

A Comparative study of financial performance of Tech and DeepTech firms in India.

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Abstract

This paper contrasts the financial resilience of listed Tech and DeepTech corporations in India using a uniform and audit-able framework. For FY2021-FY2025 secondary data was gathered for 40 companies: 19 software, IT-services, product & platform firms (Tech) and 21 defence, aerospace, shipbuilding, electronics & speciality materials firms (DeepTech). Resilience was assessed using the private firm Altman Z-score and the Safe, Grey and Distress zones it defines. Comparison across groups was done via Student's t, Welch's t, Mann-Whitney U, chi-square and Fisher's exact tests. The mean Z-score was 3.57 (Safe zone) for Tech, and 2.39 (Grey zone) for DeepTech (Welch's $t = -9.05$, $p < .001$, $d = -1.28$), with the difference in zones being significant ($\chi^2(2) = 69.1$, $p < .001$, $V = 0.592$); all seven Distress firm-years were from DeepTech. Tech and DeepTech cannot be grouped together in research, banking and policy making; a Grey zone signals caution, not predicted failure.

Keywords: financial resilience, Altman Z' score, deep tech, technology firms, distress zones, listed Indian companies

Introduction

India's technology economy now supports two conversations that sound alike but are not the same. One concerns software, platforms, payments and digitally delivered services. The other concerns hardware- and science-intensive products, such as defence electronics, aerospace systems, ships, speciality materials and propulsion, which take years to move from the drawing board to the first invoice. Both are described as innovative, both attract public attention, funding and talent, and both are routinely grouped under the label "technology". Yet they differ in the capital they require, the risks they carry and the time they need to earn revenue (Nedayvoda et al., 2021; Panchal, 2025).

Existing Indian research has examined technology firms mainly through incubation, entrepreneurial orientation, sources of finance and early-stage performance (Vincent & Zakkariya, 2021a, 2021b; Singh & Subrahmanya, 2023; Priyanka et al., 2023; Kulkarni, 2023; Pratyasha, 2025). A second stream applies Altman-type distress scores to listed Indian companies, but within a single industry or board: information technology (Kolte et al., 2022), manufacturing (Lakra et al., 2025), renewable energy (Ahmad, 2025), consumer-internet companies (Prajapat et al., 2026) or broad NSE-listed samples (Proceedings on Engineering Sciences, 2024). Studies of deep-tech financing are mostly qualitative or set in other countries (Diógenes et al., 2024; Nedayvoda et al., 2021; Panchal, 2025). A recent review concludes that evidence on high-technology ventures remains fragmented and that financial tests for developing economies are missing (Kumar & Dwivedi, 2025).

Consequently, there is no published comparison of listed Indian Tech and DeepTech firms on one audited financial grid. Without such evidence, lenders, boards, incubators and policymakers risk applying one mental model to firms whose working-capital needs, time to profit and meaning of a loss-making year are very different. This study addresses that gap. It applies the same private-firm Altman Z' formula ([Altman, 1968, 2000](#)), the same five years (FY2021–FY2025) and the same battery of statistical tests to 40 listed Indian companies, 19 classified as Tech and 21 as DeepTech. It is guided by the following research question:

RQ1: Do listed Tech and DeepTech firms in India differ in overall financial resilience, measured by the average Altman Z' score and by Safe, Grey and Distress zone membership?

This paper makes two contributions. Firstly, it provides a comparison of Tech and DeepTech firms in India in terms of a matched five-year analysis using one single formula which could be opened and repeated by others. Secondly, it shows that the resilience gap is not confined to the average score: the whole mix of Safe, Grey and Distress zones also differs between the two groups. This paper is intentionally limited in scope. This paper does not provide any rankings of the firms, estimate models of failure of individual firms or efficiency of funding, and has sampled only the listed firms and not the startups.

Theoretical Background and Hypothesis

Background Theories

There must be a measure that is applicable across industries and a justification for why the difference between the two sets of companies is expected. There are three schools of thought from where justifications stem. The first school of thought is the resource based view. It regards unique technological capabilities as sources of competitive advantage, but acknowledges that investments made in these capabilities are difficult to turn around into cash flow. A ship yard, a microwave subsystem production facility, or a satellite platform cannot be compared to software which is simply re-sold with minimal new facilities. The convergence of capability and a market in deep tech enterprises occurs much later, leading to delayed revenue in combination with substantial assets.

