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ENHANCING CORPORATE BANKRUPTCY PREDICTION MODELS: A COMPREHENSIVE ANALYSIS WITH EVIDENCE FROM THE EGYPTIAN STOCK MARKET

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Abstract
Accurately predicting corporate bankruptcy and financial failure is crucial for financial institutions, creditors, and other stakeholders engaged in credit transactions. This study investigates the effectiveness of accrual-based, cash flow-based, and hybrid models in predicting financial distress among companies listed on the Egyptian stock market. Utilizing Multiple Discriminant Analysis (MDA), the research develops three predictive models, each based on different sets of financial ratios. The cash flow-based model correctly classified 90.0% of original cases, while the accrual-based model demonstrated higher accuracy with a 96.7% classification rate. However, the hybrid model, which integrates both accrual and cash flow ratios, outperformed both, achieving a perfect 100% classification accuracy. These findings suggest that hybrid models provide superior predictive accuracy, offering a more comprehensive early warning system for bankruptcy. The study's primary limitation is its small sample size, which may affect the generalizability of the results. Future research should consider expanding the dataset and including a more diverse range of companies to enhance the robustness and applicability of the findings.

Keywords: Bankruptcy Prediction, Accrual-Based Model, Cash-Based Model, Financial Failure, Multiple Discriminant Analysis

1. Introduction

The ability to accurately predict corporate bankruptcy and financial failure is of paramount importance in the financial world. It is crucial not only for financial institutions, such as banks and factor companies, but also for suppliers, industrial enterprises, and any entity involved in credit transactions. The effectiveness of lending is closely tied to the trust between parties, the use of collateral, and the reduction of information asymmetry, all of which hinge on a clear understanding of a business's financial health. The COVID-19 pandemic has further amplified the need for robust insolvency prediction models as enterprises face unprecedented economic challenges. One of the pioneering studies in this field is Altman's (1968) work on predicting business bankruptcy using financial ratios. Altman's Z-Score model, which employs accrual-based accounting measures, laid the groundwork for subsequent research and became a foundational tool in bankruptcy prediction. However, despite the extensive research conducted since then, a consensus on the best approach—whether accrual accounting ratios or cash flow ratios—has yet to be reached. This ongoing debate underscores the complexity of accurately forecasting financial distress.

Accurately predicting bankruptcy and financial failure is essential for preserving businesses and fostering economic stability, particularly in volatile and uncertain markets such as Egypt. Bankruptcy prediction models serve as vital tools for identifying financial distress early, enabling timely interventions to mitigate risks. However, the majority of these models are based on accrual accounting principles, which record financial transactions when they are incurred, irrespective of actual cash flows. While accrual-based models offer comprehensive insights into long-term financial performance, they often fail to capture the liquidity challenges and short-term obligations that are critical for survival in markets prone to economic fluctuations.

In contrast, cash-based accounting emphasizes actual cash inflows and outflows, providing a more immediate and realistic measure of a company's liquidity and ability to meet financial obligations. Research has shown that cash flow ratios—such as cash flows to assets and cash flows to sales—can predict bankruptcy with significant accuracy, often up to two years in advance (Khani, 2015). Furthermore, cash-based metrics are less susceptible to manipulation or distortion compared to accrual-based indicators, enhancing their reliability as predictors of financial distress. This reliability is especially crucial in markets like Egypt, where accurate financial assessments are vital for decision-making amidst heightened economic uncertainties.

Despite the growing recognition of the importance of cash-based models, there remains a significant gap in the comparative evaluation of accrual-based and cash-based approaches in predicting financial failure. The lack of such studies hinders the development of tailored models that account for the unique economic conditions and market dynamics of Egypt. Traditional models often overlook macroeconomic variables and the nuances of specific industries, leading to limited applicability in addressing the liquidity concerns prevalent in emerging markets. This gap underscores the need for research that bridges the divide between accrual-based and cash-based models, offering a more holistic approach to bankruptcy prediction.

Addressing this issue is particularly critical for Egypt, where economic instability and market fluctuations demand robust and context-specific financial prediction tools. By comparing the predictive accuracy of accrual-based and cash-based models and integrating their strengths, researchers can develop hybrid approaches tailored to the Egyptian economic landscape. These advancements would not only enhance the early detection of financial distress but also support policymakers, investors, and businesses in making informed decisions to mitigate risks and promote sustainable economic growth.

Recent studies have compared the effectiveness of accrual-based and cash flow-based measures in predicting financial distress. While accrual-based ratios are commonly used, they may be vulnerable to earnings management (Karas & Režňáková, 2020). Cash flow indicators, being less susceptible to manipulation, are theoretically more suitable for predicting distress (Karas & Režňáková, 2020). Bhandari & Bradley (2019) found that a mixed model combining both accrual and cash flow ratios performed significantly better than models using only one type. The cash flow statement is considered a crucial tool for financial analysis and decision-making (Mohammed, 2022). Short-term accounting accruals have shown the ability to predict future cash flows, with significant relationships observed for most accrual components (Shubita, 2021). However, company size did not moderate the relationship between accounting accruals and operating cash flow (Shubita, 2021). These findings highlight the importance of considering both accrual and cash flow measures in financial distress prediction models.

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2. Theoretical Background

2.1 General Concept of Bankruptcy and Financial Failure

Bankruptcy is a failure or loss of financial capability in the company in some sense defined by Martin and Fahkrurozie (2007). One representative of this third option is Altman (1981), who offers a definition of failure encompassing technical insolvency. According to Altman, failure can also be understood in terms of capital deficiency, which occurs when a firm faces a significant lack of liquidity. This perspective highlights the importance of both immediate solvency issues and the broader implications of inadequate capital reserves. Deakin considers failed companies to be "those that have faced bankruptcy or have been otherwise liquidated for the benefit of creditor contractors.”. Failure is also defined as "the inability of the company's revenues to cover all costs, including the cost of capital financing, and the management's inability to achieve a return on invested capital commensurate with the expected risks of those investments."

Bankruptcy or Financial failure, as conceptualized by Schumpeter (1942), embodies the notion of "creative destruction," where in old economic structures are supplanted by new ones, fostering innovation and growth. This process is inherent to capitalism, facilitating the emergence of fresh companies and industries. Despite its role in economic evolution, bankruptcies pose significant challenges. Beyond impacting investors, they affect a multitude of stakeholders.

