Habib et al., 2020). Composite indexes seek to capture the multifaceted nature of financial health by mitigating extreme outcomes and leveraging the strengths of individual models. These approaches are particularly advantageous in contexts characterised by significant firm heterogeneity and industry diversity (Abdelkader & Wahba, 2024). Nevertheless, empirical applications of composite financial health measures remain limited for Indian small-cap manufacturing firms (Mahesh et al., 2025).

This study seeks to develop and validate a Composite Financial Health Index (CFHI) tailored for Indian small-cap manufacturing firms. The CFHI integrates the Altman Z-Score, Springate S-Score, Zmijewski X-Score, and Grover G-Score into a unified index, providing a more comprehensive and balanced assessment of financial stability. The study pursues three primary objectives: to compare the outcomes of the four established distress models, to construct the CFHI and analyse financial health across firms, sectors, and years from 2015 to 2024, and to evaluate the accuracy of the CFHI through financial ratio analysis.

This study contributes several novel insights to the existing literature. Unlike prior studies that rely on a single distress-prediction model or focus on large- and mid-cap firms, this study makes three distinct contributions. First, it focuses exclusively on Indian small-cap manufacturing firms, a segment characterised by high volatility and financial vulnerability. Second, it integrates four classical distress prediction models into a standardised composite index to mitigate model-specific bias. Third, the proposed CFHI is empirically validated using accounting- and market-based financial indicators, enhancing its interpretability and practical relevance. Methodologically, it demonstrates that a composite index captures the nuances of financial health in small-cap firms more effectively than single-model approaches. Empirically, it provides robust evidence from Indian manufacturing sectors, clarifying both overarching risks and sectoral differences. Practically, the findings offer actionable guidance for investors, creditors, and regulators seeking reliable tools to monitor financial stability among small-cap companies.

The rest of the paper is organised as follows. Section 2 reviews the literature on financial distress prediction and sets out the rationale for a composite approach. Section 3 details the data and methodology, explaining how the Composite Financial Health Index (CFHI) is constructed. Section 4 presents the empirical results, compares model classifications, and validates the CFHI. Section 5 discusses the findings and their theoretical and practical implications. Finally, Section 6 concludes the study, acknowledging its limitations and suggesting avenues for future research.

2. REVIEW OF LITERATURE

2.1 Conceptual Foundations of Financial Health and Distress Prediction

The evaluation of corporate financial health has been a central focus in accounting and finance research, reflecting its significance for investors, lenders, regulators, and corporate management (Rahman et al., 2021; Sabela et al., 2018). Foundational studies defined financial health as a firm's capacity to sustain operations, fulfil obligations, and avoid insolvency over time (Alyasari et al., 2024; Csikosova et al., 2019; Fachrudin, 2020). Early empirical investigations concentrated on identifying accounting ratios that differentiate between failed and non-failed firms.

Beaver (1966) provided foundational evidence that individual financial ratios, especially those related to liquidity, cash flow, and profitability, possess predictive power several years before bankruptcy (Rahman et al., 2021). His univariate framework laid the groundwork for systematic financial distress prediction and demonstrated that declining financial ratios serve as early warning indicators (Altman, 1968; Amoa-Gyarteng, 2021). However, this approach was constrained by its inability to account for the combined effects of multiple financial dimensions (Manh et al., 2024).

Expanding upon this foundation, Altman (1968) introduced the multivariate Z-score model through multiple discriminant analysis. By integrating liquidity, profitability, leverage, solvency, and efficiency ratios into a composite score, Altman achieved significantly improved classification accuracy for manufacturing firms (Altman, 1968). The Z-Score model established a benchmark in distress prediction research and continues to be widely utilised across various sectors and regions. Nevertheless, subsequent research has observed that the model's effectiveness fluctuates with firm size, industry structure, and economic conditions, especially when applied beyond its initial context (Abdelkader & Wahba, 2024; Dimitrijević et al., 2024; Kanoujiya et al., 2023; Mahesh et al., 2025).

2.2 Development of Classical Distress Prediction Models

After Altman's contribution, researchers introduced alternative multivariate models to address methodological and contextual limitations. Springate (1978) developed a multiple discriminant analysis (MDA)-based model that emphasised working capital efficiency and earnings performance (Alyasari et al., 2024). Although the Springate S-Score demonstrated strong discriminatory power in its initial sample, subsequent studies found that the model frequently yielded conservative distress classifications, particularly for firms with volatile earnings.

Zmijewski (1984) advanced the literature by introducing a probit-based distress prediction model, shifting focus from classification to probabilistic assessment. His model highlighted the central role of leverage, profitability, and liquidity risk in predicting financial distress (Azam et al., 2023; Zmijewski, 1984). The probabilistic framework addressed some statistical limitations of discriminant analysis but remained sensitive to sample composition and firm characteristics.