Second, there is the risk perspective. Deep tech businesses have to deal with technical, market, operational, regulatory, and financial risks simultaneously, and the latter includes lack of funding, high cash burn rates, and unclear ways of making money ([Panchal, 2025](#)). Technical and regulatory risks cannot be documented in annual reports, but their financial repercussions can be documented through the form of smaller margins, reduced turnover, and reduced equity buffers. Third, there is the institutional context. Defence and shipbuilding companies that are listed are operating within the framework of public procurement, receivable cycles, and offsets, while software companies that are listed are selling their products on the commercial and export markets.

The literature also shows that “performance” is a crowded term. Studies measure it through founder reports, innovation outcomes, workforce quality, return ratios, valuation or distress scores ([Choi et al., 2020](#); [Vincent & Zakkariya, 2021a](#); [Priyanka et al., 2023](#)). None of these substitutes for a line-by-line comparison of financial resilience across the two groups. Value creation is therefore defined narrowly, in terms that audited statements can support: the ability to turn assets into sales and sales into profit, to maintain an equity cushion, to service liabilities and to stay out of the distress zone of a published solvency model. Market capitalisation, private-round valuations and cash-burn multiples are excluded because they cannot be built with equal honesty for every firm and year.

Tech and DeepTech Firms in India

In this study, Tech firms are listed software, IT-services, product and platform companies. DeepTech firms are listed defence, aerospace, shipbuilding, electronics and speciality-materials companies, whose products rest on scientific or engineering advances and require long development cycles and substantial capital. International notes on deep-tech finance describe such firms as needing more capital and carrying higher technical risk than software companies, and observe that most are born in developed markets (Nedayvoda et al., 2021). Evidence from other emerging economies shows that financing is a central problem for deep-tech ventures (Diógenes et al., 2024), that R&D funding channels differ for young and non-state firms (Fan et al., 2024), and that heavy investment in artificial intelligence can tighten rather than ease financial constraints (Yu & Cong, 2026). Digital transformation, in turn, may reduce financial distress by improving the use of resources (Technology Analysis & Strategic Management, 2025). Taken together, these studies suggest that asset-light digital businesses and capital-intensive hardware businesses should not be expected to share one financial shape.

Financial Resilience and the Altman Z' Score

Altman (1968) collapsed five financial ratios into a single index that separated manufacturing firms that later failed from those that did not. This study uses the private-firm revision:

$$Z' = 0.717 X_1 + 0.847 X_2 + 3.107 X_3 + 0.420 X_4 + 0.998 X_5$$

where X_1 is working capital to total assets, X_2 is book equity to total assets, X_3 is earnings before interest and taxes (EBIT) to total assets, X_4 is book equity to total liabilities and X_5 is sales to total assets. In the original listed-firm version X_4 uses the market value of equity. Book equity is used here because a clean year-end market-capitalisation series was not available for all 40 firms, and mixing book and market equity across firms would make the comparison unfair. Scores above 2.90 are read as Safe, scores from 1.23 to 2.90 as Grey, and scores below 1.23 as Distress (Altman, 1968, 2000).

The model sorts firms; it does not forecast failure. A Grey firm is not necessarily headed for collapse. It is in a less comfortable position than a Safe firm on a published set of liquidity, buffer, profitability, solvency and activity measures. The Z' weights come from manufacturing firms in another country and period, so applying them to Indian software and defence companies is an act of translation. The Safe and Grey labels are therefore interpreted as relative positions on a common scale and not as certified predictions under Indian insolvency law. Altman-type scores have been applied to Indian IT firms (Kolte et al., 2022), NSE-listed companies (Proceedings on Engineering Sciences, 2024), manufacturing firms (Lakra et al., 2025), renewable energy firms (Ahmad, 2025) and consumer-internet companies (Prajapat et al., 2026), as well as to listed technology issuers in Indonesia (Jurnal Inovasi Akuntansi, 2023; Hendiansyah & Natita, 2025). One Indonesian study found that total asset turnover was the activity ratio that moved with distress among technology issuers (Ekombis Review, 2024), a ratio that is also one of the five components of Z' used here. None of these studies compares two technology groups on one grid.