2.2 Accounting-Based Models

Accounting-based models play a crucial role in assessing the risk of corporate failure by leveraging financial statement data, typically in the form of various ratios. These models analyse key financial metrics derived from balance sheets, income statements, and cash flow statements to evaluate the financial health and stability of a company. By scrutinizing indicators such as liquidity, profitability, solvency, and efficiency, accounting-based models provide insights into the likelihood of a company facing financial distress or bankruptcy. These models serve as valuable tools for investors, creditors, and financial analysts in making informed decisions about investment, lending, and risk management strategies. Additionally, accounting-based models offer a systematic approach to identifying potential warning signs and vulnerabilities within companies, allowing stakeholders to proactively address underlying issues and mitigate risks associated with corporate failure. Among the plethora of bankruptcy prediction models, we have selected four widely recognized and extensively utilized approaches that stand out for their effectiveness and widespread application. These models have earned prominence for their robustness and reliability in forecasting financial distress and bankruptcy scenarios:

2.2.1 Altman Model

The Altman Model is one of the most prominent models used for bankruptcy prediction, relying on a set of financial data that includes various key factors. Developed by researcher Altman in 1968, this model has garnered significant attention in the field of financial research and capital management. The model analyses a diverse array of financial variables that reflect the company's condition and its ability to withstand financial pressures. $\mathbf{Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.010X5}$ The Z-Score formula comprises five key financial ratios: X1 = Working Capital / Total Assets, X2 = Retained Earnings / Total Assets, X3 = Earnings Before Interest and Tax / Total Assets, X4 = Equity Capital / Total Debts, X5 = Sales Income / Total Assets

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2.2.2 Springate's Model

Proposed in 1978, is a financial distress prediction model that focuses on assessing the probability of a company facing financial difficulties. The model was developed to aid in evaluating the financial health of companies and identifying potential risks in their operations. The formula for calculating the Z-Score in Springate's model is as follows: Z = 1.3X1 +3.07X2 +0.66X3 +0.4X4. X1= Working capital /total fixed assets, X2 = Earnings before interest and tax/ fixed assets, X3 = Earning before tax / total current liability X4 =Sales / total fixed assets.

2.2.3 Kida Model

Developed by Kida in 1981, is a methodology used for predicting bankruptcy based on financial ratios. This model aims to assess the financial health of a company by analyzing various financial metrics derived from its financial statements. The objective is to generate a composite score, denoted as Z, which serves as an indicator of the likelihood of bankruptcy. Z= 1.042X1+0.42X2+0.461X3+0.463X4+0.271X5. X1 = net profit / total assets, X2 = equity/ total liability, X3= cash / current liability, X4 = sales / total assets, X5 = cash / total assets.

2.2.4 Sherrod model

In 1987, Drichasch developed a discriminant analysis method known as "Discriminant Analysis" to predict bankruptcy. This method involves analyzing financial data to determine distinct differences between financially distressed and non-distressed firms. Z= 17X1 +9X2 + 3.5X3 +20X4 +1.2X5 +1.6X6. X1= working capital / total assets, X2 = equity / total assets, X3 = cash / total assets, X4 = earnings before interest and tax / total assets, X5 = total assets / total liability, X6= equity / fixed assets.

2.2.5 Zmijewski (X-Score) Model

In 1983, Zmijewski conducted a comprehensive analysis of bankruptcy predictors based on previous studies. Through F-tests on various financial ratios and performance metrics, including group ratios, rate of return, liquidity, leverage, turnover, fixed payment coverage, trends, firm size, and stock return volatility, he identified significant differences between financially healthy and unhealthy companies. Based on his findings, Zmijewski formulated a predictive model represented as follows: X= - 4.3 − 4.5X1 + 5.7X2 − 0.004X3 Where: X1 represents the ratio of earnings after taxes (EAT) to total assets. X2 represents the ratio of total liabilities to total assets. X3 represents the ratio of current assets to current liabilities

3. Methods

3.1 Research Design

The research design of this study is a quantitative comparative approach aimed at developing and evaluating three bankruptcy prediction models for Egyptian listed companies. The study employs Multiple Discriminant Analysis (MDA), a robust statistical technique, to create and compare models based on three distinct types of financial ratios: cash flow ratios, accrual ratios, and a hybrid of both. The motivation for using MDA is rooted in its long-standing success in financial distress prediction, particularly with the Altman Z-score, which has been widely adopted in previous studies due to its high predictive accuracy across various industries and regions (Alareeni, 2019; Altman, 1968, 1993; Altman et al., 1995). The design focuses on applying these models

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to a dataset of Egyptian companies to identify the most effective approach for predicting bankruptcy in the context of the country's unique economic conditions. By using MDA, this study aims to assess the relative strengths and weaknesses of each model in classifying companies into financial distress and non-distress categories, providing a comprehensive analysis of bankruptcy prediction methodologies in emerging markets.

Multiple discriminant analysis is a statistical technique used to reduce the differences between variables in order to classify them (failing and non-failing companies under the study) into a set number of broad groups. Hair, Tatham, Anderson, & Black (2006) claimed that multivariate analysis concurrently examines several dimensions on every character or thing under study. This is prepared by the statistical judgment rule of maximizing the between group variance relative to the within-group variance and is articulated as the ratio of the between group to the within-group variance. A linear combination of the variables utilized is formed into an equation:

$$Z = a + b1\ X1 + b2\ X2 + b3X3 + \dots\dots\dots\dots\dots + bnXn$$

Where:
Z = the score,
a = the constant
b = the discriminant coefficient
X = the independent variables

3.2 Data Collection

The data for this study will be collected from financial statements of companies listed on the Egyptian stock market. The sample includes 10 companies, with 5 companies consistently making losses from 2020 to 2022 and 5 companies consistently making profits over the same period. Financial data required to calculate the cash flow and accrual ratios will be obtained from these companies' financial statements, including balance sheets, income statements, and cash flow statements.

