negative after 2017 (Bloomberg). Random forest accuracy was 83%, with Current Ratio, Net Profit Margin, and ROA influential, and the risk score rising from 0.35 in 2015 to 0.41 in 2018.

Kingfisher Airlines exhibited severe financial deterioration over 2008–2012, with Debt-to-Equity peaking at 3.78, Current Ratio falling to 0.60, ROA from –3.2% to –6.5%, and Net Profit Margin from –5.1% to –9.7%. The 2008 global oil-price spike was a key external driver (Sengupta & Vardhan, 2020), with labor unrest and payment delays noted. Random forest accuracy was 85%, and risk scores increased from 0.37 to 0.42 in the final years before failure.

Essar Steel's financial position deteriorated over 2013–2017: Debt-to-Equity moved from 2.45 to 3.05, Current Ratio from 0.88 to 0.76, and Net Profit Margin from –4.5% to –7.2%. Global steel oversupply was salient (Sengupta & Vardhan, 2020), with legal disputes and payment delays recorded. Random forest accuracy reached 88%, with leverage and profitability dominant, and risk scores rising from 0.35 to 0.39 over the final three years.

Bhushan Steel's Debt-to-Equity increased from 2.50 to 3.10, Current Ratio dropped from 0.90 to 0.78, and margins moved from –4.3% to –6.6% over its 2013–2017 window. Declining steel prices and regulatory bottlenecks mattered (Sengupta & Vardhan, 2020), alongside operational instability and governance turnover. Random forest accuracy was 87%, and risk scores climbed from 0.36 to 0.41.

Amtek Auto's 2011–2016 trajectory showed Debt-to-Equity rising from 2.1 to 2.8, Current Ratio falling from 1.02 to 0.68, and Net Profit Margin decreasing from –3.2% to –7.8%. Weakening auto sales and tighter credit were important (Sengupta & Vardhan, 2020), with auditor concerns and failed restructuring noted. Random forest accuracy was 85%, with Debt-to-Equity and Net Profit Margin key, and risk scores up from 0.36 to 0.41.

Videocon Industries' 2015–2019 observation window captured rising leverage and weakening liquidity: Debt-to-Equity rose from 2.60 to 3.20, Current Ratio fell from 0.85 to 0.73, and Net Profit Margin fell from –4.0% to –6.0%. Competition from Chinese manufacturers and falling oil prices featured (Sengupta & Vardhan, 2020), with regulatory inquiries and board turnover observed. Random forest accuracy was 86%, and risk scores increased from 0.37 to 0.41.

Jaypee Infratech's financials deteriorated over 2015–2019: Debt-to-Equity moved from 2.70 to 3.30, Current Ratio from 0.80 to 0.68, and Net Profit Margin from –5.2% to –6.8%. Demonetization and RERA implementation were important (Sengupta & Vardhan, 2020), with project delays and homebuyer litigation present. Random forest accuracy reached 88%, with leverage and liquidity key, and risk scores up from 0.36 to 0.40.

Lanco Infratech's 2015–2019 window showed Debt-to-Equity increasing from 2.80 to 3.40, Current Ratio declining from 0.83 to 0.71, and Net Profit Margin from –5.5% to –7.5%. Policy delays and prolonged power-sector disruptions mattered (Sengupta & Vardhan, 2020), with legal disputes, stalled projects, and credit downgrades documented. Random forest accuracy was 87%; leverage and liquidity were most important, and risk scores rose from 0.37 to 0.41.