Hypotheses

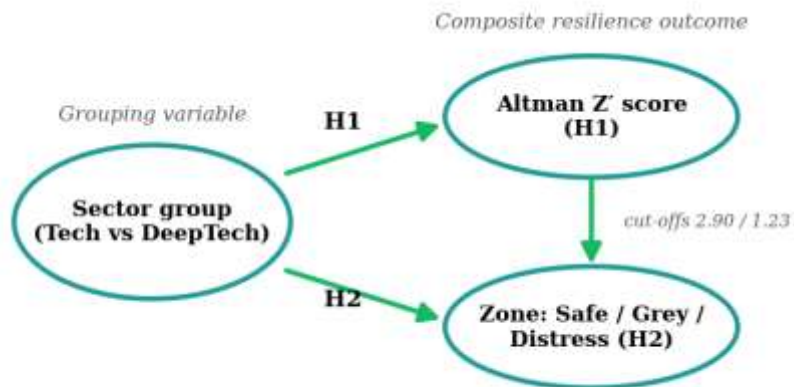
If DeepTech and Tech firms differ in resilience, the difference should show up both in the average Altman Z' score and in the way firm-years are distributed across the Safe, Grey and Distress zones. On the capital-intensity and long-cycle arguments above, differences are expected in overall resilience and in zone membership. The following two-tailed hypotheses are tested:

- H1: Mean Altman Z' differs between Tech and DeepTech firms.

- H2: Zone membership (Safe, Grey, Distress) is associated with group.

H1 and H2 address overall resilience (RQ1). Figure 1 summarises the working model. It is not a structural equation model: the sector group is examined as a two-group comparison against the Z' score (H1) and against the zone that the score implies (H2), which keeps the framework light enough for the data. Funding efficiency, another possible dimension of financial performance, is not tested because a clean series of capital raised against incremental revenue could not be assembled for all firms and years.

Figure 1
Conceptual Model



Source: Authors' own elaboration.

Materials and Methods

tool used in this study includes the use of statement of a standard template taken from annual reports. The grid used is Altman's private firm Z' score and the Safe, Grey and Distress zones it defines.

Research design

This paper uses the research approach of descriptive and comparative analysis using secondary data. Two different sets of firms from India are plotted against the same grid, over the same period of time, to examine differences. There is no intervention, and no survey has been conducted through any questionnaire. The

Sample selection

The sample includes Indian listed companies that can be categorized either as Tech or DeepTech, and for which statements were available for fiscal year 2021 to fiscal year 2025. Statements of Indian listed companies serve as an established source of data for finance and performance analysis ([Jha & Mittal, 2024](#)). Sample selection was purposeful and included two criteria: the company was required to belong to either of the two groups described above and also to have complete statements for the last five years in a comparable format on a common template. Consumer internet and space technology firms operating privately were not included as they do not provide five years of clean financial data. The final sample includes 40 firms, 19 Tech and 21 DeepTech, listed in Table 1. The group categorizations have been decided prior to running any tests and move along with the company name in the workbook.

Table 1
Listed companies in the panel

Tech firms (n = 19)	DeepTech firms (n = 21)
Affle India	Apollo Micro Systems
CE Info Systems (MapmyIndia)	Astra Microwave Products
Coforge	Avantel
Cyient	Bharat Dynamics
Happiest Minds Technologies	Bharat Electronics
Intellect Design Arena	Centum Electronics
KPIT Technologies	Cochin Shipyard
L&T Technology Services	Data Patterns (India)
Latent View Analytics	Dynamatic Technologies
Mphasis	Garden Reach Shipbuilders & Engineers
Newgen Software Technologies	Hindustan Aeronautics
Oracle Financial Services Software	Krishna Defence and Allied Industries
Persistent Systems	Mazagon Dock Shipbuilders
Route Mobile	Mishra Dhatu Nigam
Sonata Software	Nibe
Tanla Platforms	Premier Explosives
Tata Elxsi	Sika Interplant Systems
Tech Mahindra	Solar Industries India
Zensar Technologies	Taneja Aerospace and Aviation
	Walchandnagar Industries
	Zen Technologies

Source: Authors' compilation from company annual reports, FY2021–FY2025 (N = 40 companies).

