THE EVALUATION OF FINANCIAL PERFORMANCE AS A PREVENTION MECHANISM AND PREDICTIVE INSTRUMENT OF BANKRUPTCY RISK

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ABSTRACT: *In an economic environment marked by volatility and uncertainty, financial performance is a fundamental element in assessing the stability and sustainability of organisations. The early detection of financial vulnerabilities requires integrating financial performance into a predictive framework, where changes in factors such as profitability, liquidity, and financial leverage can signal an increased probability of significant difficulties. Consequently, financial performance becomes not only a reflection of past outcomes but also a prevention mechanism and a predictive instrument that aids decision-makers in implementing timely corrective actions. This study aims to analyse the role of financial performance assessment as a prevention mechanism and predictive instrument for bankruptcy risk by identifying and testing the predictive capacity of key financial indicators. This research highlights how financial performance can contribute to the development of effective early warning systems, which can support organisations ' risk management and strengthen their long-term sustainability.*

Keywords: *financial performance, financial distress, bankruptcy, financial indicators, Composite score, Altman Z'-Score*
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1. INTRODUCTION

Global financial markets have been marked by volatility and uncertainty for the last years. The Global Financial Crisis demonstrated that the persistent build-up of debt contributes to greater financial fragility and potentially negative results, which could affect the sustainability of a business. These risks have been consistently highlighted by the economic fallout from the COVID-19 pandemic, which has led to extensive economic slowdowns and financial strain that persist across many parts of the world (Issa et al., 2024). Predicting bankruptcy is one of the most important tools for analysing financial performance to avert company failure, which could lead to a systemic collapse of the economy. Bankruptcy has far-reaching implications, affecting supply chains, employment, shareholders, and investors (Rahayu et al., 2024).

Bankruptcy occurs when a company in financial distress is unable to meet its obligations, such as repaying its due liabilities, paying salaries, and meeting the due date for tax payments. Financial distress is often caused by internal failures, such as poor management, economic downturns, industry decline, decreased demand for the industry's products or services, falling revenues and profit margins, and a reduction in employment and investment. While financial distress determined by internal causes can be avoided by conducting countermeasures at an early stage, the external causes cannot be influenced by the target company (Habermann & Fischer, 2023). According to Toudas et al. (2023), the term "bankruptcy" or "insolvency" implies a negative return for a business, referring to a situation where a company is unable to meet its current payment obligations, indicating a lack of liquidity. The technical measurement of bankruptcy should be based on net cash flow concerning short-term liabilities, rather than the working capital measure. Legal insolvency, often associated with bankruptcy, extends beyond payment incapacity and involves a comprehensive assessment of a company's total liabilities relative to the fair value of its total assets. A business is typically deemed legally insolvent or bankrupt when its liabilities exceed the fair value of its assets, resulting in negative equity and sustained loss of solvency. While payment incapacity may be temporary and reversible, bankruptcy reflects a critical and chronic condition. Technical insolvency may be straightforwardly identified in clear-cut cases, whereas complex situations, such as severe conditions, often require in-depth analysis, initiating asset liquidation procedures (Altman & Hotchkiss, 2006).

In this context, the assessment of financial performance emerges as a necessary preventive measure to avoid bankruptcy. Financial performance, encompassing profitability, liquidity, and leverage, offers a multidimensional assessment of a company's operational and financial health (Brigham & Houston, 2018). Regular monitoring of these indicators enables companies to detect early signs of financial distress, allowing for timely corrective actions before financial challenges escalate into bankruptcy. Despite its significance, many companies focus on ex-post corrective measures, addressing financial distress only after imbalances arise, rather than utilising ex-ante evaluation for proactive risk management. This stress on proactive risk management is crucial for the survival and success of any business (Altman & Hotckhkiss, 2006).

Given the increasing need for systematic methods to identify potential bankruptcy risks, the application of quantitative models for bankruptcy prediction has become important in both academic research and practical financial management (Sun et al., 2014). Among these models, the Altman Z-Score is notable for its widespread use and interpretability, as it effectively combines key financial ratios to evaluate a company's likelihood of bankruptcy. However, advanced predictive methods, including machine learning algorithms and ultimate ownership networks, have gained popularity in recent years. Traditional models, such as the Z-Score, continue to be valuable due to their simplicity, transparency, and proven effectiveness in delivering early warning signals for financial distress (Rayadu et al., 2025).

Despite extensive research on financial performance indicators and bankruptcy prediction models, there is limited focus on systematically linking the evaluation of financial performance with proactive bankruptcy prevention, particularly within the Romanian corporate environment (Altman et al., 2017). Additionally, there is a scarcity of longitudinal studies examining the evolution of bankruptcy risk at the company level, using extended periods to monitor trends and identify early vulnerabilities (Bellovary et al., 2007).

To address these gaps, this study aims to validate the relationship between financial performance and bankruptcy vulnerability by employing the Altman Z'-Score as a predictive tool within a preventive financial management framework (Altman & Hotchkiss, 2006).

The remainder of the paper is structured as follows: Section 2 presents a review of the literature on financial performance and bankruptcy prediction models. Section 3 presents the objectives and the hypothesis for the study. Section 4 outlines the methodology used in collecting the data for the study. Section 5 discusses the results and their implications, while Section 6 concludes with practical recommendations for corporate financial management and suggestions for future research.

2. LITERATURE REVIEW

2.1. Financial performance as a Predictor of Corporate Stability

Financial performance is widely recognised as a significant indicator of a company's operational efficiency and long-term sustainability. It encompasses profitability measures such as Return on Assets (ROA) and Return on Equity (ROE), liquidity indicators like the Current Ratio (CR), and leverage metrics that capture a company's financial structure and risk exposure (Mahmudi & Khaerunnisa, 2023).

Profitability indicators, such as ROA and ROE, reflect the company's capacity to generate earnings relative to its assets and equity (Brigham & Houston, 2018). Consistent profitability suggests effective management, operational efficiency, and a greater ability to withstand economic downturns, thereby reducing the likelihood of financial distress (Ahmad, 2024). In contrast, declining profitability often signals operational inefficiencies or external pressures that may lead to financial instability.