Table 1. The number of companies that listed in the Egyptian stock market (2020-2022)

Number	Company	Status
1	EGTS	Failed
2	South Valley	Failed
3	Rakta	Failed
4	Maridaive	Failed
5	Yunirab	Failed
6	CIRA	Healthy
7	DOMTY	Healthy
8	ICON	Healthy
9	IDHC	Healthy
10	MTI	Healthy

3.3 Variables Selection

3.3.1Dependent Variable

The dependent variable in all models will be a binary indicator representing the financial health of the company:

a. Failed (0): Indicates that the company is financially distressed or bankrupt.
b. Healthy (1): Indicates that the company is financially sound and not at risk of bankruptcy.

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3.3.2 Independent Variable:

The variables for the models will be selected based on established literature and existing bankruptcy prediction models. The accrual-based model will include variables from the Altman Z-score (1968), Zmijewski X-score, Sherrod, Springate and Kida models. These models primarily focus on accounting ratios derived from balance sheets and income statements, such as working capital to total assets, retained earnings to total assets, and earnings before interest and taxes to total assets.

For the cash flow-based model, the variables will be derived several key cash flow ratios, including Cash Current Debt Coverage, Cash Interest Coverage, Operating Cash Flow Margins, Total Assets Return on Operating Cash Flow, and Earnings Quality, which have been shown to be significant in predicting bankruptcy. Research by Suwaidan (2003) highlights the effectiveness of Total Assets Return on Operating Cash Flow in distinguishing between insolvent and non-bankrupt companies. Alostaz (2015) further supports the predictive power of Cash Current Debt Coverage, Cash Interest Coverage, Operating Cash Flow Margins, and Earnings Quality across various sectors. Additionally, Jones (2016) indicates that higher values of Total Assets Return on Operating Cash Flow and Earnings Quality are associated with a reduced likelihood of bankruptcy, reinforcing their importance as positive indicators of financial stability. The hybrid model will combine selected variables from both the accrual-based and cash flow-based models to create a comprehensive predictive tool. The selection of variables for the hybrid model will be guided by their individual predictive power as demonstrated in the separate models.

Table 2. The total variables that used in the study as predictive indicators

Variable	Formula	Description	Type
X1	Cash Current Debt Coverage (OCF/Cl)	Measures The Ability to Cover Current Liabilities with Operating Cash Flow.	Cash
X2	Cash Interest Coverage (OCF + Int + Tax/Int)	Assesses The Ability to Cover Interest Payments with Cash Flow from Operations, Interest, And Taxes.	Cash
X3	Operating Cash Flow Margins (OCF/Sales)	Indicates The Proportion of Sales Converted into Operating Cash Flow.	Cash
X4	Operating Cash Flow Return on Total Assets (OCF/Asset)	Measures The Efficiency of Using Total Assets to Generate Operating Cash Flow.	Cash
X5	Earnings Quality (Ebit/OCF)	Evaluates The Quality of Earnings by Comparing Ebit to Operating Cash Flow.	Cash
X6	Working Capital / Total Assets	Measures The Proportion of Working Capital in Total Assets	Accrual
X7	Retained Earnings / Total Assets		Accrual

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		Indicates The Proportion of Retained Earnings in Total Assets.	
X8	Ebit / Total Assets	Assesses Profitability Relative to Total Assets	Accrual
X9	Equity Capital / Total Debts	Measures The Proportion of Equity Relative to Total Debt.	Accrual
X10	Sales Income / Total Assets	Indicates The Efficiency of Generating Sales from Total Assets.	Accrual
X11	Working Capital /Total Fixed Assets	Measures The Proportion of Working Capital Relative to Fixed Assets.	Accrual
X12	Earnings Before Interest and Tax/ Fixed Assets	Assesses Profitability Relative to Fixed Assets.	Accrual
X13	Earning Before Tax / Total Current Liability	Evaluates The Ability to Cover Current Liabilities	Accrual
X14	Sales / Total Fixed Assets	Indicates The Efficiency of Generating Sales from Fixed Assets.	Accrual
X15	Net Profit / Total Assets	Measures Profitability Relative to Total Assets	Accrual
X16	Cash / Current Liability	Measures The Ability to Cover Current Liabilities with Cash.	Cash
X17	Cash / Total Assets	Measures The Proportion of Cash in Total Assets.	Cash
X18	Equity / Total Assets	Percentage Of Equity Relative to Total Assets.	Accrual
X19	Ebit /Total Assets	Indicating How Efficiently It Uses Its Assets to Generate Earnings Before Interest and Taxes.	Accrual
X20	Total Assets / Total Liability	Assessing The Percentage of The Assets Coming from Liability	Accrual
X21	Equity / Fixed Assets	Shows How Much of a Company's Fixed Assets Are Financed by Its Own Equity	Accrual
X22	Total Liability/ Total Assets	Show How Much Assets Can Repay Their Total Debt	Accrual
X23	Current Assets / Current Liability	Show The Percentage of Current Assets Due to The Current Liability	Accrual

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3.4 Statistical Analysis

The effectiveness of the models will be evaluated using several statistical measures, including:

a. Overall Classification Accuracy: The percentage of correctly classified cases in the holdout sample.
b. Wilks' Lambda: A measure of how well the discriminant function differentiates between the two groups. A lower value indicates a better model.
c. F-Statistic: Used to test the significance of the discriminant function.

3.5 Hypothesis:

There is a difference in the financial analysis results of cash flow statement indicators compared to the financial analysis results of income statement and balance sheet indicators.

H1: The model based on cash flow ratios has higher predictive accuracy than the model based on accrual-based ratios in the field of predicting financial distress.

H2: The hybrid model has higher predictive accuracy than the model based on accrual-based ratios in the field of predicting financial distress.

H3: The hybrid model has higher predictive accuracy than the model based on cash flow ratios in the field of predicting financial distress.

4. Results and Discussion

4.1 Cash Flow Based Model for Predicting Financial Failure

4.1.1 Box's Test of Equality of Covariance Matrices

The covariance matrices of the study groups are assumed to be equal. To verify this assumption, the researcher conducted Box's M test to assess the equality of covariance matrices. This test is used to check for homogeneity between two or more groups, utilizing the Fisher distribution (F-test). If the significance level is less than 5%, indicating that the covariances of the study variables are not homogeneous. This test is determined at two levels, as shown in the attached tables

Table 3. Log Determinants of cash-based model

Company	Rank	Log Determinant
0	2	9,046
1	2	7,211
Pooled within-groups	2	10,676

The table above shows that 2 out of the 7 ratios have the ability to discriminate between whether a company is failed or healthy. Additionally, the log determinants have large values that are close to each other but not equal. A higher log determinant indicates a greater difference in the variability of the groups.

