

Predicting Bankruptcy of Companies in the Pharmacy and Technology Sectors Using Altman's Z-score model

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Abstract—Numerous bankruptcy prediction models have been proposed and tested. Among them, the influential Altman Z-Score stands out as a powerful tool for assessing a business's financial health and gauging its vulnerability to financial distress and bankruptcy. This model incorporates five key financial ratios: liquidity, profitability, efficiency, market value, and net worth. This study aims to comprehensively assess the bankruptcy risk of companies by employing three different versions of Altman's Z-Score model: Z, Z', and Z''. These models categorize companies into three classifications: the 'Safe' zone, the 'Distress' zone, or the zone in between known as the 'Gray zone'. Additionally, this work investigates the accurate classification of both bankrupt and non-bankrupt firms into their respective categories. Hence, it was utilized to assess and contrast the classification precision of three different adaptations of the Altman Z-Score model. Concurrently, we employed a stepwise T-test approach to systematically integrate multiple independent financial variables, encompassing key financial ratios such as liquidity, profitability, productivity, market value, and net worth. The inclusion of each financial variable substantially enhanced the model's discriminative capacity. This analysis delves into the financial histories of 60 companies spanning the Pharmacy and Technology sectors, encompassing the years from 2000 to 2018. Furthermore, this study utilizes K-means clustering with Z-score normalization as the primary variable to ensure impartial treatment and to mitigate scale-related biases. The K-Means algorithm, a significant clustering technique, adeptly organizes data, categorizing companies into three groups: distress zone, gray zone, and safe zone. These results offer an additional tool for predicting bankruptcies within the pharmacy, and technology sectors.

Keywords: Bankruptcy, Altman's Z-score, Paired Sample T-Test, K-Means algorithm, Financial Distress, Financial Ratios

I. INTRODUCTION

In today's dynamic business environment, companies face a myriad of financial threats. These threats stem from global events, evolving regulations, changing consumer preferences, intense competition, and economic fluctuations. The capability to anticipate and circumvent bankruptcy is paramount for sustained success, competitiveness, and survival.

Technology serves as a formidable ally in this endeavor, offering tools for proactive identification of financial distress. Models such as financial analysis, data mining, and AI are instrumental in early warning and risk mitigation. Predicting and preventing bankruptcy have emerged as top priorities, with technological innovations and data-driven strategies laying the

groundwork for resilience and financial stability. This research delves into the instrumental role of technology in determining business trajectories and ensuring lasting prosperity.

A. Altman's Z-Score Model

The Altman Z-Score is an analytical tool conceived by Edward Altman in the 1960s. It amalgamates five pivotal financial ratios to gauge the bankruptcy probability of companies. These ratios span liquidity, profitability, efficiency, market value, and net worth. The Altman Z-Score provides a numerical score to a firm by scrutinizing various financial metrics and indicators. This score emerges from a credit strength test that evaluates the company's bankruptcy risk. Typically, a diminished Z-Score indicates a heightened bankruptcy probability.

In the Altman Z-Score formula, the liquidity ratio assesses a debtor's capability to settle short-term debt without resorting to additional borrowing [1]. Profitability ratios gauge a company's potential to generate earnings over time relative to its sales, operational expenses, balance sheet assets, or shareholders' equity [2]. Efficiency ratios appraise a firm's resource utilization and short-term obligation management [3]. Market value ratios, on the other hand, compare stock prices to those of competitors and other relevant metrics, reflecting a company's market standing [4]. The net worth ratio denotes the potential return shareholders might reap from their investment if all generated profits were directly disbursed to them.

Z-scores have been adapted into various versions to cater to different markets, sectors, and research objectives. The intricate nature of the financial realm is mirrored in the deployment of multiple financial scoring models. Utilizing an array of models facilitates a holistic and tailored assessment of a firm's financial health, credit risk, or specific challenges. The model selection should resonate with the precise objectives and prerequisites of the analysis.

Hypothesis testing emerges as a potent statistical tool in the financial application of the Altman Z-Score. It employs statistical methodologies to ascertain if a firm's financial health, as denoted by its Z-Score, deviates significantly from a set benchmark or expectation [5]. Hypothesis testing aids in making informed decisions regarding a company's financial stability. Typically, it encompasses the null hypothesis (H₀) and the alternative hypothesis (H_a). These hypotheses are employed to evaluate the null hypothesis's validity and ascertain if there's sufficient evidence to reject it in favor of the alternative

hypothesis. The exact formulation of these hypotheses can vary based on the research question and the statistical test in use. T-tests are frequently employed in hypothesis testing, proving indispensable in sectors like financial research, as they discern significant differences between two scenarios or groups.

Leveraging K-Means clustering to define bespoke cutoff points for the Modified Altman Z-Score can amplify the precision of a bankruptcy prediction model. This allows the model to resonate with the unique characteristics of the scrutinized firms. K-Means, a premier clustering algorithm in machine learning and data analytics, excels in segmenting data into clusters. This ensures heightened similarity among data points within a cluster while distinctly segregating them from other clusters.

