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Abstract: This study investigates whether the prediction of financial distress is improved through narrative disclosure tone and corporate governance indicators. This study utilizes a machine learning-based logit regression technique to achieve this purpose. The data are collected from a sample of 1500 annual reports of Pakistani firms for a period of 12 years from 2011–2022. Financial distress is operationalized through two alternate measures, the Altman Z score and the Zmijewski score. The outcome of these measures is a binary variable differentiating financially distressed firms from relatively healthy firms. Narrative disclosure tone is operationalized by conducting a sentiment analysis of annual reports using natural language processing and the LM dictionary in R. Accordingly, we have a score for each of the six tones that are part of the LM dictionary. Corporate governance indicators and certain financial indicators are also taken directly from the annual reports of the firms. Finally, different models are developed, each containing a specific set of predictors. Machine learning-based logistic regression is employed as the prediction technique. Financial distress is then predicted first using the base model, which will contain financial indicators alone. Next, the predictive performance of the base model is compared with that of models containing narrative disclosure tones and corporate governance indicators in addition to financial indicators. Accordingly, the results of these comparisons indicate that both narrative disclosure tone and corporate governance indicators significantly add to the prediction of financial distress. The results of our study offer invaluable implications for investors, regulators, policymakers and firms to be able to actively anticipate and consequently take preventative measures in the event of default.

Keywords: Financial Distress, Logit Regression, Machine Learning, Artificial Intelligence, Corporate Governance, Narrative Disclosure Tone .

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1. Introduction

The COVID-19 pandemic and the global financial crisis have had devastating consequences on the financial world (Citterio & King, 2023; Wu et al., 2020). More specifically, Wu et al. (2020) suggest that the economic world is plagued by prolonged periods of financial uncertainty and instability since the crisis. They add that this has increased the likelihood of companies defaulting. Therefore, it has become crucial for investors, regulators and policymakers to be able to predict the likelihood of default, especially in times when financial instability and uncertainty are prevalent (Qian et al., 2022). Inevitably, there has been renewed interest in predicting financial distress with the utmost accuracy (Citterio & King, 2023). Despite the existence of many financial distress prediction models, they are in a continuous state of improvement and evolution (Qian et al., 2022; Tron et al., 2022; Wu et al., 2022).

For instance, Qian et al. (2022) suggests most financial distress prediction models focus on outdated statistical techniques, such as multiple discriminant analysis. However, the advent of machine learning techniques provides an apt opportunity to improve existing models of financial distress prediction (Liang et al., 2020; Qian et al., 2022). Interestingly, the prediction of financial distress using machine learning techniques and artificial intelligence is an area of relatively unexplored research (Liang et al., 2020). Consequently, Tron et al. (2022) indicate that there is an evident need to improve existing models of financial prediction by incorporating machine learning algorithms in the process. Another gap found in research relevant to financial distress prediction is the limited testing of nonfinancial predictors (Citterio & King, 2023). Furthermore, Citterio & King (2023) suggest that financial distress prediction is heavily reliant on financial indicators as predictors, and there is an increasing need to incorporate qualitative or nonfinancial indicators as determinants of distress. Accordingly, Liang et al. (2020) suggest corporate governance indicators as possible predictors of financial distress that may improve accuracy.

Corporate governance indicators have previously been associated with financial distress on several occasions (Liang et al., 2020; Shahwan, 2015). However, this area of research suffers from several limitations and gaps. For instance, Shahwan (2015) empirically analysed the association between corporate governance indicators and financial distress of 86 nonfinancial Egyptian firms. Nevertheless, they suggest that their study suffers from the limitations of a small sample size and cross-sectional analysis. Furthermore, most research in this regard is embedded in the use of traditional regression techniques (Khurshid et al., 2018; Luqman et al., 2018). Consequently, Liang et al. (2020) contend that this gap can be addressed by using much more reliable techniques with the help of artificial intelligence. More recently, Elsayed & Elshandidy (2020) contend that financial distress can be linked to another form of qualitative information that has recently gained prominence in the financial world, namely, narrative disclosures and their tone.

The concept of textual sentiment is becoming increasingly popular in the financial world and is of ever-increasing importance (Bassyouny et al., 2022; Mousa et al., 2022). In addition to financial performance, investors, customers and regulators alike are ever more concerned about narrative reporting (Bassyouny et al., 2022). Furthermore, previous literature on this matter indicates that narrative disclosure tone can provide an important indication of where the firm is headed in terms of stability and performance (Bassyouny et al., 2022; Del Gaudio et al., 2020). For instance, Mousa et al. (2022) use machine learning algorithms to prove that textual tone in annual reports improves the prediction of firm performance. However, there has been limited research regarding the notion of narrative disclosure tones being able to predict negative financial outcomes, such as bankruptcy and distress (Del Gaudio et al., 2020; Elsayed & Elshandidy, 2020; Zhang et al., 2022). For instance, Del Gaudio et al. (2020) find that the negative tone of firms´ mandatory disclosures is indicative of bank risk. However, their study was limited to banks and the use of traditional regression techniques. In another interesting analysis, Zhang et al. (2022) used various machine learning classification and prediction techniques to prove that the textual tone of financial news is an early warning indicator of financial crises in Chinese listed companies. However, their study focused on financial crisis indication rather than bankruptcy prediction and was limited to negative and positive tones only.