Five years for 40 firms define a firm-year grid of 200 rows. Three firm-years had missing line items in the source reports and were left blank rather than estimated, so the zone analysis uses 197 complete firm-years (102 DeepTech and 95 Tech). No company was removed for incomplete data. The unit of observation in the working file is the firm-year, and each company's five-year averages are repeated across its rows so that firm-year and company-level readings can be taken from one sheet; the average-score tests therefore use 105 DeepTech and 95 Tech rows. A panel of listed firms also carries survivorship bias, because firms that never reached a public five-year pack are not in the file.

Scale construct and items

The measures used in the analysis are presented in Table 2. Variables with the prefix “Avg_” in the data file are five-year company averages. Market capitalisation, Tobin's Q and stock returns are not part of the design, and funding efficiency is not measured.

Table 2
Scale constructs

Code	Variable	Definition and computation	Role
Group	Sector group	Tech or DeepTech, fixed before testing	Grouping variable
X1	Liquidity	Working capital / total assets; working capital = current assets – current liabilities	Z' component
X2	Equity buffer	Book equity / total assets	Z' component
X3	Operating profitability	EBIT / total assets	Z' component
X4	Liability coverage	Book equity / total liabilities	Z' component
X5	Asset turnover	Sales / total assets	Z' component
Z'	Altman Z' score	$0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$	Resilience score
Zone	Safe / Grey / Distress	Safe: $Z' > 2.90$; Grey: 1.23–2.90; Distress: $Z' < 1.23$	Categorical outcome

Source: Authors' own elaboration based on [Altman \(1968, 2000\)](#).

Tools used for the Study

Raw line items (revenue, profit before tax, PAT, EBIT, finance costs, total assets, current assets, current liabilities, total liabilities and equity) were collected from annual reports for FY2021–FY2025 into company-wise Excel workbooks, which feed a master Altman file and a Jamovi-ready data file. The template is identical for every firm, from a software company to a shipyard, and it plays the role that reliability testing plays in a survey study. Ratios were recomputed from the raw lines, zone labels were checked against the published cut-offs and group labels were checked against company names. All statistical tests were run in Jamovi.

Analysis proceeded in four steps. First, group descriptives (mean, median, standard deviation, standard error, minimum and maximum) were computed. Second, Shapiro–Wilk tests of normality and Levene's tests of equal variances were run for each variable. Third, mean differences were tested with Student's *t*, Welch's *t* and the Mann–Whitney *U* test, with Cohen's *d* (about 0.20 small, 0.50 medium, 0.80 large) and the rank-biserial correlation as effect sizes. Because financial ratios are bounded, skewed and prone to extreme years, Welch's *t* and the Mann–Whitney test were treated as decisive when assumptions failed, and the rank test was treated as decisive when parametric and rank tests disagreed. Fourth, the association between zone and group was tested with the chi-square test, Fisher's exact test and Cramér's *V*. All tests are two-tailed with $\alpha = .05$.

Results

Descriptive Statistics

Table 3 reports the group descriptives for the average Altman Z'. The DeepTech mean is 2.39 (median 2.11), which lies in the Grey zone, whereas the Tech mean is 3.57 (median 3.28), which lies in the Safe zone. The firm-year figures in Table 4 keep the same order (2.38 against 3.57). The lowest firm-year Z'

among Tech firms is 1.88, which is above the Distress line of 1.23, while the lowest among DeepTech firms is 1.07, which is below it.