Grover (2001) further refined distress prediction by recalibrating Altman's original model. By adjusting coefficient weights and selecting ratios, the Grover G-Score sought to enhance classification stability and minimise misclassification. Empirical studies indicate that Grover's model frequently classifies a greater proportion of firms as financially healthy, reflecting comparatively lower sensitivity to early-stage distress (Fachrudin, 2020; Saha & Ahmed, 2024).

Overall, these classical models capture distinct yet overlapping aspects of financial performance. However, variations in model structure and cutoff thresholds often lead to inconsistent classification results across various firm samples.

2.3 Comparative Evidence and Emerging Market Context

An expanding body of empirical research has documented divergence in distress classification across models, especially in emerging markets. Comparative analyses reveal that a single firm may be classified as distressed by one model and healthy by another, depending on each model's sensitivity to liquidity, leverage, or earnings volatility. For example, Saha & Ahmed (2024) In their study of non-bank financial institutions in Bangladesh, they found that Zmijewski's model identified significantly more distressed firms than Grover's model.

Empirical findings from emerging economies indicate that small-cap firms pose unique challenges for traditional distress-prediction models. Such firms frequently display irregular cash flows, high working-capital intensity, and elevated earnings volatility, which may generate false distress signals in conservative models or obscure vulnerability in more lenient models (Mahesh et al., 2025). Sector-specific studies within manufacturing industries further demonstrate that cyclical exposure intensifies these inconsistencies.

In the Indian context, earlier studies mainly used classical distress models independently for specific sectors or firm groups (e.g., textiles by Nair & Sachdeva, (2016); Pharmaceuticals by Das & Sarma, (2022). Although these studies affirm the utility of accounting-based models, they also report inconsistent classification outcomes and limited robustness when models are employed in isolation. Notably, Indian literature remains fragmented, with minimal attention given to small-cap firms as a distinct and vulnerable market segment.

2.4 Limitations of Single-Model Approaches

Despite their broad adoption, standalone distress prediction models exhibit several well-documented limitations.

First, model-specific bias results from variations in ratio selection, weighting schemes, and classification thresholds (Csikosova et al., 2019). Second, most classical models were constructed using historical data from developed economies, which raises questions about their applicability in emerging markets (Abdelkader & Wahba, 2024; Waqas & Md-Rus, 2018). Third, dependence on binary or narrowly defined classification frameworks often overlooks intermediate financial vulnerability, the so-called "grey zone" where firms are neither distinctly healthy nor severely distressed (Altman, 1968).

These limitations are especially evident in small-cap firms, where minor changes in profitability or liquidity can substantially affect classification outcomes (Mahesh et al., 2025). Consequently, decision-makers who rely on a single model may face increased risk of misclassification, potentially leading to suboptimal investment, lending, or regulatory decisions (Agarwal & Taffler, 2006).

2.5 Conceptual Framework and Research Focus

The reviewed literature highlights the need for integrated assessment frameworks that combine various financial indicators. Recent studies show a growing support for hybrid or composite methods to decrease model bias and enhance interpretability. (Vavrek et al., 2021). By consolidating information from multiple models, composite indices offer a more stable, multidimensional perspective on financial health.

Although composite approaches have been proposed conceptually, empirical applications in the Indian small-cap manufacturing sector are limited. This study addresses this gap by developing a standardised Composite Financial Health Index (CFHI) that integrates four widely recognised classical distress prediction models: Altman Z-Score, Springate S-Score, Zmijewski X-Score, and Grover G-Score. In contrast to previous research that relies on single-model assessments or sector-specific analyses, this study:

1. Constructs a statistically robust composite index through standardisation and aggregation,
2. Applies it longitudinally (2015–2024) to capture temporal dynamics, including the COVID-19 shock,
3. Analyses across three manufacturing sectors to identify sector-specific patterns, and
4. Rigorously validates the index through financial ratio analysis.

Focusing on Indian small-cap manufacturing firms addresses a significant gap in the literature, as this segment remains underexplored despite its economic importance and financial vulnerability.

2.6 Summary of Literature Review

In summary, the literature demonstrates that although accounting-based distress prediction models are valuable, they exhibit notable limitations when applied individually. The inconsistent outcomes across various models, particularly in emerging markets and small-cap firms, underscore the necessity for integrated approaches. This study addresses this gap by developing and evaluating a Composite Financial Health Index tailored to Indian small-cap manufacturing companies. It is guided by three principal research questions derived from the literature, given the divergence in model outcomes and the lack of a unified framework for Indian small-cap manufacturers.

1. How divergent are classification outcomes when four classical distress prediction models are applied to Indian small-cap manufacturing firms?
2. Can a composite index provide a more balanced and reliable assessment of financial health than individual models?
3. Is the Composite Financial Health Index empirically consistent with key accounting- and market-based indicators of financial health?

3. RESEARCH METHODOLOGY

3.1 Research Design

The study employs a quantitative, empirical research design to evaluate the financial health of Indian small-cap manufacturing firms. Given the multidimensional nature of financial health and the documented limitations of single distress prediction models, the analysis follows a multi-stage framework that combines classical bankruptcy models into a composite index and subsequently validates the index using firm-level financial

ratios. Panel data techniques are employed to capture cross-sectional and temporal variation in firm performance.