Consequently, the purpose of the current study is to fill the aforementioned gaps by testing whether corporate governance indicators and narrative disclosure tone improve the prediction of financial distress. This study achieves this goal by employing a machine learning-based technique, namely, logistic regression.

The sample of the study comprises the annual reports of 125 nonfinancial firms from Pakistan for the period 2011–2022. Corporate governance indicators, such as board characteristics, audit committee characteristics and ownership structures, are taken directly from the annual reports. For narrative disclosure tone, a sentiment analysis is performed on the annual reports in the sample using the LM dictionary and natural language processing in R. Certain financial variables normally associated with financial distress prediction are also taken directly from the annual reports. Finally, the financial distress variable is operationalized through two alternative measures to ensure the robustness of results. First, following Tron et al. (2022), we employ the Z score methodology specifically modified for emerging markets (Altman et al., 2013). This approach is suitable for the current study because the sample comprises firms from an emerging market. Second, we employ another widely used proxy of financial distress mostly used in the case of emerging markets, namely, the Zmijewski (1984) Z score (Luqman et al., 2018; Miglani et al., 2015). Finally, following the operationalization of all variables of the study, we build prediction models, each containing its own set of predictors. These models are then used for prediction via machine learning-based logistic regression. Model 1 consists of financial variables or features as predictors of distress only and is treated as the base model, while Model 2 consists of both financial and corporate governance indicators as features. In addition, Model 3 includes both financial and narrative disclosure tone as features. Finally, Model 4 consists of all the variables and features combined. By comparing the predictive power of these models with that of Model 1, we identify whether corporate governance and narrative disclosure tone play a role in the prediction of financial distress. The results show that both corporate governance indicators and narrative disclosure tone significantly enhance the prediction of financial distress.

First, the study contributes by amalgamating financial distress prediction with machine learning algorithms (Liang et al., 2020; Qian et al., 2022). According to Tron et al. (2022), machine learning prediction techniques can ensure higher reliability and accuracy of results relative to traditional statistical techniques. Second, we contribute by incorporating qualitative information, such as corporate governance indicators in annual reports, as predictors of financial distress (Liang et al., 2020; Shahwan, 2015). In doing so, we also answer the call of Di Vito & Trottier (2022) by incorporating machine learning into the corporate governance literature. In this regard, we establish corporate governance indicators as reliable predictors of distress. Third, the study contributes by including narrative disclosure tone as part of our analysis (Del Gaudio et al., 2020; Zhang et al., 2022). Accordingly, our results establish the reliability of narrative disclosure tone in the prediction of distress. Fifth, most studies investigating financial distress use a single measure for its operationalization, while it is suggested that multiple measures of distress be employed to ensure robustness (Miglani et al., 2015; Tron et al., 2022). Therefore, our study contributes by utilizing two measures commonly used for identifying financial distress in emerging markets to ensure the robustness of our results. Finally, we contribute by carrying out this analysis in Pakistan, an emerging economy plagued by financial and political instability (Ullah & Saqib, 2018). The investors in Pakistan have suffered a major loss in confidence as a result of the ensuing economic doom. Therefore, the results of the study contribute to restoring confidence by establishing nonfinancial information in annual reports as an important tool to anticipate the event of default.

2. Review of the literature and theoretical framework

2.1 Theoretical framework

In the current study, we utilize agency and signalling theories to justify the prediction of financial distress through corporate governance and narrative disclosure tone (Bassyouny et al., 2022; Elsayed & Elshandidy, 2020; Zhao et al., 2022). In particular, agency theory explains the relationship between corporate governance and financial distress, while signalling theory explains the interplay between narrative disclosure tone and financial distress.

Agency theory contends that the conflict between managers and shareholders causes information asymmetry to increase in the firm (Jensen & Meckling, 1976). Therefore, companies can plunge into financial distress as performance decreases rapidly (Mariano et al., 2021). Furthermore, Jensen & Meckling (1976) contend that good corporate governance can curb the negative impact of agency conflicts and reduce information asymmetry. Accordingly, Mariano et al. (2021) posits that this can maintain the firm´s position as a healthy firm. Therefore, based on the agency theory perspective, we include corporate governance indicators in our study as predictors of financial distress (Jensen & Meckling, 1976; Mariano et al., 2021). In addition, signalling theory is also utilized to explain the relationship between narrative disclosure tone and financial distress (Bassyouny et al., 2022; Elsayed & Elshandidy, 2020; Zhao et al., 2022).

According to Elsayed & Elshandidy (2020), signalling theory contends that managers signal the state of the company through narrative disclosures and their tone, which in turn can be used to predict financial distress. They further explain that managers are concerned with reputational risks and informational asymmetry, which feeds their motivation to signal this information to investors. In addition, Zhao et al. (2022) contends that textual information in narrative disclosures signals an early warning in case of a crisis within the firm.