Our research is organized to ensure clarity and a cohesive narrative. In Section 2, we conduct a comprehensive review of prior research related to the use of z-scores, t-tests, and k-means algorithms in bankruptcy reporting, as well as other relevant topics. Section 3 provides an in-depth explanation of the methodology employed in this study. In Section 4, we explore the analytical dimension of our research. Section 5 is dedicated to presenting our study's findings and drawing conclusions. Finally, in Section 6, we conclude our study by summarizing the key findings and offering valuable insights to guide future research endeavors in this domain.

II. LITERATURE REVIEW

The Z-Score method, devised by Edward Altman, has found extensive application across various sectors and geographic locales for scrutinizing companies' financial health and performance. One notable study exhibited a hybrid default prediction model employing Chinese data, which when juxtaposed with the Altman Z-Score model, yielded a superior average correct classification rate of 99.40% as opposed to 86.54% by the latter [6]. Furthermore, the method was leveraged to ascertain a company's financial robustness and bankruptcy susceptibility, emphasizing its utility in gauging financial stability [7].

Within the insurance realm, analysts opted for the Z-Score method as a simpler indicator of financial soundness amidst a sophisticated regulatory framework [8]. A forward-looking Z-Score variant, assimilating analyst forecasts of banks' earnings and financial standings, was deployed to prognosticate the movement of the standard Z-Score among U.S. banks listed on the S&P1500 during 2002Q1-2020Q1 [9].

A comparative discourse involving the Altman Z-Score model aimed at foreseeing companies' financial distress scenarios. This study not only reviewed the model's application in Turkey but also juxtaposed it against other models like Linear Discriminant Analysis, Quadratic Discriminant Analysis, and a Random Forest Machine Learning Model, underscoring the method's enduring relevance in contemporary financial analysis [10].

The Z''-Score Model, an extension of Altman's original Z-Score Model, has been employed to evaluate the financial stability of companies. The primary objective of your study aligns with evaluating the classification performance of the Z''-Score Model across 31 European and non-European countries.

This endeavor contributes to a broader body of literature where the Z-Score and its variants have been applied in diverse contexts to gauge financial health and bankruptcy risk:

- 1) **Overview of Altman's Z-Score Model:** Edward Altman introduced the Z-Score Model in 1968 as a numerical metric to predict bankruptcy probabilities. This model laid the groundwork for subsequent models like the Z''-Score Model used in your study [11].
- 2) **Literature Review on Z-Score Efficacy:** A literature review spanning 33 scientific papers from 2000 onward explored the global efficacy and importance of the Altman Z-Score bankruptcy prediction model, demonstrating its widespread application in finance and related fields [12].
- 3) **Application in Healthcare:** The Z-Score has transcended industries, with studies utilizing it to identify financially distressed organizations, notably within the healthcare sector, showcasing its versatility [13].
- 4) **Evaluation of Revised Altman Z'-Score Model:** A thesis validated the revised Altman Z'-Score Model's accuracy, particularly for inactive companies, indicating an accuracy of 83.3% and 66.7% in the years one and two before bankruptcy respectively [14].
- 5) **Refinement of Z-Score Parameters:** Altman's original formula has been refined over time, with a particular focus on differentiating between firms in distress and those in a safer financial zone, providing a nuanced tool for financial analysis [15].

These multifaceted applications and evaluations accentuate the Z-Score method's pivotal role and adaptability in dissecting financial performance and stability across different sectors and regions, continually aiding stakeholders in comprehending financial health, bankruptcy risks, and making enlightened decisions.

III. METHODOLOGY

A. Data Collection

Bloomberg [16] and Yahoo Finance [17] served as the primary sources of data for our research, encompassing financial information for a total of 42 institutions. This dataset includes comprehensive data on 13 pharmaceutical firms, 17 financial institutions, and 12 technology companies, spanning from 2000 to 2018. It encompasses critical financial documents such as balance sheets, income statements, and cash flow statements.

IV. METHODS

A. Approach to Calculating Altman's Z-Score

In this research, the Altman Z-Score formula was employed as a pivotal tool for predicting the likelihood of corporate bankruptcy. The study utilized three distinct versions of the Z-Score, namely the Altman Z-Score, Z'-Score, and Z''-Score, each designed to provide unique insights into a company's financial stability. The three versions of the Z-Score formula and the five financial ratios (liquidity ratio, profitability ratio, efficiency ratio, market value ratios, and net worth) can be found in Table: I.