Liquidity ratios, such as the CR, indicate a company's ability to meet its short-term obligations using its current assets. Adequate liquidity provides a buffer against unexpected financial shocks and operational disruptions, supporting the company's resilience in times of economic uncertainty (Mahmudi & Khaerunnisa, 2023). Low liquidity levels, on the other hand, may indicate potential difficulties in meeting obligations, serving as an early warning signal for financial distress.

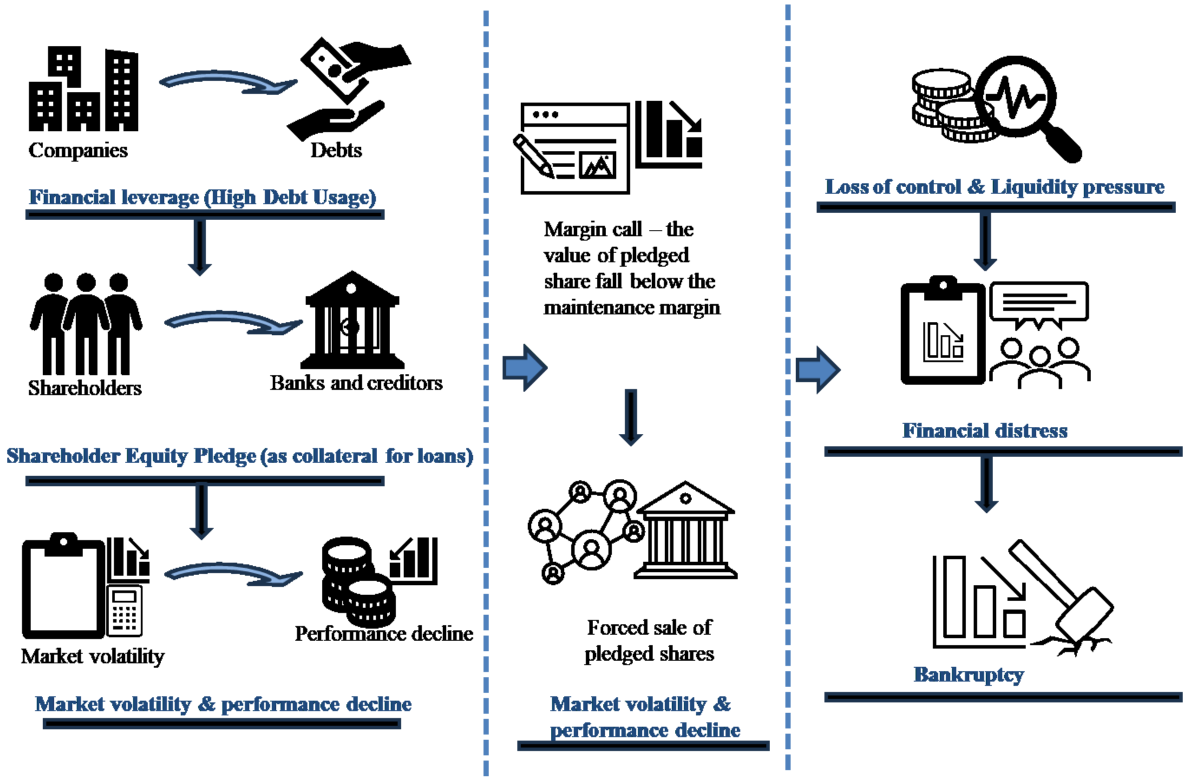
Leverage indicators measure the degree to which a company utilises debt to finance its operations. While leveraging can enhance returns during profitable periods, high leverage increases financial risk, particularly during downturns, as companies face higher debt servicing obligations regardless of operational performance (Altman et al., 2017). Monitoring leverage levels enables companies and stakeholders to assess the risk of insolvency under various economic scenarios (Issa et al., 2024).

A factor influencing corporate financial stability is the pledge of shareholders' equity. A shareholder equity pledge refers to the practice in which major shareholders use their equity holdings as collateral to secure loans, aiming to obtain liquidity while maintaining control over the company's ownership (Liu et al., 2022). Although this practice can provide immediate financial flexibility for shareholders, it introduces significant risks for the company's stability.

Firstly, the pledge of shares exposes the company to risks associated with market volatility. A decline in the company's performance may lead to a drop in stock prices, triggering margin calls that require the forced sale of shares that have been pledged. Such forced transactions can further depress stock prices, erode investor confidence, and potentially result in a loss of control over the company's governance structure (Liu et al., 2022). Secondly, shareholders under financial pressure may resort to aggressive expansion or related-party transactions using the borrowed funds, increasing the company's exposure to operational and investment risks (Issa et al., 2024). This dynamic not only amplifies the financial leverage indirectly but also accelerates the company's progression toward financial distress, particularly if the pledged shares lose value and shareholders fail to meet repayment requirements (Liu et al., 2022).

The interaction between high financial leverage and shareholder equity pledge practices creates a compounded risk, escalating the company's vulnerability to financial distress and bankruptcy during adverse market conditions. Figure 1 illustrates this conceptual relationship, highlighting how the combination of these factors can contribute to the pathway leading to the risk of bankruptcy.

Figure 1. The relationship between financial leverage, shareholder equity pledge, and corporate bankruptcy risk



Companies need to conduct financial performance analysis to detect early signs of potential bankruptcy, allowing them to identify contributing factors and take preventive measures to avoid or mitigate the risk of bankruptcy (Issa et al., 2024; Altman et al., 2017). Bankruptcy does not occur suddenly; instead, it is preceded by identifiable indicators. The risk of bankruptcy can be observed and measured through a company's financial statements, allowing for the anticipation of future challenges (Sinaga et al., 2019). Measuring a company's financial performance can be achieved by systematically analysing periodic financial statements, which provide critical insights into the company's current financial condition and future outlook (Mahmudi & Khaerunnisa, 2023). Numerous bankruptcy prediction models have been developed globally. Tools like the Altman Z-score have proven effective in detecting early warning signals of financial distress, offering high predictive accuracy while remaining practical for companies seeking to prevent bankruptcy. The Altman Z-score predicts bankruptcy based on a company's financial ratios, providing a straightforward application with an accuracy rate of up to 95% in predicting bankruptcy risk (Rahman et al., 2021).

2.2. Financial Distress and Bankruptcy Prediction Models

Financial distress represents a transitional phase between financial health, which refers to a company's ability to meet its financial obligations and maintain a stable financial position, and bankruptcy, during which companies fail to meet financial obligations but have the potential to recover (Volkov et al., 2017).