Table 3
Group descriptives for average Altman Z'

Variable	Group	N	Mean	Median	SD	SE
Avg_Z_Prime	DeepTech	105	2.39	2.11	0.987	0.0963
	Tech	95	3.57	3.28	0.856	0.0878

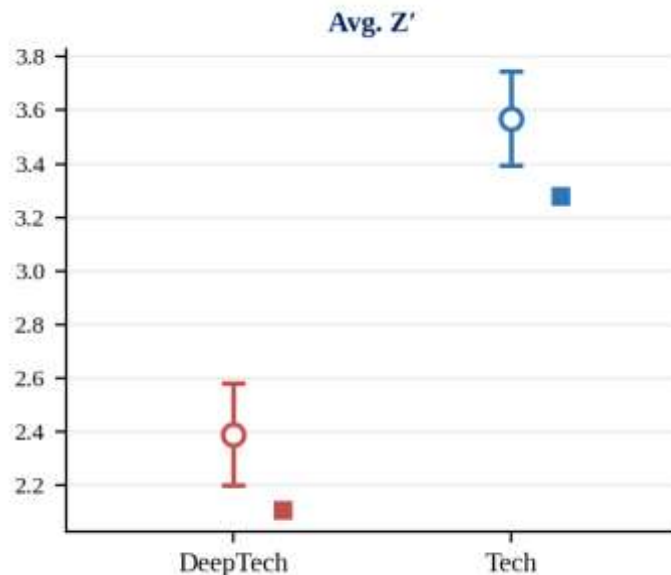
Source: Authors' calculation from Jamovi output (firm-year rows).

Table 4
Firm-year descriptives by group

Variable	DeepTech					Tech				
	Mean	Median	SD	Min.	Max.	Mean	Median	SD	Min.	Max.
Z'	2.38	2.01	1.11	1.07	6.30	3.57	3.29	0.984	1.88	9.25

Source: Authors' calculation from Jamovi output. Min. = minimum; Max. = maximum.

Figure 2
Average Altman Z' by group



Note. Circles show the mean with its 95% confidence interval; squares show the median. Intervals were derived from the reported means and standard errors.

Assumption Checks

Table 5 shows that the Shapiro–Wilk test rejects normality for the average Z' ($W = 0.877$, $p < .001$), and Levene's test rejects equal variances ($F = 5.06$, $p = .026$). Welch's t and the Mann–Whitney test are

therefore given priority in the interpretation. These violations describe the shape of the two groups and do not reverse the direction of the gap reported below.

Table 5
Normality and equal-variance tests

Variable	Shapiro–Wilk <i>W</i>	<i>p</i>	Levene <i>F</i> (df = 1, 198)	<i>p</i>
Avg_Z_Prime	0.877	< .001	5.06	.026

Source: Authors' calculation from Jamovi output ($N = 200$ firm-year rows).

Overall Resilience (H1 and H2)

Table 6 tests H1. All three tests reject equal mean Z' between the groups: Student's $t = -8.98$, Welch's $t = -9.05$ and $U = 1,700$, each with $p < .001$. Cohen's d of about -1.27 is a large separation, and the rank-biserial correlation of 0.659 tells the same story in ranks. Because normality and equal variance both fail (Table 5), the decision rests on Welch's t and the Mann–Whitney test. H1 is supported: Tech firms sit in the Safe band on average and DeepTech firms in the Grey band.

Table 6
Independent-samples tests for average Altman Z' (H1)

Test	Statistic	df	<i>p</i>	Effect size	Value
Student's t	-8.98	198	< .001	Cohen's d [95% CI]	-1.27 [–1.57, –0.97]
Welch's t	-9.05	198	< .001	Cohen's d	-1.28
Mann–Whitney U	1,700	–	< .001	Rank-biserial correlation	0.659

Note. $H_a: \mu_{\text{DeepTech}} \neq \mu_{\text{Tech}}$. Levene's test is significant ($p = .026$), indicating unequal variances.

Zone membership repeats the split in categories (Table 7, Figure 3). There are seven Distress firm-years, all DeepTech; 84 Grey firm-years, 69 of them DeepTech; and 106 Safe firm-years, 80 of them Tech. Under independence about 55 DeepTech firm-years would be expected in the Safe zone, whereas 26 are observed. The chi-square test rejects independence, $\chi^2(2, N = 197) = 69.1$, $p < .001$, and so does Fisher's exact test ($p < .001$). Cramér's $V = 0.592$ indicates a large association on a 3×2 table. H2 is supported, and the difference in means is not the product of a few unusual rows.