TABLE I: Altman Z-Score and Financial Ratios

Ratio	Public Manufacturing Firms	Private Manufacturing Firms	Private Non-Manufacturing Firms
X1 (Liquidity Ratio)	Working Capital / Total Assets	Working Capital / Total Assets	Working Capital / Total Assets
X2 (Profitability Ratio)	Retained Earnings / Total Assets	Retained Earnings / Total Assets	Retained Earnings / Total Assets
X3 (Efficiency Ratios)	Ebit / Total Assets	Ebit / Total Assets	Ebit / Total Assets
X4 (Market Value Ratios) or X6 (Net Worth Ratios)	Market Value of Equity / Total Liabilities (X4)	Book Value / Total Liabilities (X6)	Book Value / Total Liabilities (X6)
X5 (Efficiency Ratios)	Sales / Total Assets	Sales / Total Assets	None
Formula	$1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 0.999X5$	$0.717X1 + 0.847X2 + 3.107X3 + 0.42X6 + 0.998X5$	$6.56X1 + 3.26X2 + 6.72X3 + 1.05X6$
Interpretation	< 1.8 Bankruptcy Likely $\geq 1.8 - 2.99$ Zone of Uncertainty ≥ 3.0 Bankruptcy Unlikely	< 1.23 Bankruptcy Likely $\geq 1.23 - 2.90$ Zone of Uncertainty ≥ 2.9 Bankruptcy Unlikely	< 1.1 Bankruptcy Likely $\geq 1.1 - < 2.6$ Zone of Uncertainty ≥ 2.6 Bankruptcy Unlikely

V. HYPOTHESIS TESTING WITH T-TEST AND ALTMAN'S Z-SCORE

The financial ratios in one industry should still be relevant in another. As such, we hypothesize that the modified Altman Z-score approach should be a valid model to predict bankruptcy within the Pharmacy, and Technology Sectors. Therefore, the following hypothesis is proposed [18]:

Hypothesis 1: The modified Altman Z-Score effectively predicts bankruptcy in pharmacy, and technology sector companies.

A liquidity ratio is determined by dividing working capital by total assets. Working capital is derived by deducting current liabilities from current assets. In the corporate sector, liquidity plays a crucial role as it indicates how well a company can sustain its ongoing operations. The financial liquidity of a company is a fundamental measure that significantly impacts its overall success or potential failure. This leads us to formulate the following hypothesis [18]:

Hypothesis 2: The liquidity ratio will be a substantial predictor in the bankruptcy prediction model for companies within the pharmacy, and technology sectors.

The profitability ratio is calculated as retained earnings divided by total assets. This financial metric serves as an indicator of the organization's capacity to generate earnings relative to its asset base. All companies, regardless of their profit status, must ensure their financial stability to sustain their operations. Therefore, we present the following hypothesis related to predicting company bankruptcy [19]:

Hypothesis 3: The profitability ratio will be a substantial predictor in the bankruptcy prediction model for companies within the pharmacy, and technology sectors.

The efficiency ratio, sometimes referred to as the operational or activity ratio, is calculated as earnings before interest and taxes divided by total assets. It measures the effectiveness of a company's asset utilization in generating earnings. Efficiency ratios are essential components of bankruptcy prediction models because they provide important information about the operational performance and financial stability of a business, which helps identify and prevent financial hardship and bankruptcy early on. As a result, the following theory is put forth:

Hypothesis 4: The efficiency ratio will be a substantial predictor in the bankruptcy prediction model for companies within the pharmacy, and technology sectors [19].

A market value ratio is determined by dividing the market value of equity by total liabilities. The market value of a company, often determined by its stock price and market

capitalization, is a critical factor in financial analysis. It reflects investor sentiment, expectations, and the company's perceived value in the market. A declining market value may raise concerns about the company's financial health and bankruptcy risk, as it can affect its ability to raise capital and access credit. Monitoring market value is essential for assessing a company's overall financial stability and its potential vulnerability to financial distress. Therefore, we present the following hypothesis related to predicting company bankruptcy:

Hypothesis 5: The market value ratio will be a substantial predictor in the bankruptcy prediction model for companies within the pharmacy, and technology sectors [20].

The book value of equity is divided by the total liabilities to get the Net Worth ratio. It is an essential financial metric that aids in assessing a business's ability to manage financial hardships, keep its word, and avoid bankruptcy. As it provides details on a company's financial health and resilience, it is a crucial component of bankruptcy prediction models and more thorough financial research. That's why the following theory is put forth:

Hypothesis 6: The Net Worth ratio will be a substantial predictor in the bankruptcy prediction model for companies within the pharmacy, and technology sectors [20].

After formulating the hypotheses, a combination of t-tests and the Z-Score methodology to conduct financial analysis and hypothesis testing. These methods allowed us to statistically assess whether the observed data aligns with the predictions and expectations outlined in our hypotheses. To evaluate the accuracy of our hypotheses, we conducted t-tests in accordance with the criteria as outlined.

- If the p -value is less than or equal to α ($p \leq \alpha$), you reject the null hypothesis.
- If the p -value is greater than α ($p > \alpha$), you fail to reject the null hypothesis.

Typical values for α in hypothesis testing are 0.05 (5%).