3.2 Sample Selection and Data Sources

The empirical analysis is based on a balanced panel of 38 listed Indian small-cap manufacturing firms observed over the period 2015–2024, yielding 380 firm-year observations. The classification of firms as small-cap follows the official definition prescribed by the Securities and Exchange Board of India (2017).

As per SEBI's circular on categorisation and rationalisation of mutual fund schemes, small-cap companies are defined as those ranked 251st and below in terms of full market capitalisation, based on the standardised list prepared and periodically updated by the Association of Mutual Funds in India (AMFI). This ranking-based definition ensures uniformity and regulatory consistency in identifying the small-cap universe.

Accordingly, firms included in the study were selected from the AMFI small-cap classification corresponding to the relevant years of analysis. The sample represents three manufacturing sectors of economic significance in India: Automobile & Auto-Ancillary (10 firms), Construction Materials (11 firms), and Textiles (17 firms).

Firm-level financial data were obtained from the CMIE Prowess database and cross-verified using audited annual reports. Only firms with complete financial information throughout the study period were retained to ensure a balanced panel and comparability across time.

3.3 Classical Distress Prediction Models

To evaluate firm-level financial health, the study employs four well-established bankruptcy prediction models: the Altman Z-Score, Springate S-Score, Zmijewski X-Score, and Grover G-Score. These models were selected because they are widely applied in empirical finance literature and collectively capture complementary dimensions of financial performance, including liquidity, profitability, leverage, solvency, efficiency, and market valuation.

The Altman Z-Score (Altman, 1968) is a multivariate discriminant model that integrates accounting and market-based indicators to assess the likelihood of financial distress. It has been extensively used in manufacturing-sector studies and remains a benchmark model for financial health assessment.

The Springate S-Score (Springate, 1978), also based on discriminant analysis, emphasises working capital efficiency and earnings performance. Prior studies suggest that this model tends to generate more conservative distress classifications, particularly for firms with volatile cash flows.

The Zmijewski X-Score (Zmijewski, 1984) adopts a probabilistic framework and focuses primarily on leverage, profitability, and liquidity risk. By relying on a limited set of core ratios, it offers a parsimonious assessment of distress likelihood, though empirical applications indicate that it is sensitive to firm size and capital structure.

The Grover G-Score (Grover, 2001) is a recalibrated version of earlier discriminant models, designed to improve classification stability by adjusting coefficient weights and the selection of ratios. Empirical evidence suggests this model is relatively less sensitive to early-stage distress.

All four models were computed using their standard formulations, as proposed in the original studies, without any modification to variables or coefficients. Established cutoff thresholds were applied to classify firm-year observations into financially healthy, grey-zone, or distressed categories. The simultaneous application of multiple classical models enables a comparative assessment of financial health and forms the basis for constructing the Composite Financial Health Index (CFHI).

The divergence in theoretical focus and classification outcomes among these models provides the methodological rationale for constructing a composite index that integrates their complementary signals.

3.4 Construction of the Composite Financial Health Index (CFHI)

Given the observed divergence in financial health classifications across individual distress prediction models, the study constructs a Composite Financial Health Index (CFHI) to provide a more stable and multidimensional assessment of firm-level financial health. The CFHI integrates information from the Altman Z-Score, Springate S-Score, Zmijewski X-Score, and Grover G-Score, thereby reducing model-specific bias and capturing complementary financial signals.

The construction of the CFHI follows a standardised and transparent procedure. First, the raw scores obtained from each distress prediction model were standardised using a z-score transformation to eliminate scale differences and ensure comparability across models. This step is essential because the underlying models differ in magnitude, dispersion, and interpretation.

Second, the standardized scores were aggregated using an equal-weighted approach. Equal weighting was adopted to avoid dominance by any single model and to ensure that each distress framework contributes proportionately to the composite index. This approach is consistent with prior empirical studies that advocate balanced integration when no theoretical justification exists for differential weighting.

Third, the resulting CFHI values were used to classify firm-year observations into financially healthy, grey-zone, and distressed categories based on predefined threshold values. This classification framework allows the CFHI to reflect financial health along a continuum rather than as a binary outcome, which is particularly relevant for small-cap firms exhibiting intermediate financial vulnerability.

The statistical coherence of the CFHI was further assessed through internal reliability and dimensionality analysis. The composite index demonstrated strong internal consistency, with a Cronbach's alpha of 0.891, indicating high reliability among the constituent model scores. Principal component analysis confirmed the index's unidimensional structure, supporting the integration of multiple distress measures into a single composite construct.

Overall, the CFHI represents an integrated and empirically grounded measure of financial health that synthesises multiple distress perspectives into a coherent index. The composite framework provides a robust analytical foundation for subsequent validation using financial ratios and comparative analysis across time and sectors.