Table 4. Test Results of Box's M for cash-based model

Box's M		71,319
F	Approx.	21,944
	df1	3
	df2	141120,000
	Sig.	,000

*Tests null hypothesis of equal population covariance matrices.

The results of the Box's M test, as shown in the table above, indicate a significance level (Sig = 0.000), which is less than 5%. Consequently, meaning there is no homogeneity in the covariances of the study variables. The researcher notes that it is rare

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for the assumptions of normal distribution and homogeneity of covariance to be met when the study variables consist of financial ratios

To ensure that the discriminant equation includes the best variables with discriminatory power, the variables are reduced using Wilks' Lambda statistic, which aids in testing the following hypotheses to extract the variables that have the ability to discriminate effectively.

Table 5. Variables Entered/Removed of WILKS'LAMBDA for cash based model

Step	Entered	Wilks' Lambda							
		Statistic	df1	df2	df3	Exact F			
						Statistic	df1	df2	Sig.
1	X2	,703	1	1	28,000	11,853	1	28,000	,002
2	X5	,608	2	1	28,000	8,697	2	27,000	,001

At each step, the variable that minimizes the overall Wilks' Lambda is entered.

a. Maximum number of steps is 14.

b. Minimum partial F to enter is 3.84.

c. Maximum partial F to remove is 2.71.

d. F level, tolerance, or VIN insufficient for further computation.

The table shows that 14 steps were taken to achieve the lowest value of Wilks' Lambda. In each step, variables with the highest Wilks' Lambda value, representing the least discriminatory power, are excluded. The table also indicates that all variables are significant (sig < 0.05), except for the following two variables: x2 and x5. These independent variables are considered the most important and have the greatest ability to distinguish between failed and successful companies, as they possess the highest F-ratio and the lowest Wilks' Lambda value. The remaining variables will be excluded, as shown in the table. According to the Fisher statistic (F), the significance level is around sig = 0.000, which is less than 5%., indicating that these variables collectively have a high discriminatory ability. Therefore, the study variables that contribute to the discriminant function consist of 2 out of the original 7 ratios. Which is x2 = cash interest coverage and x5 = earning quality.

Table 6. Standardized Canonical Discriminant Function Coefficients of Cash-Based Model

	Function
	1
X2	,854
X5	,587

In the table above, the first column lists the variables included in the formation of the function, which are x2 and x5. The "Function" column provides the coefficients for each variable, which are 0.854 and 0.587, respectively. Accordingly, the standardized canonical discriminant function is as follows: $Z = 0.854X2 + 0.587X5$ As we can see, the cash interest coverage ratio has a strong ability to discriminate, while the earnings quality ratio is less predictive.

The following table illustrates the coefficients of the canonical discriminant function, which are used to construct the current prediction equation. This equation can be employed to classify new cases. While the standardized canonical discriminant function serves the purpose of estimation, the canonical discriminant function is useful for achieving the goal of prediction.

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Table 7. Canonical Discriminant Function Coefficients of cash-based model

	Function
	1
X2	,125
X5	,019
(Constant)	-,307

*Unstandardized coefficients

From the table above, we can see the variables or ratios included in the function, which are x2 and x5. In the "Function" column, the coefficients for each variable are 0.125 and 0.019, respectively, with a constant of -0.307. So, the canonical discriminant function is Z= ,125X2 + ,019X5 -,307

The table provides the centroid values for each group, representing the centre of gravity of the discriminant function values in the discriminant analysis. The "Function" column shows that the centroid for the group of failed companies is -0.775, while the centroid for the successful companies is 0.775. These two values are located at opposite positions, and the distance between them is the sum of these values, which is 0

Table 8. Functions at Group Centroids of cash-based model

Company	Function
	1
0	-,775
1	,775

*Unstandardized canonical discriminant functions evaluated at group means

The table above shows that if the Z value of any company is close to 0.775, it indicates a healthy company, while if it is close to -0.775, it indicates a failed company. The small distance between these two function values suggests that the discriminant function has limited discriminatory power. To distinguish between the group of successful and failed companies and to facilitate the classification process, it is better to establish a decision rule by calculating the cutoff point *Z. This cutoff point helps determine the group to which a new observation belongs. If we divide a particular sample into two groups, we can identify whether a new observation belongs to one of the groups by comparing the value of the discriminant function with *Z, which serves as a measure of the distance between the two groups. This cutoff point *Z is determined by substituting the means of the variables in the first group into the equation to obtain Z1, and in the second group to obtain Z2. The value of *Z is then calculated as follows: Z*= (,775-,775)/2 = 0

If Z is greater than or equal to 0, the company is considered failed. If Z is less than or equal to 0, the company is considered healthy. Values in between fall into a gray area and require further analysis.

An eigenvalue is defined as "the ratio of the sum of squares between the groups to the sum of squares within the groups for the analysis of variance, where the dependent variable is the discriminant function and the groups are the levels of the factor. “The following table shows the eigenvalue obtained through the program.

Table 9. Eigenvalues of cash-based model

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	,644a	100,0	100,0	,626

*a. First 1 canonical discriminant functions were used in the analysis.

The results from Table above show the following statistics: Since the dependent variable in our study has only two classifications (failed companies and successful

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companies), and by observing the "Function" column, we find it equals 1. This means we have one discriminant function. The larger the eigenvalue, the greater the variance captured in the linear combination of the variables, indicating better performance of the discriminant function. The table shows that the eigenvalue equals 0.644 which is a good value, indicating strong predictive power of the discriminant function. The variance percentage, which reached 100%, indicates the importance of the discriminant function. Regarding the cumulative variance, it shows the percentage of accumulated variances for discriminant functions added each time in the table The canonical correlation value shows the relationship between the discriminant score and the groups. The closer this value is to one, the better the model. The table shows that the canonical correlation equals 0.626 indicating a strong relationship and good discriminatory ability of the discriminant function.