In the specific literature, financial distress has been defined in various ways, most of them describing the company's inability to meet its debt obligations, which may lead to bankruptcy, liquidation, or asset seizure and distribution (Sun et al., 2002; Ikpesu, 2019; Ray, 2011). Companies experiencing financial distress often incur higher costs than financially healthy companies, which may reduce a company's value through both direct and indirect channels (Dou et al., 2021). Direct costs include expenses during legal bankruptcy processes, such as attorney's fees, administrator remuneration, and other legal costs, while indirect costs represent hidden losses due to temporary liquidity issues (Farooq & Jibran, 2018).

Assessing financial distress is crucial in credit risk management, as it enables financial institutions to safeguard themselves against borrower defaults, comply with regulations, manage their portfolios effectively, and maintain systemic stability. It helps banks decide whom to lend to, under what circumstances, and how to mitigate potential losses, forming a core pillar of prudent banking operations (Farooq et al., 2023).

Bankruptcy represents the final stage of financial distress, occurring when companies have exhausted a viable recovery pathway (Farooq et al., 2023). However, not all financially distressed companies proceed to insolvency, as some can navigate out of distress through effective restructuring and prudent financial management strategies. This perspective is supported by studies that highlight the significant influence of the asset structure and liability composition of companies on the success of voluntary restructuring efforts, thereby preventing insolvency (Cheng Ee Wan et al., 2021; Wang & Liu, 2024). Specifically, lower equity levels, excessive leverage, and unstructured debt tend to increase the likelihood of involuntary business exit. In contrast, companies with stronger corporate governance frameworks and diversified asset portfolios demonstrate improved prospects for recovery (Farooq et al., 2023; Altman et al., 2017). Furthermore, Kou et al. (2021) emphasise that the early detection of financial distress through advanced predictive models enables timely interventions, thereby reducing the risk of bankruptcy. Collectively, these insights align with the argument that while financial distress often precedes insolvency, strategic restructuring and effective financial management practices can facilitate recovery, allowing companies to avoid bankruptcy as the ultimate stage of financial decline (Farooq et al., 2023).

Effective identification and management of financial distress can enable companies to recover, thereby preventing bankruptcy as the terminal stage of financial decline (Altman et al., 2017). Given the severe implications of bankruptcy for stakeholders and the economy, considerable scholarly attention has been devoted to developing models that can predict financial distress early, allowing companies and financial institutions to take preventative measures (Faroog et al., 2023; Sun et al., 2014).

Over the years, many methods have been developed to assess the financial distress risk of companies, reflecting the evolution from traditional to more advanced predictive approaches. Ratio-based models utilise financial indicators such as liquidity, leverage, profitability, and activity to assess bankruptcy risk (Rahman et al., 2021). The Altman Z-Score Model, which combines five financial ratios using discriminant analysis, has been widely adopted due to its simplicity and predictive capabilities (Altman et al., 2017). Similarly, the Springate Model adopts this approach, using four ratios (Springate, 1978, as cited in Grice & Ingram, 2001), while the Grover Model modifies the Z-score to improve prediction accuracy within manufacturing industries (Indriyanti, 2019). Although these models offer ease of application for practitioners, their predictive power may vary across industries and accounting environments (Rahman et al., 2021). The traditional Altman Z-Score Model was developed using multivariate discriminant analysis, resulting in the Zeta model, which consists of seven variables: return on assets, stability of earnings, interest coverage, cumulative profitability, liquidity, capitalisation, and size (Rahman et al., 2021).

Statistical models apply logistics and probit regressions to predict bankruptcy probabilities based on financial ratios. The Ohlson O-Score Model, created in 1980 (Ohlson, 1980), and the Zmijewski Model (Zmijewski, 1984) are prominent examples within the category of statistical models used for bankruptcy prediction, providing interpretable probabilities that assist stakeholders in understanding default risk (Rahman et al., 2021; Michalkova & Ponisciakova, 2025).

The emergence of machine learning models has enhanced the predictive accuracy of bankruptcy prediction by capturing complex, non-linear relationships within financial and non-financial data. Techniques such as Random Forest, Support Vector Machine, Artificial Neural Networks, and Deep Learning have been employed to improve classification performance in bankruptcy prediction (Shetty et al., 2022). Several studies have demonstrated that machine learning models substantially enhance bankruptcy prediction accuracy, providing valuable tools for stakeholders seeking timely and reliable assessments of bankruptcy risk (Barboza et al., 2017; Adnan and Dar, 2006, as cited in Shetty et al., 2022).

Hybrid and ensemble models integrate traditional statistical or ratio-based approaches with machine learning to increase prediction robustness and accuracy. These models combine the interpretability of classical approaches with the predictive power of advanced techniques, addressing the limitations inherent in relying on a single method (Sun et al., 2014). Hybrid frameworks may incorporate financial ratios derived from models such as Altman's Z-Score or Ohlson's O-Score as inputs into machine learning classifiers, thereby preserving domain-specific interpretability while improving predictive performance. Ensemble methods, such as bagging, boosting and stacking, aggregate multiple model predictions to reduce variance and bias, addressing the limitations inherent in using a single predictive approach (Barboza et al., 2017; Ling & Wang, 2024). This integration enables stakeholders to conduct a more reliable assessment of financial distress risk, thereby supporting early intervention and informed decision-making in corporate risk management (Ling & Wang, 2024).

Despite the allure of advanced machine learning techniques, the study by Shetty et al. (2022) demonstrated that simple models using three easily obtainable financial ratios (ROA, current ratio, and solvency ratio) can achieve high prediction accuracy (around 81%), comparable to more complex methods. This finding not only underscores the reliability of these simple models but also their practicality and attractiveness as tools in assessing bankruptcy risks.

3. METHODOLOGY

The primary objective of this study is to explore the role of financial performance evaluation as a preventive mechanism and predictive tool for bankruptcy risk within corporate financial management. By applying the Altman Z-Score model in conjunction with key financial performance indicators, such as profitability, liquidity, and leverage, over thirteen years for a Romanian company, the study aims to validate the relationship between declining financial performance and the increasing risk of financial distress and bankruptcy. The potential impact of this research is significant, as it can provide a robust framework for early detection and prevention of financial crises in corporate finance, thereby contributing to the stability and sustainability of businesses.