3.5 Analytical Framework

The empirical analysis follows a structured and objective-oriented analytical framework designed to evaluate financial health using classical distress models and to validate the Composite Financial Health Index (CFHI). The framework proceeds sequentially to ensure logical consistency between model construction, comparison, and validation.

In the first stage, descriptive statistics are computed for each classical distress prediction model and for the CFHI to examine the distributional characteristics and variability of financial health indicators across firms and time. This stage provides an initial assessment of heterogeneity among small-cap manufacturing firms.

In the second stage, model-wise classification analysis is conducted using established cutoff thresholds to classify firm-year observations into financially healthy, grey-zone, and distressed categories. Comparative assessment across models is undertaken to identify inconsistencies in classification outcomes and to highlight the limitations of standalone distress prediction approaches.

In the third stage, the analysis focuses on the CFHI-based assessment of financial health. Firm-year observations are classified using CFHI thresholds, and temporal (year-wise) and sectoral distributions are examined to capture variations in financial health across time and manufacturing sectors.

In the final stage, the CFHI is subjected to external validation using correlation and regression techniques. This stage evaluates whether the composite index aligns with fundamental financial performance indicators and provides empirical support for its interpretability and robustness.

Overall, this analytical framework ensures that the CFHI is evaluated not only as a composite construct but also as a practical and empirically grounded measure of firm-level financial health.

3.6 Statistical Software

All statistical analyses were performed using SPSS and Stata. SPSS was used for computing descriptive statistics, correlation matrices, and Ordinary Least Squares (OLS) regression models. Stata was employed for supplementary robustness diagnostics and consistency checks. The combined use of these statistical packages ensured computational accuracy and methodological reliability throughout the analysis.

Having outlined the research design, data sources, model selection, construction of the Composite Financial Health Index (CFHI), and the validation framework, the following section presents the empirical results. The analysis is structured in line with the research questions posed in the literature review, beginning with a comparison of classical distress prediction models and subsequently examining the construction, distribution, and validation of the CFHI.

4. RESULT AND ANALYSIS

This section presents the study's empirical findings in accordance with the research questions formulated in Section 2.6. The results are organised into three subsections. First, the classification outcomes of classical financial distress prediction models are compared to assess their consistency. Second, the construction and distribution of the Composite Financial Health Index (CFHI) are examined to evaluate its stability and interpretability. Finally, the CFHI is empirically validated using key accounting- and market-based financial indicators.

4.1 Comparison of Financial Health Classification Across Classical Distress Prediction Models (RQ1)

To address **RQ1**, firm-level financial health was evaluated using four classical distress prediction models: Altman Z-Score, Springate S-Score, Zmijewski X-Score, and Grover G-Score. Descriptive statistics were first examined to understand the distributional characteristics of each model.

Model	N	Minimum	Maximum	Mean	Std. Deviation
Altman Z-Score	380	–1.13	50.73	4.53	4.51
Zmijewski X-Score	380	–7.18	4.32	–1.80	1.31
Springate S-Score	380	–1.79	8.91	1.09	0.80
Grover G-Score	380	–1.35	5.25	0.66	0.55
Composite Financial Health Index (CFHI)	380	–2.54	5.76	0.00	0.87

Table 4.1: Descriptive Statistics of Classical Distress Prediction Models and CFHI (2015–2024)

The statistics demonstrate notable differences in scale and variability. The Altman Z-Score exhibits the greatest variability (SD=4.51), whereas Grover's model is the most consistent (SD=0.55). The average Altman (4.53) and Zmijewski (–1.80) scores reflect overall financial health, while Springate (1.09) and Grover (0.66) suggest borderline statuses. The CFHI, with a mean of 0 and an SD of 0.87, offers a standardised comparison metric.

4.2 Divergence in Classification Outcomes

To address **RQ1**, firms were classified using each model's established thresholds.

Model	Healthy (%)	Grey Zone (%)	Distressed (%)
Altman Z-Score	54.5	25.5	20.0
Springate S-Score	60.3	NA	39.7
Zmijewski X-Score	93.7	NA	6.3
Grover G-Score	93.7	0.5	5.8

Table 4.2 Classification of firm-years by individual distress models

Note: *Springate and Zmijewski models do not have a defined grey zone.*

The classification results demonstrate substantial divergence across the classical distress prediction models. The Springate S-Score flags a markedly higher proportion of distressed firms, indicating its greater sensitivity to liquidity and earnings volatility. Conversely, the Zmijewski X-Score and Grover G-Score produce comparatively optimistic assessments, classifying over 93% of observations as financially healthy. The Altman Z-Score provides a more moderate, tripartite classification that distinguishes healthy, grey-zone, and distressed firms. These stark inconsistencies underscore that the diagnosis of financial health is fundamentally contingent on model selection, revealing a critical limitation of standalone models and underscoring the necessity for an integrated assessment framework.

4.3 Performance of the Composite Financial Health Index (RQ2)

The Composite Financial Health Index (CFHI) exhibits strong internal reliability, with a Cronbach's alpha of 0.891, indicating high internal consistency among its constituent distress prediction models. Classification based on CFHI thresholds yields a more balanced and nuanced financial health profile relative to individual distress prediction models.