The Wilk's Lambda test indicates the significance of the discriminant function in distinguishing between the two groups. This statistic is used to test the extracted discriminant function by determining whether there are statistically significant differences between the two groups in the predictor variables, which, in this study, are the financial ratios. The test results were as follows.

Table 10. Wilks' Lambda of cash-based model

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,608	13,427	2	,001

Table above shows that the value of the Wilks' Lambda statistic is ,608, indicating that the variables combined in the discriminant function play a significant role in differentiation. The lower this value, the better the analysis. The Chi-square statistic, which tests the significance of Wilks' Lambda, reached 13,427 with a significance level of 0.001, which is less than the 0.05 significance level. This indicates that the resulting discriminant function represents a good and consistent set of financial ratios, allowing for accurate prediction.

Table 11. Classification Results of cash-based model

		Company	Predicted Group Membership		Total
			0	1	
Original	Count	0	15	0	15
		1	3	12	15
	%	0	100,0	,0	100,0
		1	20,0	80,0	100,0
Cross-validated	Count	0	15	0	15
		1	5	10	15
	%	0	100,0	,0	100,0
		1	33,3	66,7	100,0

a. 90,0% of original grouped cases correctly classified.
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
c. 83,3% of cross-validated grouped cases correctly classified.

The classification results indicate that the discriminant function is quite effective in predicting financial failure. In the original classification, the model accurately classified 90% of the cases, demonstrating strong performance in differentiating between failed and healthy companies. Specifically, for failed companies (Group 0), the model achieved 100% accuracy in predicting them, reflecting its high reliability in identifying companies at risk of failure. However, for healthy companies (Group 1), the accuracy was 80% in

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the original dataset, which dropped to 66.7% in cross-validation. This decline suggests that while the model performs well overall, there is some variability in its ability to classify healthy companies. The cross-validation accuracy of 83.3% confirms that the model is generally robust but highlights areas where improvements could be made, particularly in enhancing the accuracy of healthy company classifications.

4.2 Accrual Based Model for Predicting Financial Failure

Table 12. Log Determinants of accrual-based model

Company	Rank	Log Determinant
0	3	-12,036
1	3	-18,638
Pooled within-groups	3	-12,334

The table above shows that 3 out of the 16 ratios have the ability to discriminate between whether a company is failed or healthy. Additionally, the log determinants have large values that are close to each other but not equal. A higher log determinant indicates a greater difference in the variability of the groups.

Table 13. Test Results of box’s m

Box's M		84,079
F	Approx.	12,372
	df1	6
	df2	5680,302
	Sig.	,000

The results of the Box's M test, as shown in the table above, indicate a significance level (Sig = 0.000), which is less than 5%. Consequently, meaning there is no homogeneity in the covariances of the study variables. The researcher notes that it is rare for the assumptions of normal distribution and homogeneity of covariance to be met when the study variables consist of financial ratios

Table 14. Variables Entered/Removed of accrual-based model

Step	Entered	Wilks' Lambda							
		Statistic	df1	df2	df3	Exact F			
						Statistic	df1	df2	Sig.
1	X19	,493	1	1	28,000	28,786	1	28,000	,000
2	X15	,283	2	1	28,000	34,127	2	27,000	,000
3	X7	,245	3	1	28,000	26,768	3	26,000	,000

At each step, the variable that minimizes the overall Wilks' Lambda is entered.

a. Maximum number of steps is 32.

b. Minimum partial F to enter is 3.84.

c. Maximum partial F to remove is 2.71.

The table shows that 32 steps were taken to achieve the lowest value of Wilks' Lambda. In each step, variables with the highest Wilks' Lambda value, representing the least discriminatory power, are excluded. The table also indicates that all variables are significant (sig < 0.05), except for the following two variables: x19, x15 and x7. These independent variables are considered the most important and have the greatest ability to distinguish between failed and successful companies, as they possess the highest F-ratio and the lowest Wilks' Lambda value. The remaining variables will be excluded, as shown in the table. According to the Fisher statistic (F), the significance level is sig = 0.000, which is less than 5%., indicating that these variables collectively have a high

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discriminatory ability. Therefore, the study variables that contribute to the discriminant function consist of 3 out of the original 16 ratios. Which is X19 = EBIT/TOTAL ASSETS and X15 = PROFT/TOTAL ASSETS AND X7 = R/E / TOTAL ASSETS

Table 15. Standardized Canonical Discriminant Function Coefficients of accrual-based model

	Function
	1
X7	1,100
X15	-5,979
X19	5,543

In the table above, the first column lists the variables included in the formation of the function, which are X7 and X15 and X19. The "Function" column provides the coefficients for each variable, which are 1,100 and -5,979 and 5,543, respectively. Accordingly, the standardized canonical discriminant function is as follows: Z= 1,100X7 - 5,979X15 + 5,543X19

As we can see, EBIT/TOTAL ASSETS has a strong ability to discriminate, while the PROFIT /TOTAL ASSETS ratio is less predictive.

Table 16. Canonical Discriminant Function Coefficients of accrual-based model

	Function
	1
X7	,962
X15	-34,350
X19	39,892
(Constant)	-,768

*Unstandardized coefficients

From the table above, we can see the variables or ratios included in the function, which are X7 and X15 and X19. In the "Function" column, the coefficients for each variable are ,962 and -34,350 and 39,892, respectively, with a constant of -0.768. So, the canonical discriminant function is Z= ,962X7 - 34,350X15 + 39,892X19 -,768

Table 17. Functions at Group Centroids of accrual-based model

COMPANY	Function
	1
0	-1,698
1	1,698

*Unstandardized canonical discriminant functions evaluated at group means

The table above shows that if the Z value of any company is close to 1,698 it indicates a healthy company, while if it is close to -1,698, it indicates a failed company. The small distance between these two function values suggests that the discriminant function has limited discriminatory power. To distinguish between the group of successful and failed companies and to facilitate the classification process, it is better to establish a decision rule by calculating the cutoff point *Z. This cutoff point helps determine the group to which a new observation belongs. If we divide a particular sample into two groups, we can identify whether a new observation belongs to one of the groups by comparing the value of the discriminant function with *Z, which serves as a measure of the distance between the two groups. This cutoff point *Z is determined by substituting the means of the variables in the first group into the equation to obtain Z1, and in the second group to obtain Z2. The value of *Z is then calculated as follows: Z*= (1,698 -1,698)/2 = 0

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If Z is greater than or equal to 0, the company is considered failed. If Z is less than or equal to 0, the company is considered healthy. Values in between fall into a gray area and require further analysis.