A. Altman's Z-Score Standardization in K-Means Clustering

After the modified Altman Z-score calculations, we combined the Z-score normalization with the K-means clustering technique. This combination was specifically chosen to guarantee that every variable in the dataset was treated fairly. We reduced the excessive impact of scale variances by creating a level playing field for all variables by normalizing data scales using Z-score normalization. The K-means algorithm was able to cluster data based on relative differences more

easily because to this standardization, producing a reliable and fair analysis.

B. Methodology Visualization

Figure 1 serves as a visual representation of our entire methodology, providing a comprehensive and intuitive overview of the steps involved in our model. It aids in the understanding of our research process, making it more accessible to readers.

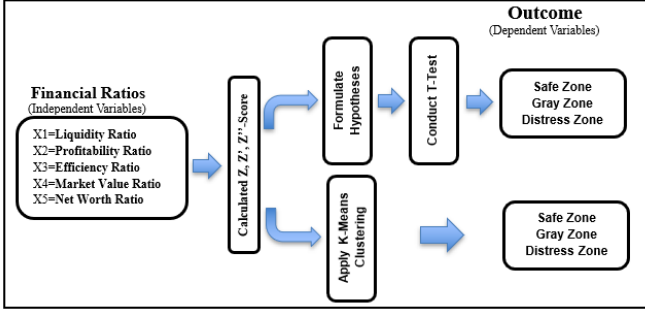


Fig. 1: Structural Flow of the model

VI. ANALYSIS

A. Data Researchers for Altman's Z-Score

To distinguish between financially failed and non-failed companies using Altman's Z-score model, we've categorized companies within the Pharmacy, and Technology sectors into three distinct groups: Distressed Zone, Gray Zone, and Safe Zone. While the 'Grey Zone' characterizes companies that do not fail but rather exist in a state of uncertainty, the 'Safe Zone' designates companies that are considered successful. The 'Distressed Zone' refers to companies experiencing financial failure. As we assess companies' bankruptcy risk annually, it's important to note that the same company may appear in multiple distinct groups. These classifications are outlined in Table 3 for the Pharmacy sector, Table 4 for the Technology sector.

When we examined the Figure 2 visualization, it became evident that the companies in the Pharmacy Industry were correctly categorized into the 'Safe,' 'Gray,' and Distress Zone.

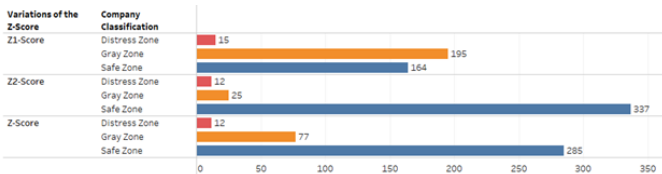


Fig. 2: Pharmacy Sector companies correctly categorized into 'Safe,' 'Gray,' and 'Distress' Zones.

Upon reviewing Table II, we found more detailed information, revealing that companies in the Pharmacy Industry were accurately classified into the 'Safe,' 'Gray,' and 'Distress' zones.

TABLE II: Pharmacy Sector companies correctly categorized into 'Safe,' 'Gray,' and 'Distress' Zones.

Zones	Total	N	Mean	SD	Min	Max
Z Score	374					
Safe Zone		285	4.72	1.30	3.00	15.33
Gray Zone		77	2.44	0.30	1.81	2.99
Distress Zone		12	1.36	0.40	0.28	1.80
Z' Score	374					
Safe Zone		164	3.96	0.83	2.90	6.38
Gray Zone		195	2.16	0.43	1.24	2.89
Distress Zone		15	0.89	0.39	-0.21	1.21
Z'' Score	374					
Safe Zone		337	6.55	2.15	2.65	12.63
Gray Zone		25	1.96	0.50	1.10	2.58
Distress Zone		12	0.29	0.85	-1.99	0.99

When we examined the Figure 3 visualization, it became evident that the companies in the Pharmacy Industry were correctly categorized into the 'Safe,' 'Gray,' and 'Distress' zones.

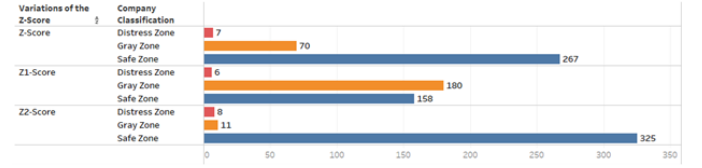


Fig. 3: Technology Sector companies correctly categorized into 'Safe,' 'Gray,' and 'Distress' Zones.

Upon reviewing Table III we found more detailed information, revealing that companies in the Pharmacy Industry were accurately classified into the 'Safe,' 'Gray,' and 'Distress' zones, like Table II.

TABLE III: Technology Sector companies correctly categorized into 'Safe,' 'Gray,' and 'Distress' Zones.