Category	Frequency	Percent (%)
Distressed	114	30.0
Grey Zone	171	45.0
Safe/Healthy	95	25.0
Total	**380**	**100.0**

Table 4.3. Classification of Firms under Composite Financial Health Index (2015–2024)

The CFHI allocates a substantial proportion of firm-year observations 45% to the grey-zone category, effectively capturing the intermediate financial vulnerability characteristic of Indian small-cap manufacturing firms. Compared to individual distress prediction models, the CFHI moderates the extreme optimism observed in the Grover and Zmijewski models and the relatively conservative classification produced by the Springate model, thereby offering a more balanced and reliable assessment of financial health.

4.4. Temporal and sectoral distribution of CFHI classifications

The CFHI's sensitivity to economic cycles and sectoral dynamics is shown in Tables 4.4 and 4.5. The year-wise analysis (Table 4.4) reflects the impact of the COVID-19 shock in 2020, while the sectoral breakdown (Table 4.5) reveals entrenched distress in Construction Materials and persistent vulnerability in Textiles and Automobiles.

Year	Distressed	Grey Zone	Safe	Total
2015	11	22	5	38
2016	12	19	7	38
2017	14	14	10	38
2018	12	16	10	38
2019	14	15	9	38
2020	16	16	6	38
2021	12	16	10	38
2022	9	15	14	38
2023	7	18	13	38
2024	7	20	11	38
Total	114	171	95	380

Table 4.4. Year-wise distribution of CFHI classification (2015–2024)

Sector	Distressed	Grey Zone	Safe	Total
Automobile & Auto Components	12	52	36	100
Construction Materials	74	31	5	110
Textiles	28	88	54	170
Total	**114**	**171**	**95**	**380**

Table 4.5. sector-wise classification of firms under CFHI (2015–2024)

These distributions confirm that the CFHI captures both systemic shocks and structural vulnerabilities, reinforcing its utility as a comprehensive diagnostic tool.

4.5 Empirical Validation of CFHI Against Financial Indicators (RQ3)

To address **RQ3**, the Composite Financial Health Index (CFHI) was empirically validated by examining its relationship with key accounting- and market-based financial indicators. The objective of this analysis is not hypothesis testing but to assess whether CFHI aligns with established determinants of firm-level financial health.

Accordingly, correlation and regression analyses were employed to evaluate the direction, strength, and statistical reliability of associations between CFHI. They selected financial variables representing profitability, liquidity, leverage, operational efficiency, and market valuation.

4.5.1 Correlation Analysis between CFHI and Financial Indicators

Table 4.6 presents the Pearson correlation coefficients between CFHI and selected financial indicators.

Variable	ROE	OPM	CA/CL	D/E	Sales/TA	MVE/BVL	CFHI
ROE	1						
OPM	0.190**	1					
CA/CL	0.087	0.070	1				
D/E	–0.575**	0.234**	–0.147**	1			
Sales/TA	0.026	0.118*	0.077	0.077	1		
MVE/BVL	0.023	0.061	0.340**	–0.068	–0.016	1	
CFHI	**0.173****	**0.190****	**0.655****	**–0.106***	**0.306****	**0.651****	1

Table 4.6. Correlation between CFHI and Financial Indicators

*Note: **p < 0.01, *p < 0.05*

The correlation results indicate that CFHI is positively and significantly associated with profitability measures, including return on equity (ROE) (r = 0.173, p < 0.01) and operating profit margin (OPM) (r = 0.190, p < 0.01).

Liquidity, measured by the current ratio (CA/CL), exhibits a strong positive relationship with CFHI (r = 0.655, p < 0.01), underscoring the importance of short-term solvency in the financial health of small-cap firms.

CFHI is negatively correlated with leverage, proxied by the debt–equity ratio (r = –0.106, p < 0.05), suggesting that higher leverage is generally associated with weaker financial health.

However, the magnitude of this relationship is modest. Operational efficiency (Sales/TA) shows a positive and statistically significant association with CFHI (r = 0.306, p < 0.01). Market-based valuation (MVE/BVL) also shows a strong positive correlation with CFHI (r = 0.651, p < 0.01), indicating that firms with greater market confidence tend to exhibit higher composite financial health.

Overall, the correlation analysis provides preliminary empirical support for the validity of CFHI as a multidimensional measure of financial health.

4.5.2 Regression Analysis: Financial Determinants of CFHI (Main Model)

To further validate CFHI, an ordinary least squares (OLS) regression model is estimated with CFHI as the dependent variable and selected financial indicators as explanatory variables.