Table 18. Eigenvalues of accrual-based model

Function	Eigenvalue	% Of Variance	Cumulative %	Canonical Correlation
1	3,089a	100,0	100,0	,869

a. First 1 canonical discriminant functions were used in the analysis.

The results from Table above show the following statistics: The larger the eigenvalue, the greater the variance captured in the linear combination of the variables, indicating better performance of the discriminant function. The table shows that the eigenvalue equals 3,089 which is a good value, indicating strong predictive power of the discriminant function. The variance percentage, which reached 100%, indicates the importance of the discriminant function. Regarding the cumulative variance, it shows the percentage of accumulated variances for discriminant functions added each time in the table The canonical correlation value shows the relationship between the discriminant score and the groups. The closer this value is to one, the better the model. The table shows that the canonical correlation equals 0.869 indicating a strong relationship and good discriminatory ability of the discriminant function.

Table 19. Wilks' Lambda of accrual-based model

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,245	37,317	3	,000

Table above shows that the value of the Wilks' Lambda statistic is ,245, indicating that the variables combined in the discriminant function play a significant role in differentiation. The lower this value, the better the analysis. The Chi-square statistic, which tests the significance of Wilks' Lambda, reached 37,317 with a significance level of 0.000, which is less than the 0.05 significance level. This indicates that the resulting discriminant function represents a good and consistent set of financial ratios, allowing for accurate prediction

Table 20. Classification Results of accrual-based model

		COMPANY	Predicted Group Membership		Total
			0	1	
Original	Count	0	15	0	15
		1	1	14	15
	%	0	100,0	,0	100,0
		1	6,7	93,3	100,0
Cross-validatedb	Count	0	14	1	15
		1	1	14	15
	%	0	93,3	6,7	100,0
		1	6,7	93,3	100,0

a. 96,7% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 93,3% of cross-validated grouped cases correctly classified.

The classification results of the Multiple Discriminant Analysis (MDA) show a high level of accuracy in predicting group membership for companies. The model originally classified 96.7% of the cases correctly, as 15 out of 15 companies in Group 0 (non-

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bankrupt) were accurately identified, and 14 out of 15 companies in Group 1 (bankrupt) were correctly classified. This demonstrates the model's strong performance in distinguishing between bankrupt and non-bankrupt companies based on the selected variables. When cross-validation was applied, which provides a more robust assessment by classifying each case based on a model derived from all other cases, the accuracy slightly decreased but remained high. Specifically, 93.3% of the cross-validated cases were correctly classified. This indicates that 14 out of 15 companies in Group 0 were still correctly identified, while the model misclassified one company, and all 14 companies in Group 1 were accurately classified. Overall, the results suggest that the model has a strong predictive capability, with minor variations between the original classification and cross-validated classification, highlighting the model's reliability and robustness in predicting financial distress.

4.3 Hybrid based model of predicting financial failure:

Table 21. Log Determinants of hybrid-based model

COMPANY	Rank	Log Determinant
0	3	-10,456
1	3	-9,355
Pooled within-groups	3	-6,961

The table above shows that 3 out of the 23 ratios have the ability to discriminate between whether a company is failed or healthy. Additionally, the log determinants have large values that are close to each other but not equal. A higher log determinant indicates a greater difference in the variability of the groups.

Table 22. Test Results of hybrid-based model

Box's M		82,444
F	Approx.	12,131
	df1	6
	df2	5680,302
	Sig.	,000

*Tests null hypothesis of equal population covariance matrices.

The results of the Box's M test, as shown in the table above, indicate a significance level (Sig = 0.000), which is less than 5%. Consequently, meaning there is no homogeneity in the covariances of the study variables. The researcher notes that it is rare for the assumptions of normal distribution and homogeneity of covariance to be met when the study variables consist of financial ratios.

Table 23. Variables Entered/Removed of hybrid-based model

Step	Entered	Wilks' Lambda							
		Statistic	df1	df2	df3	Exact F			
						Statistic	df1	df2	Sig.
1	X19	,493	1	1	28,000	28,786	1	28,000	,000
2	X15	,283	2	1	28,000	34,127	2	27,000	,000
3	X2	,223	3	1	28,000	30,209	3	26,000	,000

At each step, the variable that minimizes the overall Wilks' Lambda is entered.

a. Maximum number of steps is 46.

b. Minimum partial F to enter is 3.84.

c. Maximum partial F to remove is 2.71.

d. F level, tolerance, or VIN insufficient for further computation.

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The table shows that 46 steps were taken to achieve the lowest value of Wilks' Lambda. In each step, variables with the highest Wilks' Lambda value, representing the least discriminatory power, are excluded. The table also indicates that all variables are significant (sig < 0.05), except for the following two variables: X19, X15and X2. These independent variables are considered the most important and have the greatest ability to distinguish between failed and successful companies, as they possess the highest F-ratio and the lowest Wilks' Lambda value. The remaining variables will be excluded, as shown in the table. According to the Fisher statistic (F), the significance level is sig = 0.000, which is less than 5%., indicating that these variables collectively have a high discriminatory ability. Therefore, the study variables that contribute to the discriminant function consist of 3 out of the original 23 ratios. Which is X19 = EBIT/TOTAL ASSETS and X15 = PROFT/TOTAL ASSETS AND X2 = cash interest coverage

Table 24. Standardized Canonical Discriminant Function Coefficients of hybrid-based model

	Function
	1
X15	-4,157
X19	4,583
X2	,549

In the table above, the first column lists the variables included in the formation of the function, which are X15 and X19 and X2. The "Function" column provides the coefficients for each variable, which are -4,157 and 4,583 and ,549, respectively. Accordingly, the standardized canonical discriminant function is as follows: Z= -4,157X15 + 4,583X19 +,549X2

Table 25. Canonical Discriminant Function Coefficients of hybrid-based model

	Function
	1
X15	-23,886
X19	32,985
X2	,081
(Constant)	-1,130

From the table above, we can see the variables or ratios included in the function, which are X15 and X19 and X2. In the "Function" column, the coefficients for each variable are -23,886 and 32,985 and ,081, respectively, with a constant of -1.130.