Zones	Total	N	Mean	SD	Min	Max
Z Score	344					
Safe Zone		267	8.17	11.49	3.01	163.92
Gray Zone		70	2.45	0.32	1.87	2.96
Distress Zone		7	1.45	0.31	0.94	1.70
Z' Score	344					
Safe Zone		158	3.90	0.73	2.90	5.81
Gray Zone		180	2.17	0.40	1.28	2.88
Distress Zone		6	1.04	0.13	0.85	1.19
Z'' Score	344					
Safe Zone		325	8.53	3.47	2.60	18.50
Gray Zone		11	1.99	0.37	1.44	2.54
Distress Zone		8	-0.24	0.95	-2.19	1.07

When we reviewed Figure 4, regrettably, we noticed that companies were not accurately categorized into the 'Safe,' 'Grey,' and 'Danger' zones. This incorrect classification in Figure 4 led us to the conclusion that the Z-Score is an inadequate criterion for assessing the finance sector. To attain more precise results, we opted to proceed to the "Result" section. In this section, we presented and expounded upon these findings in greater detail. Consequently, we have determined that there

is no necessity to employ T-test and K-means algorithms for the analysis of financial sector data.

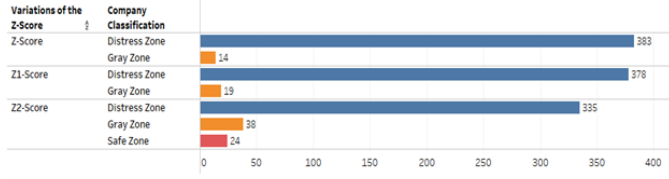


Fig. 4: Finance Sector companies is not correctly categorized into 'Safe,' 'Gray,' and 'Distress' Zones.

Upon reviewing Table IV, we found more detailed information, revealing that companies in the Pharmacy Industry were accurately classified into the 'Safe,' 'Gray,' and 'Distress' zones.

TABLE IV: Finance Sector companies are not correctly categorized into 'Safe,' 'Gray,' and 'Distress' Zones.

Zones	Total	N	Mean	SD	Min	Max
Z Score	397					
Gray Zone		14	2.06	0.21	1.88	2.59
Distress Zone		383	0.29	0.30	-0.44	1.79
Z' Score	397					
Gray Zone		19	1.49	0.15	1.33	2.04
Distress Zone		378	0.18	0.14	-0.36	1.18
Z'' Score	397					
Safe Zone		24	5.10	0.76	7.03	3.37
Gray Zone		38	1.21	0.19	2.09	1.10
Distress Zone		335	0.57	0.30	1.10	-1.04

VII. APPLICATION OF K-MEANS CLUSTERING WITH Z-SCORE STANDARDIZATION

K-Means clustering, enhances bankruptcy prediction in the pharmacy, and technology sectors by categorizing companies into Distress, gray, and safe zones based on Z-scores.

Upon reviewing Table ??, we found more detailed information, revealing that companies in the Pharmacy Sector were accurately classified into the 'Safe,' 'Gray,' and 'Distress' zones using K-Means Clustering.

VIII. K-MEANS CLUSTERING WITH Z-SCORE STANDARDIZATION IN SECTOR ANALYSIS

Using K-Means clustering with Z-scores, companies in the pharmacy and technology sectors were segmented into three financial health categories: Safe, Gray, and Distress zones.

Pharmacy Sector:

- **Safe Zone:** 38% (138/362) of companies were identified as financially stable with a mean Z-score of 5.65.
- **Gray Zone:** Approximately 46% (166/362) lie in an intermediary zone with a mean Z-score of 3.73, requiring vigilant monitoring.
- **Distress Zone:** About 19% (70/362) were in potential distress with a mean Z-score of 2.15, indicating higher bankruptcy risks.

Technology Sector:

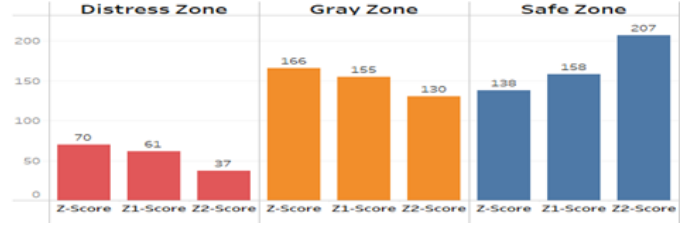


Fig. 5: Pharmacy Sector companies

- **Safe Zone:** A mere 6% (21/344) were classified as safe, albeit with a considerably high mean Z-score of 32.09.
- **Gray Zone:** Approximately 41% (141/344) fall into the gray zone with a mean Z-score of 8.05.
- **Distress Zone:** A significant 53% (182/344) are potentially distressed, with a mean Z-score of 3.04.