Hypothesis 1: There is a significant relationship between the evolution of financial performance indicators and the Altman Z'-Score over time, indicating that declining financial performance increases the risk of financial distress or bankruptcy.

Hypothesis 2: The Altman Z'-Score can be used as an effective early warning tool for predicting bankruptcy risk and guiding preventive financial management.

This study employs a quantitative research design, allowing for the systematic measurement and analysis of numerical data to identify patterns and relationships between financial performance indicators and bankruptcy risk (Creswell & Creswell, 2018). The study also utilises a longitudinal analysis, a method that has been proven to be particularly effective in capturing the dynamic nature of financial health over time (Altman et al., 2017). This approach, compared to cross-sectional methods, enables the observation of temporal trends and cause-effect relationships, thereby facilitating a more accurate assessment of how financial performance evaluation can predict and prevent bankruptcy (Issa et al., 2024). The effectiveness of this method provides reassurance and confidence in the study's findings.

Financial ratios play a pivotal role in bankruptcy analysis, serving as a grounded quantitative means to evaluate a company's financial health and potential distress (Issa et al., 2024). By leveraging these ratios, early warning indicators of financial distress can be identified, trends reflecting potential deterioration can be monitored, and comparative assessment with industry peers can be conducted. The financial ratios summarised in Table 1 have been selected as part of the initial analysis framework within this study, providing a comprehensive understanding of the company's financial standing.

Table 1. Financial ratios

Ratio	Category	Formula	References
Return on Assets (ROA)	Efficiency and Profitability Ratios	$ROA = \frac{\text{Net Profit}}{\text{Average Total Assets}} \text{ x } 100$	(Asiani & Rahayu, 2024)
Return on Equity (ROE)		$ROE = \frac{Net\ Profit}{Equity} \text{ x } 100$	(Handayani & Winarningsih, 2020)
Net Profit Margin (NPM)		$NPM = \frac{Net\ Profit}{Turnover} \text{ x } 100$	(Handayani & Winarningsih, 2020)
Current Ratio (CR)	Liquidity Ratios	$Current\ Ratio = \frac{Current\ Assets}{Current\ Liabilities}$	(Asiani & Rahayu, 2024)
Quick Ratio (QR)		$Quick\ Ratio = \frac{Current\ Assets\text{-}Inventory}{Current\ Liabilities}$	(Issa et al., 2024)
Cash Ratio (CR)		$Cash\ Ratio = \frac{Cash\ \&\ Cash\ Equivalents}{Total\ Current\ Liabilities}$	(Indah et al., 2023)
Debt to Equity Ratio D/E Ratio	Leverage	$D/E\ Ratio = \frac{Total\ Debt}{Shareholder's\ Equity}$	(Indah et al., 2023)
Debt Ratio		$Debt\ Ratio = \frac{Total\ Debt}{Total\ Assets}$	(Indah et al., 2023)
Debt to EBITDA (D/EBITDA Ratio)		$Debt\ to\ EBITDA\ Ratio = \frac{Total\ Debt}{Total\ EBITDA}$	(Issa et al., 2024)

For the empirical analysis (Figure 2), the focus is placed on the seven primary indicators – NPM, ROA, ROE, CR, D/E Ratio, Debt Ratio and Debt to EBITDA Ratio – used to conduct analyses for hypothesis testing. The additional indicators presented in table no. 1 remain valuable for scholars and researchers, serving as useful tools for broader financial performance evaluation and bankruptcy prevention strategies.

Figure 2. Methodological Framework for Testing the Relationship between Financial Performance and Bankruptcy Risk

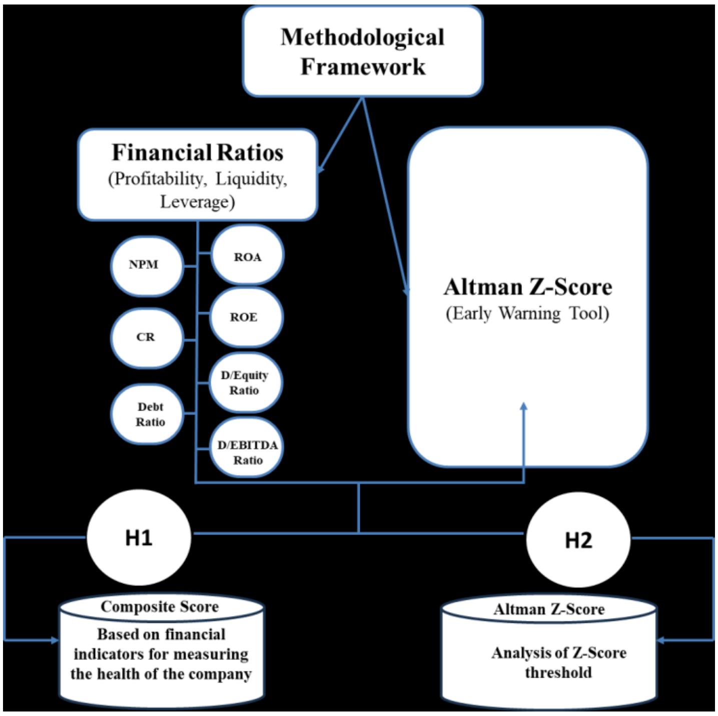


Figure 2 illustrates the comprehensive methodological framework adopted in this study, which integrates seven financial indicators – NPM, ROA, ROE, CR, D/E Ratio, Debt Ratio and Debt to EBITDA Ratio – along with the Altman Z'-Score as an early warning tool. H1 is examined through the construction of a standardised composite score based on these financial ratios, aiming to assess the overall financial health of the company and its capacity to prevent bankruptcy. H2 evaluates the predictive relevance of the composite score and key financial metrics. This combined approach enhances the understanding of financial vulnerability and strengthens early detection mechanisms. Therefore, to evaluate the company's financial performance and anticipate bankruptcy risk beyond the classical models, a composite score was constructed using financial indicators. Composite financial scores have been successfully applied in diverse settings. Jurado et al. (2024) introduce a Composite Indicator Based on Ratios (CIBOR), which aggregates multiple financial metrics into a unified stress indicator. Similarly, Sabău et al. (2021) construct a Composite Financial Performance Index from eight indicators using principal component analysis, demonstrating its predictive utility for company performance. The seven indicators selected for our study were designed to capture a multidimensional view of the company's financial health, encompassing profitability, liquidity, and leverage. To allow aggregation, each indicator was statistically standardised using the Z-score formula:

$$Z = \frac{X - \mu}{\sigma}$$

Where x is the individual value, μ is the mean of the series, and σ is the standard deviation (Hair et al., 2010). Given that higher values of leverage indicators (D/E Ratio, Debt Ratio, and D/EBITDA Ratio) signal greater financial risk, their standardised scores were multiplied by -1 to ensure consistency in interpretation: higher composite scores always reflect stronger financial health.