So, the canonical discriminant function is Z= -23,886X15 +32,985X19+ ,081X2 -1,130.

Table 26. Functions at Group Centroids of hybrid-based model

	1
0	-1,804
1	1,804

*Unstandardized canonical discriminant functions evaluated at group means

The table above shows that if the Z value of any company is close to 1,804 it indicates a healthy company, while if it is close to -1,804, it indicates a failed company. The value of *Z is then calculated as follows: Z*= (1,804 -1,804)/2 = 0

If Z is greater than or equal to 0, the company is considered failed. If Z is less than or equal to 0, the company is considered healthy. Values in between fall into a Gray area and require further analysis.

Table 27. Eigenvalues of hybrid-based model

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	3,486a	100,0	100,0	,882

a. First 1 canonical discriminant functions were used in the analysis.

The results from Table above show the following statistics: The larger the eigenvalue, the greater the variance captured in the linear combination of the variables, indicating better performance of the discriminant function. The table shows that the eigenvalue equals 3,486 which is a good value, indicating strong predictive power of the discriminant function. The variance percentage, which reached 100%, indicates the importance of the discriminant function. Regarding the cumulative variance, it shows the percentage of accumulated variances for discriminant functions added each time in the table The canonical correlation value shows the relationship between the discriminant score and the groups. The closer this value is to one, the better the model. The table shows that the canonical correlation equals 0.882 indicating a strong relationship and good discriminatory ability of the discriminant function.

Table 28. Wilks' Lambda of hybrid-based model

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,223	39,774	3	,000

Table above shows that the value of the Wilks' Lambda statistic is ,223, indicating that the variables combined in the discriminant function play a significant role in differentiation. The lower this value, the better the analysis. The Chi-square statistic, which tests the significance of Wilks' Lambda, reached 39,774 with a significance level of 0.000, which is less than the 0.05 significance level. This indicates that the resulting discriminant function represents a good and consistent set of financial ratios, allowing for accurate prediction.

Table 29. Classification Results of hybrid-based model

<table>
<tr><th colspan="2" rowspan="2"></th><th rowspan="2">COMPANY</th><th colspan="2">Predicted Group Membership</th><th rowspan="2">Total</th></tr>
<tr><th>0</th><th>1</th></tr>
<tr><td rowspan="4">Original</td><td rowspan="2">Count</td><td>0</td><td>15</td><td>0</td><td>15</td></tr>
<tr><td>1</td><td>0</td><td>15</td><td>15</td></tr>
<tr><td rowspan="2">%</td><td>0</td><td>100,0</td><td>,0</td><td>100,0</td></tr>
<tr><td>1</td><td>,0</td><td>100,0</td><td>100,0</td></tr>
<tr><td rowspan="4">Cross-validated</td><td rowspan="2">Count</td><td>0</td><td>15</td><td>0</td><td>15</td></tr>
<tr><td>1</td><td>0</td><td>15</td><td>15</td></tr>
<tr><td rowspan="2">%</td><td>0</td><td>100,0</td><td>,0</td><td>100,0</td></tr>
<tr><td>1</td><td>,0</td><td>100,0</td><td>100,0</td></tr>
</table>

a. 100,0% of original grouped cases correctly classified.
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
c. 100,0% of cross-validated grouped cases correctly classified.

The classification results from the Multiple Discriminant Analysis (MDA) demonstrate an exceptional level of accuracy in predicting the group membership of companies. The model achieved a perfect classification rate, with 100% of the original cases correctly classified. Specifically, all 15 companies in Group 0 (non-bankrupt) and all 15 companies in Group 1 (bankrupt) were accurately identified, indicating that the model made no errors in its predictions.

Moreover, when cross-validation was applied—a technique that tests the model's robustness by classifying each case using a function derived from all other cases—the model maintained its flawless performance. The cross-validated results also showed 100% accuracy, with all companies in both groups being correctly classified.

4.4 Discussion

The findings from this study offer valuable insights into the predictive accuracy of various bankruptcy prediction models, highlighting the strengths of both cash flow-based and accrual-based measures, and most notably, the hybrid model that integrates both approaches. By comparing these models in the context of the Egyptian stock market, the research not only expands our understanding of financial distress prediction but also offers practical implications for businesses and financial institutions operating in emerging economies.

The cash flow-based model in this study demonstrated strong predictive capabilities, correctly classifying 90.0% of the original grouped cases and 83.3% of the cross-validated cases. This finding aligns with the Cash Flow Theory of bankruptcy prediction, which emphasizes the importance of a company's liquidity and its ability to meet short-term obligations. As described by Beaver (1966), a firm is like a reservoir of liquid assets, and its solvency is determined by the ability of this reservoir to absorb variations in cash inflows and outflows. The two key ratios—Cash Interest Coverage and Earnings Quality—captured in this study are reflective of this theory, showing that companies with sufficient cash flow to cover interest debt and taxes are less likely to face bankruptcy. These ratios are integral to understanding the firm’s ability to maintain solvency under fluctuating financial conditions, especially in markets with high volatility like Egypt.

However, while the cash flow-based model showed strong results, the accrual-based model outperformed it in terms of predictive accuracy, with a correct classification rate of 96.7% for original cases and 93.3% for cross-validated cases. This result suggests that the accrual model, which reflects long-term profitability and asset utilization, can provide a more comprehensive understanding of a company's financial health. The three ratios in this model—EBIT/Total Assets, Profit/Total Assets, and Retained Earnings/Total Assets—align with traditional financial performance indicators that focus on the long-term potential of a company to generate profit. These findings support prior research by Altman (1968) and others, who demonstrated that profitability and asset efficiency are critical indicators of financial distress. The higher predictive power of the accrual-based model could be due to its broader focus on profitability over time, rather than just short-term cash flow.