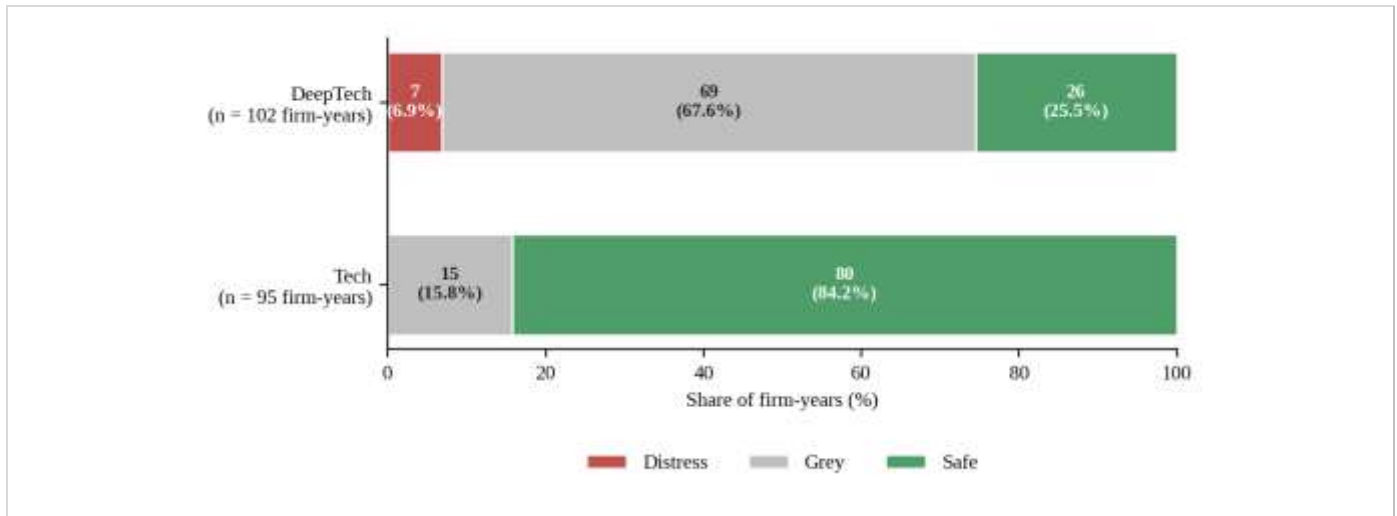
Table 7
Contingency table of zone by group (H2)

Zone	DeepTech		Tech		Total
	Observed (%)	Expected	Observed (%)	Expected	
Distress	7 (6.9%)	3.62	0 (0.0%)	3.38	7
Grey	69 (67.6%)	43.49	15 (15.8%)	40.51	84
Safe	26 (25.5%)	54.88	80 (84.2%)	51.12	106

Zone	DeepTech		Tech		Total
	Observed (%)	Expected	Observed (%)	Expected	
Total	102	102	95	95	197

Note. $\chi^2(2) = 69.1$, $p < .001$, $N = 197$; Cramér's $V = 0.592$; Fisher's exact test $p < .001$. Percentages are within group.

Figure 3
Zone membership by group



Source: Authors' calculation from Table 7.

Table 8 summarises the decisions for both hypotheses. H1 and H2 are supported: Tech firms show the higher Z' and a much larger share of Safe-zone firm-years.

Table 8
Summary of hypothesis decisions

Hypotheses	Statement	Main test used	p	Decision
H1	Mean Z' differs	Welch / Mann-Whitney	$< .001$	Supported; Tech higher
H2	Zone mix differs	χ^2 / Fisher	$< .001$	Supported

Source: Authors' own elaboration from Tables 6 and 7.