Although the standardisation formula follows the classical Z-score method, the final aggregated result is referred to as the C-Score (Composite Score) to distinguish it from the Altman Z'-Score used for bankruptcy prediction. The final C-Score was computed as the arithmetic mean of all seven standardised (and sign-adjusted, where necessary) indicators for each year:

$$\text{Composite Score}_{t} = \frac{\text{Z\_NPM} + \text{Z\_ROA} + \text{Z\_ROE} + \text{Z\_CR-Z\_CD/E - Z\_CDebt Ratio-Z\_CD/EBITDA Ratio}}{7}$$

The Altman Z-Score, a widely recognised tool for predicting financial distress and bankruptcy risk, is beneficial for privately held (non-listed) companies. This model, which adjusts the original coefficients to reflect the data environment of non-listed companies better, enables the classification of companies into safe, grey, and distressed zones based on their financial performance (Altman et al., 2017). In this study, we demonstrate the practical application of the Altman Z-Score model, specifically adapted for a private services company, which integrates liquidity, profitability, leverage, and activity measures to assess bankruptcy risk. The formula is expressed as follows: (Altman & Hotchkiss, 2006):

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

Table 2. Altman Z-Score

Weights	X Formula	Interpretation thresholds
Woking Capital	$X_1 = \frac{Working\ Capital}{Total\ Assets}$	$Z^{'} > 2.9$ Safe Zone (low risk of bankruptcy)
Total Assets		
Retained earnings	$X_2 = \frac{Retained\ earnings}{Total\ Assets}$	1.23 < Z' < 2.9: Grey Zone (potential risk, requires monitoring)
Earnings Before Interest and Taxes (EBIT)	$X_3 = \frac{EBIT}{Total\ Assets}$	
Equity	$X_4 = \frac{Total\ Equity}{Total\ Liabilities}$	Z' < 1.23: Distress Zone (high risk of bankruptcy)
Total Liabilities	$X_5 = \frac{Sales}{Total\ Assets}$	
Sales		

(Altman & Hotchkiss, 2006)

5. RESULTS

In this section, the study presents the results of the comprehensive financial analysis conducted over the 2012-2024 period. The focus is on the evolution of the company's financial health and bankruptcy risk, using a range of financial indicators to construct the composite score (C-Score) and calculate the Altman Z'-Score. These indicators were extracted and computed from the company's annual financial statements and Profit and Loss (P&L) Accounts, ensuring a thorough and accurate assessment.

Table 3 presents the annual evolution of the C-Score, a key metric calculated using seven indicators: NPM, ROA, ROE, Current Ratio, D/E Ratio, Debt Ratio, and Debt/EBITDA Ratio. The original values, standardised Z-score, and adjusted (inverted) values for the leverage-related indicators are all included. The final C-Score for each year was calculated as the arithmetic mean of the adjusted Z-scores, ensuring that all components contributed in the same direction to the composite financial health metric.

Table 3. Composite Score Components and Final C-Score, 2012-2024

Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
NPM	6,2093	8,2811	9,9791	13,4299	7,0053	4,1942	6,6128	8,1981	13,1485	15,2404	11,4481	7,7174	2,8940
ROA	9,5883	25,8847	23,4670	24,8586	10,9227	6,8879	10,2923	13,0578	18,3659	20,6341	15,6456	9,1719	4,7944
ROE	99,7638	70,1147	42,6626	33,6301	13,3050	7,8318	11,3158	16,4074	27,4919	39,1687	33,0483	18,0808	6,4502
CR	1,0996	1,6673	2,5061	3,4844	8,3008	7,9385	6,9554	3,3485	2,7526	1,9113	1,5752	2,1701	7,4536
D/E Ratio	6,7579	1,7124	0,6637	0,4035	0,1228	0,1286	0,1534	0,3866	0,5234	0,9556	1,3261	0,7033	0,1374
Debt Ratio	0,8881	0,5448	0,3619	0,2711	0,1071	0,1165	0,1364	0,2875	0,3529	0,5053	0,5805	0,4223	0,1213
Debt/EBITDA	5,3908	1,7457	1,0794	0,8544	0,5415	0,7891	0,7806	1,6166	1,5100	1,9449	2,9528	2,3876	0,9182
Z_NPM	-0,7024	-0,1400	0,3210	1,2577	-0,4863	-1,2494	-0,5929	-0,1625	1,1813	1,7492	0,7197	-0,2930	-1,6024
Z_ROA	-0,7458	1,5466	1,2065	1,4022	-0,5581	-1,1256	-0,6468	-0,2577	0,4889	0,8080	0,1063	-0,8044	-1,4201
Z_ROE	2,5096	1,4075	0,3870	0,0512	-0,7043	-0,9078	-0,7782	-0,5890	-0,1769	0,2571	0,0296	-0,5268	-0,9591
Z_CR	-1,0561	-0,8447	-0,5323	-0,1680	1,6255	1,4906	1,1245	-0,2186	-0,4405	-0,7538	-0,8790	-0,6575	1,3100
Z_D/E Ratio	3,2000	0,3589	-0,2316	-0,3781	-0,5362	-0,5329	-0,5189	-0,3876	-0,3106	-0,0672	0,1414	-0,2093	-0,5279
Z_Debt Ratio	2,2993	0,8013	0,0031	-0,3934	-1,1088	-1,0679	-0,9812	-0,3219	-0,0361	0,6290	0,9571	0,2665	-1,0470
Z_Debt/EBITDA	2,8006	0,0107	-0,4992	-0,6714	-0,9109	-0,7214	-0,7279	-0,0881	-0,1696	0,1632	0,9346	0,5020	-0,6226
Z_D/E Ratio*(-1)	-3,2000	-0,3589	0,2316	0,3781	0,5362	0,5329	0,5189	0,3876	0,3106	0,0672	-0,1414	0,2093	0,5279
Z_Debt Ratio*(-1)	-2,2993	-0,8013	-0,0031	0,3934	1,1088	1,0679	0,9812	0,3219	0,0361	-0,6290	-0,9571	-0,2665	1,0470
Z_Debt/EBITDA*(-1)	-2,8006	-0,0107	0,4992	0,6714	0,9109	0,7214	0,7279	0,0881	0,1696	-0,1632	-0,9346	-0,5020	0,6226
C-Score	**-1,1849**	**0,1141**	**0,3014**	**0,5694**	**0,3475**	**0,0757**	**0,1907**	**-0,0615**	**0,2242**	**0,1908**	**-0,2938**	**-0,4058**	**-0,0677**