The hybrid model, combining both accrual and cash flow ratios, provided the highest predictive accuracy, correctly classifying 100% of the cases. This model’s performance supports the idea that integrating both financial perspectives—liquidity (cash flow) and profitability (accrual)—offers the most robust prediction of financial distress. This finding is in line with research by Charitou & Trigeorgis (2000), which argued that models incorporating both cash flow and accrual metrics provide a more comprehensive approach to bankruptcy prediction. By leveraging both short-term liquidity and long-term profitability indicators, the hybrid model reflects a more balanced view of a firm's financial condition, capturing the dynamics of both operational efficiency and financial solvency. The superior performance of the hybrid model suggests that bankruptcy prediction models should not rely solely on one type of financial indicator but instead combine both perspectives to enhance predictive power.

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In light of these findings, the alternative hypothesis (H1), which posited that the hybrid model would outperform both the accrual-based and cash flow-based models, is supported. The hybrid model's ability to achieve perfect classification accuracy highlights its superiority, which corroborates earlier studies (e.g., Altman et al., 1995) suggesting that combining different types of financial ratios enhances predictive outcomes. These results are significant for financial institutions and investors who rely on bankruptcy prediction models to assess the creditworthiness of companies, especially in unstable economic environments.

The Cash Flow Theory provides a strong theoretical foundation for understanding the predictive power of cash flow ratios in bankruptcy prediction. As Beaver (1966) described, a firm's ability to manage its cash inflows and outflows is crucial to its survival. A negative or insufficient cash flow, particularly in the context of emerging markets like Egypt, where economic instability may exacerbate liquidity problems, greatly increases the likelihood of financial failure. The findings of this study support this notion, as companies that are able to cover their short-term obligations through positive cash flow are less likely to face bankruptcy.

Moreover, Scott's (1981) interpretation of bankruptcy as a consequence of insufficient profit or cash flow to meet debt obligations aligns with the outcomes observed in the cash flow-based model. The model's ability to identify companies that struggle to meet their immediate debt obligations highlights the importance of liquidity measures in the bankruptcy prediction process.

5. Conclusion

This study aimed to address the critical need for effective bankruptcy prediction models, particularly in the context of emerging markets like Egypt, where financial instability and economic volatility present unique challenges for businesses and financial institutions. The research specifically focused on comparing the predictive accuracy of different models—accrual-based, cash flow-based, and hybrid models—using financial data from companies listed on the Egyptian stock market. The findings contribute to the ongoing debate regarding the relative effectiveness of these models in forecasting corporate bankruptcy and financial failure, providing a clearer understanding of the advantages and limitations of each approach.

The cash flow-based model demonstrated strong predictive accuracy, correctly classifying 90.0% of the original grouped cases and 83.3% of the cross-validated cases. This model's reliance on ratios such as Cash Interest Coverage and Earnings Quality emphasizes the importance of a company's ability to generate sufficient cash to meet its immediate financial obligations. This aligns with the Cash Flow Theory of bankruptcy prediction, which posits that companies experiencing negative or insufficient cash flows are at a higher risk of failure due to their inability to meet short-term obligations. As Beaver (1966) highlighted, the ability to maintain positive cash flow is essential for a firm's survival, and this study reinforces the notion that liquidity is a crucial determinant of financial stability, particularly in uncertain market conditions.

On the other hand, the accrual-based model showed even greater predictive power, correctly classifying 96.7% of the original cases and 93.3% of the cross-validated cases. The accrual model's reliance on key ratios such as EBIT/Total Assets, Profit/Total Assets, and Retained Earnings/Total Assets reflects the firm's ability to generate profits over time, utilizing its assets efficiently. This model supports prior research by Altman (1968), which emphasized the role of profitability and asset utilization in predicting financial distress. The superior performance of the accrual-based model underscores the importance of considering long-term profitability and the firm's overall financial health when assessing bankruptcy risk.

However, the most significant finding from this study is that the hybrid model, which combines both accrual and cash flow ratios, outperformed both the cash flow-based and accrual-based models. The hybrid model achieved perfect classification accuracy, correctly classifying 100% of the cases. This result strongly supports the hypotheses that combining both liquidity (cash flow) and profitability (accrual) indicators provides a more comprehensive and accurate prediction of financial distress. By integrating these two perspectives, the hybrid model offers a balanced approach that accounts for both short-term financial stability and long-term profitability, making it the most effective tool for predicting bankruptcy in this study. These findings are consistent with previous research by Charitou & Trigeorgis (2000), which argued that combining different types of financial ratios improves the predictive power of bankruptcy models.

The findings from this study provide a direct answer to the research problem by demonstrating that while both cash flow and accrual-based models have strong predictive abilities, the hybrid model—which integrates both types of ratios—provides the most accurate prediction of corporate bankruptcy and financial failure. This confirms that the most effective bankruptcy prediction models are those that incorporate a comprehensive set of financial indicators, combining the strengths of both liquidity and profitability measures. For financial institutions, investors, and policymakers, these results emphasize the importance of using a holistic approach to assess the risk of bankruptcy, especially in volatile and fluctuating markets like Egypt.

Despite the valuable insights this study provides, it is important to acknowledge the limitations inherent in its design. The small sample size, consisting of only 10 companies listed on the Egyptian stock market, may limit the generalizability of the results. While the findings offer important contributions to the literature, expanding the sample size to include a more diverse range of companies across different industries and regions would be essential for further validating these conclusions. Additionally, longitudinal data spanning multiple years could provide a deeper understanding of the dynamic nature of financial distress, allowing for the development of even more accurate predictive models.

In conclusion, this research underscores the importance of combining cash flow and accrual measures to predict bankruptcy. The hybrid model's superior performance highlights the need for more comprehensive predictive models that integrate both short-term liquidity and long-term profitability indicators. As emerging markets continue to face economic uncertainty, the findings of this study provide valuable guidance for developing early warning systems that can help mitigate the risks of corporate bankruptcy. Future research with larger datasets and extended time frames will be critical in refining these models and further enhancing their predictive accuracy, ensuring that financial institutions and businesses have the tools they need to navigate an increasingly complex and volatile economic environment.

For future research, expanding the sample size to include a larger and more diverse set of companies from different industries and regions would be beneficial. A broader dataset would enable a more comprehensive analysis, potentially leading to more robust conclusions and a deeper understanding of the effectiveness of these models across various contexts. Additionally, incorporating longitudinal data over a longer period could help capture the dynamic nature of financial distress and improve the predictive power of the models.

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