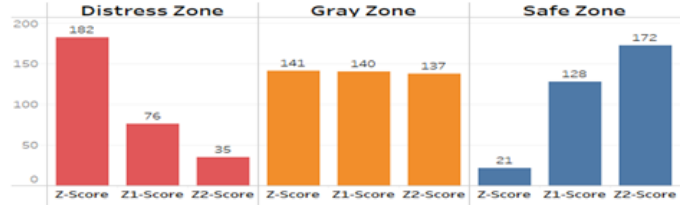


Fig. 6: Technology Sector companies

Incorporating K-Means clustering with Z-score standardization facilitates a nuanced understanding of company financial health across sectors, aiding preemptive decision-making.

- **Sectoral Differences:** The notable variance in Z-scores between the pharmacy and technology sectors, especially in the safe zone, highlights distinct financial landscapes.
- **Gray Zone Significance:** The sizable gray zone population across both sectors underscores the importance of ongoing financial scrutiny.

IX. T-TEST ANALYSIS AND SIGNIFICANCE ASSESSMENT IN Z-SCORE STANDARDIZATION

A. Bivariate Analysis

Bivariate analysis was performed to compare the financial variables of both bankrupt and non-bankrupt companies as determined by the modified Altman model. This analysis encompassed five key financial factors: liquidity, profitability, efficiency, market value, and net worth. The results of this analysis are succinctly presented in Tables V and VI.

B. Statistical Significance

When analyzing Table V, t-test analysis for Z-Score, Z'-Score, and Z''-Score showed significant differences, except for Z-Score liquidity. Significant variations were found in liquidity, profitability, efficiency, market value, and net worth between bankrupt and non-bankrupt companies ($p < 0.05$). However, there was no significant difference in Z-Score liquidity ($p = 0.06$).

When analyzing Table VI, t-test results for Z-Score, Z'-Score, and Z''-Score showed significant differences, except

	Altman variables	Bankrupt			Non-Bankrupt			T-Statistic	P-Value
		N	Mean	SD	N	Mean	SD		
$T_{for Z}$	Liquidity ratio(X1)	362	0.44	0.16	12	0.36	0.18	1.87	0.06
	Profitability ratio(X2)	362	0.40	0.22	12	0.03	0.17	5.79	0.00
	Efficiency ratio(X3)	362	0.14	0.09	12	-0.02	0.13	5.70	0.00
	Market Value ratio(X4)	362	2.02	1.98	12	0.77	0.51	2.17	0.03
	Efficiency ratio(X5)	362	1.49	1.42	12	0.48	0.15	2.46	0.01
$T_{for Z'}$	Liquidity ratio(X1)	359	0.45	0.16	15	0.27	0.18	4.16	0.00
	Profitability ratio(X2)	359	0.41	0.21	15	-0.01	0.14	7.45	0.00
	Efficiency ratio(X3)	359	0.14	0.09	15	0.01	0.13	4.99	0.00
	Net Worth ratio(X6)	359	0.97	0.64	15	0.44	0.41	3.15	0.00
	Efficiency ratio(X5)	359	1.49	1.42	15	0.47	0.11	2.78	0.01
$T_{for Z''}$	Liquidity ratio(X1)	362	0.45	0.15	12	0.06	0.13	9.09	0.00
	Profitability ratio(X2)	362	0.41	0.21	12	-0.09	0.12	8.05	0.00
	Efficiency ratio(X3)	362	0.13	0.09	12	0.01	0.12	4.43	0.00
	Net Worth ratio(X6)	362	0.98	0.63	12	0.08	0.22	4.90	0.00

TABLE V: Bivariate Analysis of Modified Altman Financial Metrics: Bankruptcy vs. Non-Bankruptcy Status in the Pharmacy Industry

for Z-Score profitability, market value, efficiency, and Z'-Score efficiency. Significant variations were found in liquidity, profitability, efficiency, market value, and net worth between bankrupt and non-bankrupt companies ($p < 0.05$). However, there was no significant difference in Z-Score profitability ($p = 0.06$), market value ($p = 0.28$), efficiency ($p = 0.71$), and Z'-Score efficiency ($p = 0.10$).

	Altman variables	Bankrupt			Non-Bankrupt			T-Statistic	P-Value
		N	Mean	SD	N	Mean	SD		
$T_{for Z}$	Liquidity ratio(X1)	337	0.56	0.21	7	0.32	0.10	3.01	0.00
	Profitability ratio(X2)	337	0.42	0.32	7	0.19	0.06	1.88	0.06
	Efficiency ratio(X3)	337	0.17	0.11	7	-0.07	0.10	5.60	0.00
	Market Value ratio(X4)	337	7.14	17.11	7	0.18	0.15	1.08	0.28
	Efficiency ratio(X5)	337	0.88	0.42	7	0.94	0.35	-0.37	0.71
$T_{for Z'}$	Liquidity ratio(X1)	338	0.56	0.21	6	0.27	0.06	3.43	0.00
	Profitability ratio(X2)	338	0.42	0.32	6	0.11	0.10	2.33	0.02
	Efficiency ratio(X3)	338	0.17	0.12	6	-0.00	0.11	3.55	0.00
	Net Worth ratio(X6)	338	1.95	1.67	6	0.37	0.11	2.31	0.02
	Efficiency ratio(X5)	338	0.89	0.42	6	0.61	0.32	1.64	0.10
$T_{for Z''}$	Liquidity ratio(X1)	336	0.57	0.19	8	0.01	0.14	8.07	0.00
	Profitability ratio(X2)	336	0.43	0.31	8	-0.22	0.31	5.92	0.00
	Efficiency ratio(X3)	336	0.17	0.12	8	0.06	0.12	2.61	0.01
	Net Worth ratio(X6)	336	1.97	1.66	8	0.03	0.17	3.30	0.00