Variable	B	Std. Error	t	p-value	Standardised β
Constant	–1.370	0.065	–21.02	< .001	–
ROE	0.002	0.001	4.08	< .001	0.134
OPM	0.048	0.014	3.35	.001	0.094
CA/CL	0.339	0.022	15.72	< .001	0.452
D/E	0.008	0.010	0.86	.389	0.030
Sales/TA	0.504	0.052	9.70	< .001	0.262
MVE/BVL	0.061	0.004	17.42	< .001	0.494

Table 4.7. ordinary least squares (OLS) regression main model

Dependent Variable: CFHI (2015–2024)

Note. p < .05 is significant at the 5 % level; p < .01 is significant at the 1 % level (two-tailed test).

Model Summary = 0.858 | $R^2 = 0.736$ | Adjusted $R^2 = 0.732$ $F(6, 373) = 173.20$ | $p < .001$ | N = 380

The regression model is statistically significant and exhibits strong explanatory power, explaining approximately 73% of the variation in CFHI. Profitability indicators (ROE and OPM) show positive, statistically significant effects, indicating that more profitable firms tend to exhibit stronger composite financial health.

Liquidity emerges as a key determinant of CFHI, with the current ratio (CA/CL) showing a strong, highly significant positive relationship ($\beta = 0.452$, $p < .001$). Operational efficiency, measured by sales-to-total-assets, also exerts a positive and significant influence ($\beta = 0.262$, $p < .001$). Market-based valuation (MVE/BVL) demonstrates the most substantial standardised effect ($\beta = 0.494$, $p < .001$), reflecting the importance of investor perception and market confidence in shaping financial health.

In contrast, leverage measured by the debt–equity ratio does not exhibit a statistically significant effect (p=.389), suggesting that capital structure alone does not independently determine financial health once profitability, liquidity, efficiency, and market valuation are accounted for.

4.5.3 Robustness Analysis: Alternative Leverage Specification

To assess the robustness of the validation results, leverage is re-specified using the total liabilities-to-total assets ratio (TL/TA), which captures balance-sheet-based financial risk more comprehensively.

Variable	B	Std. Error	t	p-value	Standardised β
Constant	0.003	0.115	0.03	.977	–
ROE	0.003	0.000	8.61	< .001	0.197
OPM	0.023	0.012	1.94	.053	0.044
CA/CL	0.161	0.022	7.31	< .001	0.215
Sales/TA	0.456	0.043	10.61	< .001	0.237
MVE/BVL	0.045	0.003	14.29	< .001	0.363
TL/TA	–1.942	0.147	–13.23	< .001	–0.433

Table 4.8. Robustness Regression Results: Alternative Leverage Specification (TL/TA)

Dependent Variable: CFHI (2015–2024)

The robustness results largely corroborate the main regression model's findings. Profitability, liquidity, operational efficiency, and market valuation remain positively and significantly associated with CFHI. While the significance of operating profit margin weakens marginally ($p = .053$), its coefficient remains positive.

Importantly, leverage, as measured by TL/TA, exhibits a strong negative and statistically significant relationship with CFHI ($\beta = –0.433$, $p < .001$). This contrasts with the insignificance of the debt–equity ratio in the baseline model and suggests that balance-sheet-based leverage more effectively captures financial risk among small-cap manufacturing firms.

4.5.4 Summary of Empirical Validation Results

Taken together, the correlation, regression, and robustness analyses provide strong empirical validation for the Composite Financial Health Index. CFHI exhibits statistically significant and economically meaningful relationships with key indicators of profitability, liquidity, efficiency, and market valuation, while leverage effects depend on the measurement approach. These findings confirm that CFHI is a coherent, reliable, and interpretable measure of firm-level financial health, thereby directly addressing **RQ3**.

5. DISCUSSION

This section examines the empirical findings in relation to the research questions and, in doing so, situates them within the broader context of financial distress prediction and financial health assessment literature.

The discussion is organised around three central themes: the limitations of standalone distress prediction models, the performance advantages of the Composite Financial Health Index (CFHI), and the empirical validity of CFHI as a multidimensional measure of financial health for Indian small-cap manufacturing firms. Each theme is addressed in relation to the study's research questions.

5.1 Interpretation of Findings Related to RQ1: Model Dependency in Financial Health Assessment

The findings for **RQ1** show substantial divergence in financial health classifications across classical distress prediction models. The Springate S-Score identifies a much higher proportion of distressed firm-year observations. The Zmijewski X-Score and Grover G-Score classify an overwhelming majority of observations as financially healthy. The Altman Z-Score provides a more moderate three-way classification, distinguishing between healthy, grey-zone, and distressed firms.

These inconsistencies highlight a fundamental limitation of standalone distress prediction models: the assessment of financial health depends heavily on the model used. Differences in model design, including underlying assumptions, variable selection, and threshold criteria, can yield materially different interpretations of identical financial data (Fachrudin, 2020). Evidence from emerging markets supports this concern, as prior research shows significant variation in distress rates across models applied to the same set of firms (Saha & Ahmed, 2024).