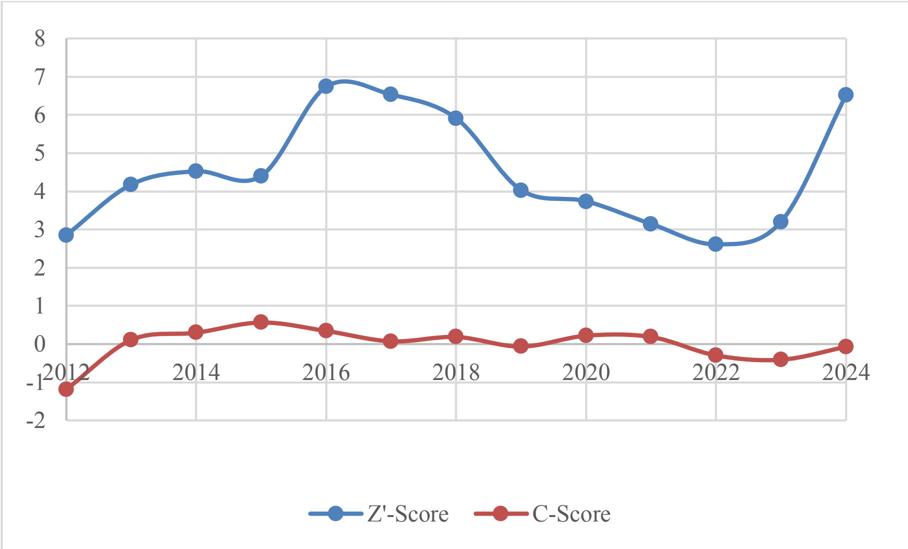
The Altman Z'-Score, used as a benchmark for bankruptcy prediction, was computed separately based on the company's annual financial data over the period 2012-2024. The Z'-Score values for each year are summarised in Table 4, which enables a direct comparison with the C-Score shown in Table 4.

Table 4. Altman Z-Score, 2012-2024

Year	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
Total Assets	3.221.147	4.451.219	4.529.876	5.539.917	4.918.279	4.634.583	4.854.560	5.587.339	5.483.831	5.442.124	6.407.363	4.685.604	3.406.979
Retained Earnings	422.293	422.093	1.415.077	2.468.874	3.720.478	3.870.586	3.825.900	3.472.119	2.680.174	1.749.464	1.876.702	2.303.661	2.812.377
Equity	423.293	1.416.227	2.470.074	3.721.679	4.292.839	4.200.784	4.315.424	4.155.058	3.698.033	2.877.901	2.804.861	2.813.577	3.007.572
Sales	6.800.944	11.991.009	10.560.038	9.319.516	8.153.245	7.844.186	7.384.491	8.315.767	7.732.105	7.396.375	8.097.052	6.591.832	6.703.413
Debt	2.860.582	2.425.127	1.639.484	1.501.734	526.954	540.076	662.116	1.606.161	1.935.478	2.750.075	3.719.550	1.978.667	413.289
EBIT	522.841	1.291.474	1.321.396	1.465.371	729.342	429.983	629.731	803.114	1.179.279	1.301.309	1.115.267	649.784	263.629
Working Capital	284.885	1.618.229	2.469.249	3.730.841	3.847.171	3.747.296	3.943.158	3.772.010	3.392.194	2.506.200	2.139.417	2.315.160	2.667.189
X1 (WC/TA)	0,0884	0,3635	0,5451	0,6734	0,7822	0,8086	0,8123	0,6751	0,6186	0,4605	0,3339	0,4941	0,7829
X2 (RE/TA)	0,1311	0,0948	0,3124	0,4457	0,7565	0,8352	0,7881	0,6214	0,4887	0,3215	0,2929	0,4916	0,8255
X3 (EBIT/TA)	0,1623	0,2901	0,2917	0,2645	0,1483	0,0928	0,1297	0,1437	0,2150	0,2391	0,1741	0,1387	0,0774
X4 (Equity/Debt)	0,1480	0,5840	1,5066	2,4783	8,1465	7,7781	6,5176	2,5869	1,9107	1,0465	0,7541	1,4220	7,2772
X5 (Sales/TA)	2,1113	2,6939	2,3312	1,6822	1,6577	1,6925	1,5211	1,4883	1,4100	1,3591	1,2637	1,4068	1,9676
Z'-Score	**2,8480**	**4,1762**	**4,5211**	**4,4019**	**6,7383**	**6,5313**	**5,9085**	**4,0289**	**3,7353**	**3,1413**	**2,6062**	**3,2028**	**6,5209**

To visually illustrate the comparative dynamics between the C-Score and Z'-Score, Figure 3 presents their evolution over the 2012-2024 period. The graph provides a clear overview of how both scoring models reflect the company's financial trajectory, highlighting areas of convergence as well as divergence between the two approaches.

Figure 3. Comparative evolution of the C-Score and Z'-Score, 2012-2024



While the Z-score reflects solvency and long-term risk, the C-score offers a broader view of operational health, incorporating profitability, liquidity, and leverage indicators. Divergences between the two scores, particularly in the later years, highlight how each tool captures distinct dimensions of financial performance. Both scores tend to follow similar directional trends during several years, particularly between 2013 and 2021, suggesting that internal financial indicators are effective in anticipating shifts in bankruptcy risk. Divergences, such as in 2024, when the Z'-Score indicates recovery while the C-Score remains low, reveal how the C-Score may detect performance deterioration earlier through sensitivity to declining profitability or worsening capital structure. Although not always perfectly aligned, the consistency of overlapping trends confirms that financial performance analysis is a valuable tool for forecasting potential insolvency and guiding risk mitigation strategies.