Discussion

The central result is that listed Tech and DeepTech firms in India do not share a resilience band. On the private-firm Altman scale, the Tech mean sits in the Safe zone and the DeepTech mean in the Grey zone, a gap of a little more than one point on a scale whose Safe line is 2.90 and whose Distress line is 1.23. The gap is not an artefact of a few firms, since the whole zone mix shifts: Safe is predominantly a Tech outcome, while Grey and Distress are predominantly DeepTech outcomes, and every Distress firm-year in the panel is DeepTech. These findings are consistent with the argument that firms with heavy asset

bases, long commercialisation cycles and late revenue should look different on the statements from asset-light software and services firms ([Nedayvoda et al., 2021](#)).

These results are consistent with the resource-based and risk arguments set out earlier: capital-intensive, long-cycle businesses are expected to look less resilient on the statements than asset-light software and services firms. However, Z' is a composite index, and this study tests only the score and the zone mix. It does not establish which part of the accounts, whether liquidity, profitability, equity buffer, liability coverage or asset turnover, produces the gap, so the mechanism is left open for future work.

Statement resilience is also a different object from market risk. Research on tail and systemic risk of technology firms in equity markets ([Chaudhry et al., 2022](#)) focuses on price movements, whereas a high Z' value in this study implies balance sheet and income statement resilience rather than price movements. In practice, the study implies a simple message for credit officers, boards, incubators and ministry desks that have to deal with a DeepTech company name alongside a Tech name: the two should not be benchmarked against a single set of expectations, and a Z' score is a screening device rather than a lending policy. For policymakers, the study shows that DeepTech firms as a group sit lower on a common resilience scale, so assessment and support designed with software-type firms in mind may not fit them; the data do not, however, identify what that support should be. Funding efficiency was among the dimensions of financial performance, but not included in the scorecard, so nothing can be said about relative capital utilization efficiency of Tech and DeepTech firms.

Conclusion

In this research, 19 listed Tech and 21 listed DeepTech firms in India were studied in the years FY2021-FY2025 on a single financial grid. The private firm's Altman Z' score of Tech firms is higher on average (3.57 against 2.39), and the Safe zone is far more prevalent among them, while every Distress firm-year belongs to DeepTech. Both H1 and H2 are supported. The two groups should therefore not be treated as one "technology" category in research, lending or policy.

The research makes two contributions. First, it gives an Indian panel, matched, where two sectors that are typically referred to as "technology" are measured by using the same formula over the same five years. Second, it shows that the gap in resilience appears both in the average Z' score and in the distribution of firm-years across the Safe, Grey and Distress zones, which is the question most relevant for banks, board members and policymakers.

A number of qualifications to the results apply. First, firm-years were considered as independent observations, but the five years of one company are related – this gives rise to underestimation of standard errors and optimism of p-values, which is the biggest design issue. Second, the panel includes listed firms, the majority of which are not start-ups, therefore, the results are not to be interpreted as an account of Indian start-ups in general, since the consumer-internet and pre-revenue deep-tech private companies are not included. Third, X_4 relies on book equity, and neither Z' coefficients nor cut-offs were re-estimated using Indian data. Fourth, because of non-normality and inequality of variance for most of the series used as well as unbalancedness of the panel (21 versus 19 firms), effect size and ranks have to be taken into consideration equally important as p-values. Fifth, there are three blank firm-years, efficiency of financing was not calculated, and there is no default/difficulty observed, hence, zones are only the result of formula and do not represent observed defaults. Finally, five-year period covers And the categorization of companies into Tech and DeepTech, while predetermined prior to testing, is an interpretation that can be made for some borderline cases elsewhere.

These constraints suggest an obvious research agenda for future studies. Future investigations need to replicate H1 and H2 using a row per firm sample (N=40) or by adjusting for clustered errors; recalculate X4 using market equity if a time-series is available without contamination; construct and test a funding efficiency measure, like incremental sales to incremental capital; extend the panel to include private firms when at least five years of statements can be compared; decompose the gap into the five Z' components and test revenue growth; estimate a multinomial or binary logistic regression model of zone as a function of X1 to X5 and group; include dummy variables for years and variations in Z'; segment the DeepTech group into public sector defense units, private defense electronics firms, shipyards and speciality materials; validate the segmentation using a second distress measure based on other frameworks like the Springate or Zmijewski models; and include FY2026 as a robustness window. Any of these modifications that contradict H1 and H2 would call for reconsidering the present results.

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