The present findings strongly reinforce this concern. For the same set of firm-year observations, the Springate S-Score classifies 39.7% of firms as financially distressed. By contrast, the Grover G-Score and Zmijewski X-Score identify only 5.8% and 6.3% of firms as distressed, respectively. This stark divergence means a stakeholder relying on a single model could receive a wildly optimistic or overly alarming assessment, leading to potentially misguided investment or credit decisions. This extreme model dependency underscores the critical need

for an integrated framework that synthesises multiple diagnostic perspectives, which is the core rationale for the CFHI.

This evidence underscores the need to adopt a multidimensional assessment framework. For Indian small-cap manufacturing firms, which often exhibit fluctuating cash flows, constrained access to capital, and sector-specific cyclicality, reliance on any single distress model may therefore lead to misleading assessments. The results underscore the need for an integrated framework that synthesises multiple diagnostic perspectives rather than privileging one model's assumptions.

5.2 Discussion of RQ2: CFHI as a Balanced and Context-Sensitive Assessment Tool

Addressing RQ2, the Composite Financial Health Index shows a clear advantage over individual distress prediction models. By providing a tripartite classification, the CFHI yields a more balanced distribution of firms, with a substantial share (45%) correctly allocated to a financially ambiguous "grey zone." This outcome is particularly meaningful for small-cap firms, where vulnerability exists on a continuum, aligning with the view that financial distress is a gradual process rather than a binary event (Platt & Platt,(2002).

An analysis of year-wise CFHI classifications underscores the index's capacity to capture temporal financial dynamics. Before 2020, distressed classifications consistently exceeded safe classifications, suggesting persistent structural fragility during relatively stable macroeconomic periods. Financial stress increased in 2020, evidenced by a peak in distressed observations and a decline in safe classifications, indicating heightened systemic pressure. In the post-2020 period, the data do not suggest a rapid or uniform recovery; instead, there is a gradual shift from distressed to grey-zone and safe categories between 2021 and 2023. This trend reflects a partial and uneven recovery, supporting the view that improvements in financial health among small-cap firms are incremental and heterogeneous.

Furthermore, sector-wise analysis reveals stark contrasts that align with underlying industry economics. Construction Materials firms exhibit severe distress (67%), consistent with the sector's high operational leverage, sensitivity to input costs and economic cycles, and dependence on government infrastructure spending. In contrast, Automobile and Auto-Ancillary firms show relative strength (36% 'Safe'), potentially due to more integrated supply chains and steady replacement demand. The majority of Textile firms are in the grey zone (52%), indicative of an industry characterised by thin margins, intense competition, and high working capital intensity, where firms perpetually navigate financial vulnerability without immediate collapse.

These sectoral distinctions validate the CFHI's sensitivity to industry-specific risk profiles. In summary, the CFHI avoids the polarisation inherent in single-distress models. By capturing broad economic shocks, fundamental sectoral variations, and the gradual, non-linear nature of financial recovery, it proves to be a robust and contextually intelligent tool for monitoring financial health in the volatile small-cap segment.

5.3 Discussion of RQ3: Empirical Validity of CFHI

Empirical validation addressing **RQ3** demonstrates that the Composite Financial Health Index (CFHI) is not solely a statistical construct but also a theoretically coherent measure of financial health for Indian small-cap manufacturers. The strong and significant relationships between the CFHI and fundamental financial indicators provide robust construct validity, confirming that the index effectively synthesises the multidimensional signals from its constituent models into a single, meaningful metric.

The analysis indicates that liquidity (Current Ratio) and market valuation (MVE/BVL) are the most influential determinants of the CFHI, as evidenced by the highest standardised coefficients ($\beta = 0.452$ and $\beta = 0.494$, respectively, in Table 4.7). This result is particularly relevant for small-cap firms, highlighting that investor confidence (as reflected in market value) and short-term solvency are primary concerns, potentially surpassing profitability in assessing immediate financial stability for these volatile entities. This observation supports the premise that small-cap firms face greater scrutiny and tighter liquidity constraints, making market sentiment and cash conversion cycles essential to their perceived financial health. Additionally, the positive and significant role of operational efficiency (Sales/TA) demonstrates that asset utilisation, a key indicator of managerial effectiveness and competitive positioning, is a fundamental component of financial resilience in the capital-intensive manufacturing sector.

A notable finding is the leverage paradox. The baseline regression shows that the debt-to-equity (D/E) ratio is not significant ($p = 0.389$), whereas the robustness check using total liabilities to total assets (TL/TA) shows a strong negative relationship ($\beta = -0.433$, $p < 0.001$). This discrepancy is not a methodological flaw but a characteristic feature of small-cap finance. The D/E ratio's denominator, equity, is often small and highly sensitive to market sentiment in these firms, making it a volatile and potentially misleading measure of risk. By contrast, TL/TA uses total assets as a more stable, balance-sheet-based denominator. These results suggest that, for Indian small-cap manufacturers, balance-sheet leverage is a more reliable and critical indicator of financial risk than capital structure leverage. Consequently, creditors and analysts should prioritise the scale of a firm's obligations relative to its total asset base, rather than its debt-equity mix, when evaluating financial health.