TABLE VI: Bivariate Analysis of Modified Altman Financial Metrics: Bankruptcy vs. Non-Bankruptcy Status in the Technology Industry

X. RESULTS

Our application of Altman's Z-Score analysis highlighted potential bankruptcy risks within companies in both the Pharmacy and Technology sectors. For instance, in the Pharmacy sector between 1995 and 2020, companies like GSK, PFE, and PRGO were frequently flagged across different Z-Score variations. Similarly, in the Technology sector between 1990 and 2020, companies like AAPL, HPQ, and IBM were noted as at-risk.

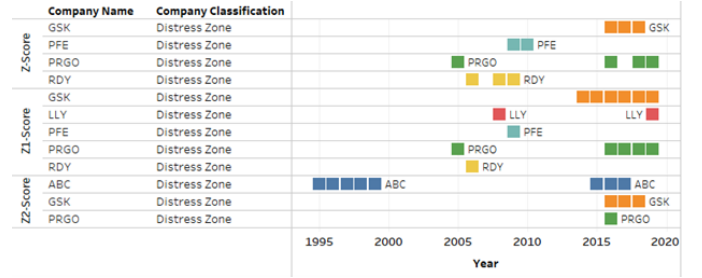


Fig. 7: Bankrupt Companies Using Altman's Z-Score in the Pharmacy Sector

When we turned to K-Means clustering, the results aligned with some earlier findings but also introduced new companies under potential risk. For instance, the Pharmacy sector analysis flagged ABC, ABT, and LLY, while the Technology sector spotlighted firms like MSFT and ORCL. These analyses underscore the necessity of utilizing diverse metrics to achieve a holistic understanding of potential bankruptcy risks within sectors.

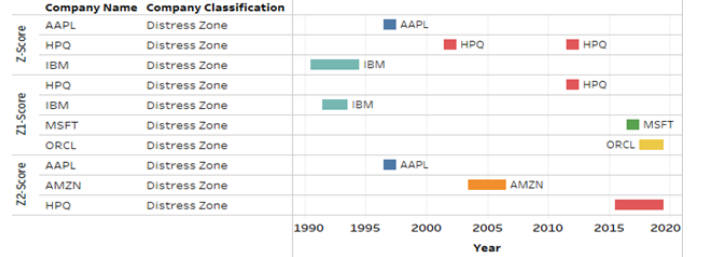


Fig. 8: Bankrupt Companies Using Altman's Z-Score in the Technology Sector

XI. DISCUSSION AND FUTURE WORK

We can be sure that our forecasting models will face new difficulties in the future due to the financial markets' dynamic and constantly changing character. A crucial task in this ever-changing environment is the constant search for more precise and flexible instruments to evaluate bankruptcy risk. With its insightful findings and guidance for future research in the field of financial risk assessment, our study provides a strong basis for this continuous journey.

Although our research has yielded valuable insights into the forecast of bankruptcy in particular industries, it is imperative to recognize the inherent constraints of this study. Because the financial industry is complex and constantly changing, no model is perfect. Future studies ought to investigate the incorporation of supplementary factors and data sources to augment the accuracy and adaptability of models for predicting bankruptcy.

Moreover, our findings have unmistakably highlighted that when the Z-Score model is employed in isolation, it may not provide a sufficiently comprehensive evaluation, particularly within the intricate financial sector. Therefore, in future research, it would be judicious to investigate advanced Z-Score versions or alternative methodologies precisely tailored to the unique intricacies of the financial industry.

XII. CONCLUSION

In this study, we assessed bankruptcy risk in the Pharmacy and Technology sectors from 2000 to 2018 using three versions of Altman's Z-Score model. Our findings affirm the effectiveness of the Z-Score model in evaluating bankruptcy risk within the Pharmacy and Technology sectors. However, it became evident that when applied in isolation, the Z-Score model may not provide a sufficiently comprehensive evaluation of the financial sector.

Moreover, our comparative analysis of the three different adaptations of Altman's Z-Score model demonstrated remarkable consistency in the results. This outcome underscores the pivotal role played by these three distinct Z-Scores as essential tools in the prediction of bankruptcy. This research contributes valuable insights and practical implications for financial analysts, investors, and policymakers.