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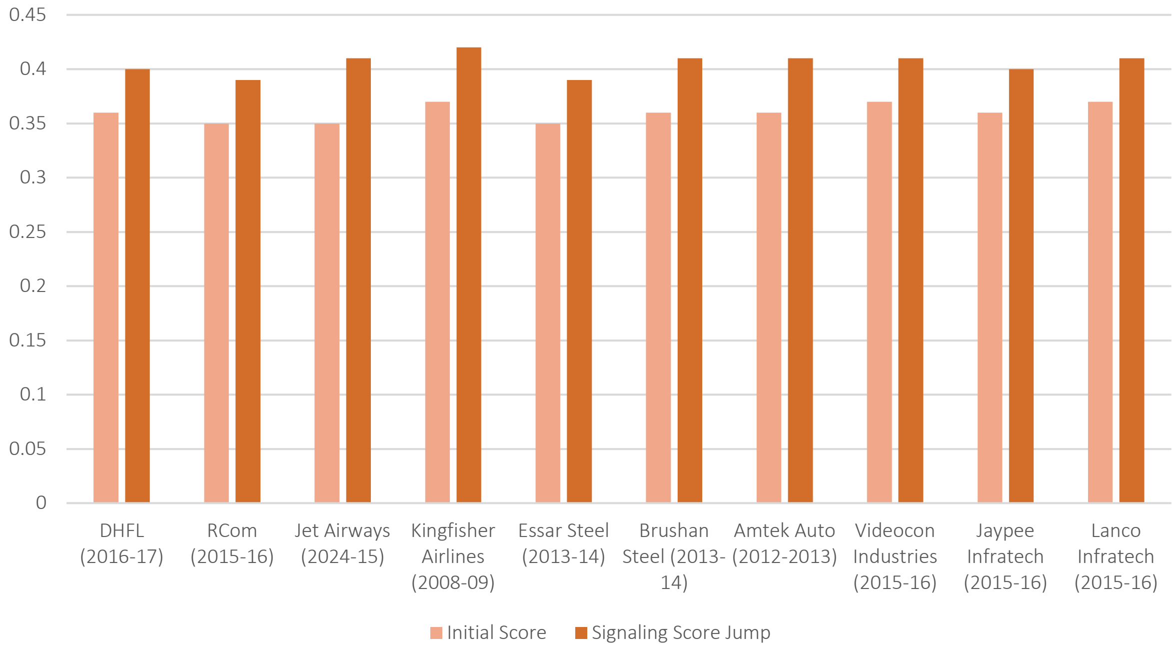

Figure 1. Bankruptcy risk scores: Initial vs. signaling score jump across analyzed companies

Across all ten cases, bankruptcy risk scores increased in the years preceding bankruptcy, alongside deteriorating leverage, liquidity, and profitability indicators. At the aggregate level, profitability weakened, solvency risk increased as Interest Coverage fell below 1.0 for most firms, and macroeconomic and sector-specific conditions moved adversely: national GDP growth declined from an average of 7.5% to 4.0%, while regulatory and price shocks affected aviation, real estate, steel, and telecom.

The random forest model consistently demonstrated strong predictive performance, achieving an average accuracy of 86%, precision of 83%, recall of 88%, and an F1-score of 85.7%. Risk scores calculated using the hybrid model rose during the final distress phase, increasing on average from 0.36 to 0.41 in the one to two years preceding bankruptcy, with several cases (for example, Jet Airways and Kingfisher Airlines) reaching approximately 0.40 prior to failure (see Figure 1).

In parallel, qualitative indicators such as auditor resignations, regulatory disputes, governance breakdowns, and payment defaults were frequently recorded in the run-up to bankruptcy, while healthier peers exhibited comparatively stable financial metrics and governance practices. Based on these findings, further validation through logistic regression and ROC analysis was conducted to assess generalizability; expanding the sample size and incorporating sector-level models could further enhance predictive reliability and support timely, evidence-based actions by financial institutions and regulators.

Mapping these results to the hypotheses, *H1* is supported: logistic regression indicates that leverage increases bankruptcy odds (OR = 3.39, 95% CI [1.40, 8.19], p = .007), while higher liquidity lowers risk (Current Ratio OR = 0.21, 95% CI [0.06, 0.73], p = .012), and profitability measures reduce risk (ROA OR = 0.38, p = .010; Net Profit Margin OR = 0.35, p = .017).