Examining specific years, such as 2019, we observe a significant divergence between the Z-score, which remains relatively high, and the C-score, which drops into negative territory. This discrepancy suggests that while the company maintains sufficient solvency according to Altman's formula, its operational efficiency or internal profitability may be deteriorating. The signal captured by the C-Score reflects weakened performance in indicators such as ROA or ROE, in conjunction with the D/EBITDA Ratio, indicating a potential worsening of profitability and cost structure, which is not fully reflected in the Z-Score.

The divergence observed in 2019, where the Altman Z'-Score indicates stability, but the C-score reflects weakening performance, can be partially explained through liquidity preference theory. During economically uncertain periods, companies may prioritise liquidity over profitability in the short term to build reserves for long-term survival (Nguyen & Tran, 2024). This behaviour, while stabilising solvency metrics, may temporarily reduce ratios such as ROA and NPM, thereby lowering the C-score, while the Z-score remains strong.

In 2022, the Z-score shows a notable decline, approaching the risk threshold (scores below 2.6 typically fall into the distress zone). Simultaneously, the C-Score turns negative, indicating weakening performance across the underlying financial indicators. This alignment between the two scores reinforces H1. In 2023, the Z-score suggests mild recovery, moving into the so-called "grey zone", where the risk of insolvency is not critical, but caution is warranted. In contrast, the S-score declines even further, reaching the lowest point across the entire 13-year period. This divergence suggests that while the company maintains acceptable solvency (as per Altman's model), its internal financial performance, especially operational efficiency, is deteriorating. The C-score captures this decline more sharply, driven by weakening values in ratios such as ROA, ROE, and NPM, which are not directly incorporated into the Z'-Score formula. Therefore, the C-score offers a more sensitive and timely reflection of internal performance weaknesses, supporting the validity of H1 as a predictive tool for financial distress and bankruptcy.

The assessment of the computed Altman Z'-Score enables a more precise classification of the company's financial health across the analysed period. It provides a structured basis for evaluating the presence or absence of bankruptcy risk. The threshold categories – distress, grey, and safe zones – offer a standardised framework through which each year's score can be interpreted in context. To interpret the results, the standard Z'-Score thresholds were applied: i) Z'-Score < 1.8 reveals distress zone (high risk of bankruptcy); ii) 1.8 ≤ Z'-Score ≤ 2.6 reveals grey zone (moderate risk), whereas iii) Z'-Score> 6 reveals safe zone (low risk).

Between 2012 and 2015, the Z-score ranged from 2.85 to 4.52, placing the company firmly in the safe zone, indicating strong solvency and minimal risk of bankruptcy. In 2016 and 2017, the score continued to rise above 6, suggesting excellent financial health, supported by high working capital and low leverage. From 2018 to 2022, the Z'-Score shows a steady decline, with 2022 approaching the grey zone threshold at 2.61. This signals emerging risks and weakening fundamentals. In 2023, the score increases to 3.20, and by 2024, it reaches 6.52, showing a strong rebound and indicating a return to financial stability. These movements demonstrate that the Altman Z'-Score performs well as an early warning system, particularly during the downturn years. The decline prior to 2022 aligns with known patterns of financial strain, and its recovery afterwards corresponds with improved balance sheet indicators such as increased working capital and reduced debt levels.

In 2012, the company exhibited an extremely high D/Equity Ratio of 6.76 and a Debt Ratio of 0.89, indicating that nearly 90% of its assets were financed through debt. Its D/EBITDA stood at 5.39, suggesting a high level of financial strain, as the company would have needed more than five years of operating earnings to repay its obligations. These figures reflect a high-risk financial profile, consistent with the distress zone according to the Altman Z'-Score methodology. However, over time, the company's strategic financial restructuring resulted in a significant reduction of its leverage. By 2016-2018, the Debt-to-Equity Ratio had dropped below 0.2, and the Debt Ratio was near 0.11-0.14. This shift was accompanied by improved profitability and liquidity, as indicated by declining debt burdens relative to earnings (D/EBITDA around 0.78 in 2018). These improvements in financial health instil confidence in the company's future. This financial restructuring positioned the company within a low-risk zone, thereby enhancing its Z-Score.

In recent years, 2023 and 2024, leverage has remained low. The D/Equity Ratio stays well under 1.0, while the Debt Ratio continues to signal low asset-based indebtedness (around 12%). This progression means that the company has prioritised stability over aggressive financing, especially following early periods of high leverage and potential vulnerability. It also aligns with the logic of Altman's Z-score, where reductions in financial leverage and improvements in liquidity contribute significantly to risk mitigation and long-term solvency.

The company's gradual transition from a highly leveraged structure in the early years (2012-2014) to a more conservative financial position by 2024 signifies a strategic shift towards financial stability and improved access to capital. This shift aligns with the strategic dilemma between equity and debt, a fundamental aspect of corporate financial management.

The decision between external financing through debt or internal equity remains one of the most critical and complex managerial considerations. Higher reliance on equity may dilute ownership and reduce company value, while excessive debt increases financial risk and the likelihood of distress.

It is generally accepted that more liquid companies are better positioned to meet short-term obligations, which increases their credibility and access to external funding. This duality is at the core of the Trade-Off Theory, which posits that firms aim to balance the tax advantages of debt against the costs of potential financial distress (Ghasemi & Razak, 2016). In this context, Altman's Z-score serves as a relevant and theoretically grounded tool. It integrates variables related to liquidity, leverage, and profitability, capturing the company's position within the capital structure spectrum. The Z'-Score not only aligns with the Trade-Off Theory but also operationalises it by offering a quantifiable threshold for financial stability, distress, or insolvency risk (Altman & Hotchkiss, 2006).