As financial markets continue to evolve, our study emphasizes the need for a multi-dimensional approach to bankruptcy risk assessment, particularly in complex sectors. By advancing our understanding of bankruptcy risk assessment, our research supports the broader goal of enhancing financial stability and risk management, ultimately benefiting the financial community and the broader economy. We anticipate that these insights will lead to more informed financial decisions and strengthen the resilience of these critical sectors.

REFERENCES

- [1] "Business bankruptcy prediction models: A significant study of the altman z-score model," *SSRN*. [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3486612
- [2] A. Ghosh, "Is altman's model efficient in predicting bankruptcy? – a comparison among the altman z-score, dea, and ann models," *Taylor & Francis Online*. [Online]. Available: <https://www.tandfonline.com/doi/full/10.1080/23311975.2022.1963749>
- [3] "Thomas cook(ed): using altman's z-score analysis to examine predictors," *Emerald Insight*. [Online]. Available: <https://www.emerald.com/insight/content/doi/10.1108/WHATT-04-2020-0027/full/html>
- [4] "Bankruptcy prediction for the european aviation industry: An analysis using the updated altman z-score model (1983 and 2017)," *Semantic Scholar*. [Online]. Available: <https://www.semanticscholar.org/>
- [5] B. Sebasian, "A study on the accuracy of bankruptcy models predicting," *SSRN*, 2023. [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4422924
- [6] D. Wu, X. Ma, and D. L. Olson, "Financial distress prediction using integrated z-score and multilayer perceptron neural networks," *Decision Support Systems*, vol. 159, no. C, August 2022. [Online]. Available: <https://doi.org/10.1016/j.dss.2022.113814>
- [7] M. S. AlAli, "The application of altman's z-score model in determining the financial soundness of healthcare companies listed in kuwait stock exchange," *International Journal of Economic Papers*, vol. 3, no. 1, pp. 1–5, April 2018. [Online]. Available: <http://scigatejournals.com/publications/index.php/ijeconomic>
- [8] I. Moreno, P. Parrado-Martínez, and A. Trujillo-Ponce, "Using the z-score to analyze the financial soundness of insurance firms," *European Journal of Management and Business Economics*, July 2021, open Access. Issue publication date: 17 February 2022.
- [9] B. Hafeez, X. Li, M. H. Kabir, and D. Tripe, "Measuring bank risk: Forward-looking z-score," *International Review of Financial Analysis*, vol. 80, p. 102039, March 2022. [Online]. Available: <https://doi.org/10.1016/j.irfa.2022.102039>
- [10] Z. Cindik and I. H. Armutlulu, "A revision of altman z-score model and a comparative analysis of turkish companies' financial distress prediction," *National Accounting Review*, vol. 3, no. 2, pp. 237–255, 2021. [Online]. Available: <https://www.aimspress.com/article/doi/10.3934/NAR.2021012>
- [11] Unknown, "Altman's z-score model - overview, formula, interpretation," *Corporate Finance Institute*, 1968. [Online]. Available: <https://corporatefinanceinstitute.com/>
- [12] E. I. Altman, "Review of the altman z-score bankruptcy prediction model," *SSRN*, 2000. [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2536340
- [13] J. Lord, A. Landry, G. Savage, and R. Weech-Maldonado, "Predicting nursing home financial distress using the altman z-score," *Inquiry*, vol. 57, 2020. [Online]. Available: <https://doi.org/10.1177/0046958020934946>
- [14] S. N. 129009402, "The revised altman z'-score model: Verifying its validity as a predictor of corporate failure in the case of uk private companies," 2015, mSc Banking and Finance.
- [15] W. Qiu, S. Rudkin, and P. Dłotko, "Refining understanding of corporate failure through a topological data analysis mapping of altman's z-score model," *Expert Systems with Applications*, vol. 156, p. 113475, October 2020. [Online]. Available: <https://doi.org/10.1016/j.eswa.2020.113475>
- [16] "Bloomberg," <https://www.bloomberg.com/>, accessed: 10/2023.
- [17] "Yahoo finance," <https://finance.yahoo.com/>, accessed: 20/2023.
- [18] I. Fitriani and P. Muniarty, "Bankruptcy prediction analysis using the altman z-score method at pt aneka tambang (persero) tbk," *International Journal of Management*, vol. 1, no. 2, 2020. [Online]. Available: <https://www.ilomata.org/index.php/ijm/article/download/86/44>
- [19] J. Lord, A. Landry, G. Savage, and R. Weech-Maldonado, "Predicting nursing home financial distress using the altman z-score," *Inquiry: The Journal of Health Care Organization, Provision, and Financing*, vol. 57, 2020. [Online]. Available: <https://europepmc.org/articles/pmc7333488?pdf=render>
- [20] Parameshwara and A. Rahman, "Analysis of a credit strength of selected automobile companies: A quantitative approach using the z-score-based on five financial ratios," 2020.