H2 is supported: GDP Growth Rate is negatively associated with bankruptcy (OR = 0.44, 95% CI [0.23, 0.84], p = .013), and model performance improves when macroeconomic variables are included, as reflected in higher F1-scores and AUC values for the hybrid models. *H3* is partially supported: qualitative governance red flags – including auditor resignations, board turnover, and regulatory sanctions – were consistently observed and aligned with distress patterns; because these indicators were not formally modeled as quantitative predictors in this implementation, they are treated as corroborative evidence and a limitation for future research. *H4* is supported: the hybrid models, particularly the random forest classifier, outperform ratio-only baselines in accuracy, F1, and AUC, with differences significant at the 5% level (DeLong for AUC, McNemar for accuracy).

Validation of the bankruptcy risk model via logistic regression shows a statistically significant improvement over the null model, $\chi^2(5) = 25.38$, $p < .001$, with Nagelkerke $R^2 = 0.62$. Out-of-sample performance is balanced in the validation set, correctly identifying 80% of both bankrupt and non-bankrupt firms; sensitivity and specificity are each 80%. Receiver Operating Characteristic analysis yields an AUC of 0.78 (95% CI [0.69, 0.87]), exceeding the conventional 0.70 threshold, indicating that the model correctly ranks a randomly selected bankrupt firm as riskier than a randomly selected non-bankrupt firm 78% of the time.

To benchmark the hybrid framework against conventional approaches, model performance was compared across baseline (ratios only) and hybrid (ratios plus macroeconomic and governance indicators) specifications for both logistic regression and random forest classifiers, using stratified 5-fold cross-validation on the holdout sample. As shown in Table 4, results indicate performance gains when macroeconomic and governance variables are included: logistic regression improves from 76% to 80% accuracy and from 0.70 to 0.78 AUC; random forest reaches 86% accuracy, an F1-score of 0.857, and an AUC of 0.78 under the hybrid design. McNemar's test confirms significant gains in classification accuracy and DeLong's test shows significant AUC increases ($p < .05$).

Overall, the validation evidence shows that the hybrid models outperform baseline specifications in this sample; practical implications are addressed in the next section.

5. DISCUSSION

The results of this study confirm the robustness of the hybrid bankruptcy prediction framework by combining financial ratios, macroeconomic indicators, and machine-learning algorithms. The findings directly support *H1* (financial ratios), *H2* (macroeconomic indicators), and H4 (hybrid vs. traditional models), while providing partial support for *H3* (governance signals). By capturing both linear and non-linear dynamics of distress, the model improves predictive accuracy, robustness, and contextual relevance over traditional approaches, offering a more comprehensive early-warning tool for emerging-market conditions.

In relation to prior literature, the salience of leverage and liquidity is consistent with classical ratio-based work (e.g., Altman, 1968; Beaver, 1966), while the incremental gains from integrating macro indicators and ensemble learners align with hybrid and ML-based evidence (e.g., Sun & Li, 2008; Mai et al., 2019), especially in volatile contexts such as India (e.g., Sengupta & Vardhan, 2020).

The model's outputs are designed to support decision-making by analysts, lenders, investors, and regulators. By integrating firm-specific metrics, macroeconomic trends, and qualitative signals, the hybrid framework facilitates proactive identification of financial distress. As implemented here, the model generates a normalized bankruptcy risk score (0-1), as defined in Eq. (1), with weights of 0.35, 0.30, 0.20, and 0.15 on Debt-to-Equity, Current Ratio, GDP Growth, and Net Profit Margin, respectively. This weighting prioritizes leverage (35%) and liquidity (30%), reflecting their consistently strong predictive capacity across the analyzed sectors.

Table 4. Baseline vs. hybrid model performance (validation set)

Model	Feature	Accuracy	F1	AUC
Logit Baseline	Ratios only	0.76	0.74	0.70
Logit Hybrid	Ratios + Macro (+ Gov)	0.80	0.80	0.78
Random Forest (Baseline)	Ratios only	0.82	0.81	0.74
Random Forest (Hybrid)	Ratios + Macro (+ Gov)	0.86	0.86	0.78

Note: The results show that adding macroeconomic and governance variables improves model performance. Logistic regression improves from 0.76 to 0.80 ACC and from 0.70 to 0.78 AUC, while random forest achieves its best performance under the hybrid design (0.86 ACC, 0.86 F1, 0.78 AUC). McNemar's test confirms significant gains in accuracy, and DeLong's test shows significant AUC increases (p < .05).