Considering the results obtained in the longitudinal analysis, we propose an operational model for integrating composite financial scores (C-Score) and Altman Z'-Score into the ERP systems used by companies. The model aims to strengthen internal capacity for monitoring and preventing insolvency risk by automating the process of calculating, interpreting, and signalling deviations from optimal financial performance parameters. The proposed structure includes functional modules that periodically retrieve essential accounting data, calculate relevant scores, interpret results based on predefined thresholds, and generate alerts and recommendations directed to the financial management team. The model is designed exclusively for internal use, without the involvement of external actors, and is intended to be seamlessly integrated into the existing ERP architecture, offering a high degree of flexibility and adaptability. Through its direct applicability, the model not only facilitates proactive managerial decision-making but also supports the implementation of evidence-based financial governance mechanisms, providing reassurance and confidence in the decision-making process. At the same time, it can contribute to the institutionalization of a systematic framework for continuous risk assessment, with an impact on the long-term sustainability and resilience of the organization. The detailed structure of this framework is presented in Table 5.

The presented model provides a practical framework for translating financial scores into an operational tool integrated into existing ERP systems. Through its modular and extensible architecture, it can be adapted to various organizational structures. This adaptability not only supports recurring financial analysis but also empowers data-driven managerial decision-making and systemic risk prevention, instilling confidence in the audience. The proposed extensions, such as integrating ESG criteria, internal benchmarking, or prediction assisted by intelligent algorithms, enable the gradual development of the model in line with the digital maturity of the organization. Thus, the implementation of this framework can contribute not only to improving financial control, but also to developing an organizational culture oriented towards anticipation, adaptability and long-term sustainability.

Table 5. Operational model for integrating C-Score and Altman Z'-Score into the company's ERP

Section	Component	Description / Function
1. Data retrieval	Data source	Monthly/quarterly accounting data from the Balance Sheet, Profit and Loss Account, Cash Flow
	Necessary indicators	NPM, ROA, ROE, Current Ratio, D/E Ratio, Debt Ratio, D/EBITDA Ratio
	ERP integration mode	Automatic import from ERP accounting modules
2. Score calculation	C-Score	Arithmetic average of the 7 indicators, standardized (with inversion for leverage indicators)
	Altman Z'-Score	Calculation according to the formula for private companies (Z' = 0.717X1 + 0.847X2 + 3.107X3 + 0.420X4 + 0.998X5)
	Calculation frequency	Monthly or quarterly, depending on accounting cyclicality
3. Risk assessment	Interpretation thresholds C-Score	< -0.5: High risk -0.5 to 0.5: attention zone > 0.5 financial stability
	Interpretation thresholds Z'-Score	< 1.8: Distress 1.8 – 2.6: Grey Zone > 2.6: Safe Zone
	Dashboard ERP	View scores, trend graphs, visual cues
	Automatic Alerting	Notifications to the CFO/CFO when scores enter the yellow or red zone
4. Automatic recommendations	Suggested strategic decision	Ex: leverage reduction, liquidity conservation, investment revaluation
	Scenarios „what-if"	Impact simulations: e.g. "What happens if profit drops by 20%?"
	Action plan	Lists of suggested corrective steps: debt reduction, contract renegotiation, dividend deferral
5. Monitoring	Frequency of review of scores	Quarterly (board engagement), monthly (for CFOs)
	Score History	Automatic archiving, analysis of the evolution of scores over time
	Benchmark intern	Comparison of scores between departments / cost centers / previous years
6. Optional extensions	Artificial Intelligence (AI)	Automatic predictions of future scores based on trends
	KPIs and bonuses	Integrating scores as part of managerial performance
	Export for internal report	Automatic generation of strategic financial reports for the Board of Directors
7. KPIs and managerial control	Integration of scores into annual goals	Scores become part of the financial management performance evaluation system
8. Advanced Benchmarking	Comparison of scores between divisions	Monthly/quarterly view of comparative risk across your organization
9. AI Prediction	6-month score prediction	Algorithms that identify potential dips and additional signals early on
10. ESG integration	Mixed alert financial score + ESG	Automatic flags in case of discrepancies between financial and sustainability performance

6. CONCLUSIONS

This study delved into the intricate relationship between financial performance and bankruptcy risk, culminating in the development of a standardised Composite Score (C-Score) based on seven key financial indicators. These indicators, which span profitability (NPM, ROA, ROE), liquidity (CR), and leverage (D/Equity, Debt Ratio, D/EBITDA Ratio), were meticulously extracted from annual financial statements and normalised for aggregation into a single, interpretable metric. Comparing this C-Score to the Altman Z-Score over 13 years for a single private company yielded insightful results.

The results underscore the unique contribution of the Composite Score, which offers a comprehensive view of the company's financial dynamics. It effectively captures year-to-year fluctuations in operational efficiency, capital structure, and liquidity. While the C-score and Z'-score align in many periods, their conceptual differences are highlighted by divergences, especially in the most recent years. The Altman Z-Score, which focuses primarily on solvency and long-term default risk, contrasts with the C-Score, which reflects more immediate performance concerns, including profitability erosion and capital allocation efficiency.

The evaluation of the two hypotheses led to nuanced conclusions. H1, which proposed that evaluation of financial performance can serve as early warning signals for bankruptcy, even though it does not have a perfect match with the Altman Z'-Score. The standardised indicators and their composite formulation do highlight financial weaknesses and inflexion points, though they may not fully capture all structural risks. H2, concerning the Altman Z'-Score's reliability as a distress prediction tool, is supported. The Z'-Score consistently classified financial risk across time, aligning with the company's leverage profile and aligning with theoretical expectations from capital structure literature. However, it is important to note that the study has its limitations and may not fully capture all structural risks.

These findings reinforce the notion that financial health is a multidimensional concept. The use of composite performance metrics alongside classic risk models, such as the Z-Score, provides a more robust framework for early warning, strategic decision-making, and long-term financial planning. However, this study also highlights the need for further research to extend this approach to multiple companies in various sectors, exploring the predictive value of composite indicators in broader contexts.

In addition to the conclusions obtained through the comparative analysis of C-Score and Altman Z-Score, the proposal of an operational model integrated into ERP systems offers a practical and scalable solution for companies interested in preventive financial risk management. The model indirectly validates classical financial theories, such as the Trade-Off Theory and Signal Theory, while providing a concrete framework for implementing data-driven financial governance. The practicality of the model's implementation is a reassuring factor for companies. At the same time, the application of the model in a single organizational context limits the possibility of generalizing the results. In this regard, future research could aim at its sectoral scale-up, validation through multiple case studies, and integration with advanced analytical tools, including artificial intelligence algorithms. Through its direct applicability, the model has the potential to support not only the finance function but also the strategic decision-making process, thereby contributing to the long-term resilience and sustainability of companies.

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