Taken together, these validation results achieve two key objectives. First, they demonstrate that the CFHI is consistent with established financial theory, moving beyond mechanical score aggregation to become an interpretable gauge of underlying economic reality. Second, they provide nuanced insights into the specific drivers of financial health in this segment, emphasising liquidity, market faith, operational efficiency, and balance-sheet prudence rather than mere profitability or a specific debt-to-equity target. Therefore, the CFHI is empirically validated not only as a statistically reliable composite but also as a contextually intelligent tool that captures the unique financial dynamics of small-cap manufacturing firms.

5.4 Theoretical and Methodological Implications

From a theoretical perspective, the findings contribute to the literature by demonstrating the limitations of single-model distress prediction frameworks and by offering an integrated alternative that accommodates multiple diagnostic viewpoints. The CFHI aligns with the broader shift in financial distress research toward multidimensional and composite assessment approaches.

Methodologically, the study illustrates the value of combining classical distress prediction models into a composite index and validating the resulting measure through correlation, regression, and robustness analysis.

The research-question-driven design, rather than hypothesis testing, is particularly appropriate for index construction and validation studies and enhances methodological transparency.

5.5 Practical Implications

The findings have important practical implications for investors, lenders, regulators, and corporate managers. The CFHI provides a more reliable tool for monitoring financial health, identifying early warning signals, and distinguishing between transient financial weakness and structural distress. For regulators and policymakers, the index offers a scalable framework for assessing systemic vulnerability within the small-cap segment. For firm management, CFHI-based insights can inform strategic decisions related to liquidity management, capital structure, and operational efficiency.

The following section synthesises the study's key findings, highlights the main contributions, acknowledges the limitations, and outlines directions for future research.

6. CONCLUSION, LIMITATIONS, AND DIRECTIONS FOR FUTURE RESEARCH

6.1 Conclusion

The findings indicate that a composite index addresses key limitations inherent in single-model analyses for Indian small-cap manufacturers. The investigation, structured around three research questions, yields three principal insights. First, there is substantial divergence in distress classifications across classical models (e.g., distress rates of 39.7% versus 6.3%), demonstrating that reliance on a single model may yield contradictory and potentially misleading assessments. Second, the Composite Financial Health Index (CFHI) developed in this study mitigates this issue by offering a balanced, tripartite classification. The CFHI's substantial grey zone (45% of observations) and its responsiveness to economic cycles and sectoral conditions underscore its effectiveness in capturing the nuanced, continuous nature of financial vulnerability within this segment. Third, rigorous validation confirms the CFHI as a theoretically coherent measure. The analysis identifies liquidity and market confidence as primary determinants of financial health for small-cap firms, and further demonstrates that balance-sheet leverage (TL/TA), rather than capital structure (D/E), is the more relevant indicator of financial risk for these companies.

In summary, this study provides a validated, practical tool for stakeholders while advancing the literature by demonstrating that an integrated composite framework is not only statistically superior but also essential for accurately assessing the financial health of heterogeneous, volatile small-cap manufacturing firms in emerging markets.

6.2 Limitations of the Study

Despite its contributions, the study has certain limitations that should be acknowledged.

First, the analysis is restricted to listed Indian small-cap manufacturing firms, which limits the generalizability of the findings to unlisted firms or to firms operating in service-oriented or financial sectors. Second, the CFHI is constructed using classical distress prediction models and financial ratios;. At the same time, this ensures transparency and interpretability, but it excludes non-financial indicators such as managerial quality, innovation capability, or qualitative governance attributes.

Third, although the study incorporates robustness checks through alternative leverage specifications, the empirical analysis relies on linear regression techniques and does not explicitly model dynamic adjustment processes or non-linear relationships. Finally, the study period, while covering multiple economic phases, does not capture very long-term structural shifts or post-pandemic adjustments beyond the sample horizon.

These limitations do not undermine the validity of the findings but instead delineate the scope within which the results should be interpreted.

6.3 Directions for Future Research

Future research can extend this study in several meaningful directions. First, the CFHI framework can be applied to other firm segments, such as mid-cap or unlisted firms, as well as to non-manufacturing sectors, to assess its broader applicability. Comparative cross-country studies could further examine how institutional and regulatory environments influence financial health dynamics.

Second, future studies may enhance the CFHI by incorporating corporate governance variables, ownership structure, or macroeconomic indicators to develop a more comprehensive financial sustainability index. Third, integrating advanced analytical techniques, such as panel data models, machine learning methods, and early-warning systems, may improve predictive accuracy while preserving interpretability.

Finally, longitudinal extensions of the dataset could enable the examination of financial health transitions over longer horizons, providing deeper insights into the persistence and reversibility of financial distress among small-cap firms.

By advancing a validated composite framework for financial health assessment, this study provides a foundation for both academic inquiry and practical application. The CFHI offers a flexible and robust tool that can be adapted and extended to meet the evolving needs of researchers, practitioners, and policymakers concerned with firm-level financial stability.

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