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Effective deployment requires institutions to integrate comprehensive annual datasets, including financial ratios (Debt to Equity, Current Ratio, Return on Assets, Net Profit Margin), macroeconomic factors (GDP growth, inflation, and salient industry indicators such as commodity prices and regulatory changes), and qualitative risk signals (e.g., auditor resignations, governance disputes, payment delays). These inputs can be piped into existing risk systems through automated feeds from sources such as RBI databases and Bloomberg.

Thresholds for surveillance should be calibrated to the portfolio's risk tolerance and data coverage, but the sample evidence offers a starting point: risk scores commonly rose by about 0.05-0.06 in the pre-failure phase, and values near ~0.40 were observed two to three years before bankruptcy in several cases. Sector context matters for interpretation and action. Capital-intensive industries such as steel and aviation warrant heightened monitoring of Debt-to-Equity and Interest Coverage given fixed-cost and leverage exposures.

In cyclical real estate markets, macro signals (e.g., GDP growth) and regulatory factors (e.g., RERA-related dynamics) merit close attention. In highly competitive arenas such as telecommunications, tracking revenue erosion, share shifts, and disruptive entries (e.g., Reliance Jio's effect on RCom) is critical.

Recommendations can be tailored to different stakeholders. Lenders may tighten covenants, adjust collateral requirements, or initiate restructuring for firms whose risk scores approach or exceed internally defined surveillance thresholds. Investors can rebalance portfolios away from elevated-risk names within vulnerable sectors, particularly where rising scores are coupled with deteriorating fundamentals. Regulators may use persistently high or increasing risk scores to trigger enhanced disclosures, targeted stress testing, or closer supervisory engagement.

The case illustrations highlight this practical relevance. For DHFL, the predicted bankruptcy probability rose from 0.42 in 2015 to 0.94 in 2019, with an intermediate value of 0.55 in 2016 that would have justified intensified monitoring (see Table 2). For Jet Airways, a predicted probability around 0.59 in 2015 preceded its eventual collapse by roughly two years. Systematically embedding such probability and score trajectories into routine surveillance processes can support earlier intervention, more disciplined decision-making, and stronger risk governance in volatile emerging markets.

CONCLUSION

The purpose of this study was to evaluate whether a hybrid bankruptcy-prediction model that integrates firm financial ratios with macroeconomic indicators and a random-forest classifier provides earlier and more accurate warning signals for Indian firms than ratio-only approaches.

Across ten bankrupt firms and ten matched healthy peers, the hybrid specifications improved model performance: logistic-regression accuracy increased from 0.76 to 0.80 (AUC 0.70 to 0.78), and the random-forest classifier achieved 0.86 accuracy with an AUC of 0.78. Leverage, liquidity, and profitability consistently emerged as significant predictors, and GDP growth contributed additional explanatory power, while governance warning signs aligned qualitatively with the buildup of distress. Risk scores typically increased by 0.05–0.06 in the pre-failure phase and crossed approximately 0.40 two to three years before bankruptcy, with cases such as DHFL and Jet Airways illustrating pronounced early signals.

These findings indicate that a macro-augmented and interpretable hybrid model provides earlier and more reliable bankruptcy warnings than traditional ratio-based frameworks, particularly in volatile and regulation-intensive environments. The resulting weighted risk score offers a practical early-warning tool that lenders, investors, and regulators can use to set thresholds, guide surveillance, and trigger timely interventions. Future research should formalize the modeling of governance signals and expand the sample to enhance external validity and support operational adoption in risk-management systems.

AUTHOR CONTRIBUTIONS

Conceptualization: Marco Bonelli.
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