Guided by the overarching theoretical framework discussed above, below, we delineate the relevant literature regarding the prediction of financial distress and accordingly build our hypotheses.

2.2 Traditional predictors of financial distress and relevant gaps

Financial ratios and indicators have been linked to the prediction of financial distress time and time again in the academic literature (Geng et al., 2015; Paule-Vianez et al., 2020). For instance, Geng et al. (2015) utilize financial ratios to predict financial distress in Chinese companies. They find that financial ratios such as return on assets and cash flow per share highly contribute to the prediction of financial distress. However, Citterio & King (2023) posit that the testing of nonfinancial disclosures as predictors of financial outcomes is scarce. This is alarming as investors look towards these disclosures in times of financial uncertainty for investment decision-making (Aly et al., 2019). Consequently, Geng et al. (2015) and Citterio & King (2023) contend that future studies should test the prediction of financial distress by utilizing nonfinancial information as predictors. In another similar study, Mselmi et al. (2017) utilized 41 financial indicators for the prediction of financial distress in French small and medium enterprises. However, their study is limited to French SMEs and considers only financial ratios. Therefore, they identify the need to incorporate nonfinancial information, such as corporate governance indicators, as predictors of financial distress. Furthermore, Waqas & Md-Rus (2018) carry out a similar analysis in Pakistani listed firms and find that in addition to liquidity and leverage ratios, firm size and cash flow from operations are important indicators of financial distress. However, their study used a traditional logistic regression model and only financial information as predictors. Consequently, they also suggest incorporating nonfinancial information, such as corporate governance indicators, and advanced machine learning algorithms for the prediction of distress. Despite financial distress being a heavily researched subject in the financial literature, we find certain gaps in imminent need of addressing (Geng et al., 2015; Mselmi et al., 2017; Waqas & Md-Rus, 2018).

As mentioned above, one of the most prominent gaps in the financial distress literature concerns the scarce use of nonfinancial or qualitative indicators as predictors of financial distress (Geng et al., 2015; Mselmi et al., 2017; Waqas & Md-Rus, 2018). In this regard, Mselmi et al. (2017) and Waqas & Md-Rus (2018) identify the need to explore corporate governance indicators as potential predictors of financial distress.

2.3 Corporate governance as a predictor of financial distress

From a theoretical standpoint, the relationship between corporate governance and financial distress can be explained through agency theory (Jensen & Meckling, 1976; Mariano et al., 2021). As mentioned above, agency theory rests on agency conflicts and the ensuing informational asymmetries within a firm (Jensen & Meckling, 1976). Accordingly, Jensen & Meckling (1976) offer a potential solution to reduce the negative impacts of agency conflicts in the shape of good corporate governance. Based on this explanation, Mariano et al. (2021) contend that good corporate governance can reduce financial distress by reducing the negative impacts of agency conflicts. However, empirical evidence regarding this relationship is mildly limited (Bravo-Urquiza & Moreno-Ureba, 2021; Khurshid et al., 2018; Liang et al., 2020).

For instance, Liang et al. (2020) analysed US companies data from 2006–2014 to test whether existing financial distress models based on financial ratios can be improved by incorporating corporate governance indicators in the set of predictors. Consequently, they find encouraging results. In addition, they utilize the Support Vector Machine (SVM) algorithm to carry out their analysis and accordingly suggest incorporating other machine learning techniques, such as random forest, into the analysis. Furthermore, Liang et al. (2020) have a smaller sample size with firms limited to the US and suggest using a larger sample size. In addition, Khurshid et al. (2018) provide empirical and encouraging evidence regarding the impact of corporate governance indicators on financial distress within Pakistani firms. However, their study is limited by the use of traditional statistical logistic regression-based econometric models and only one measure of financial distress. Consequently, they suggest incorporating multiple measures of financial distress and other advanced statistical techniques to enhance the robustness of results. In another similar study, Truong (2022) provide evidence that corporate governance indicators impact the financial distress of firms in Vietnam. However, similar to most studies in this regard, they incorporate econometric models in their analysis. In addition, Truong (2022) suggests comparing their results with those of other developing countries.

In this context, Pakistan is a suitable setting as it is subject to rising economic uncertainties and diminishing investor confidence (Rashid *et al.,* 2022). In such settings, investors anticipate the future of the firm through nonfinancial information in annual reports for investment related decisions (Aly et al., 2019). Therefore, it would be interesting to investigate the predictive ability of corporate governance indicators in this regard. Accordingly, based on relevant empirical and theoretical findings, we form the following hypothesis:

H1: Corporate governance indicators improve the ability of traditional financial or quantitative indicators to predict financial distress.

Despite the limited research capturing the impact of corporate governance on the prediction of financial distress, there are still prominent gaps regarding the incorporation of other qualitative information in this regard (Bassyouny et al., 2022; Elsayed & Elshandidy, 2020; Zhang et al., 2022; Zhao et al., 2022). One such form of qualitative information that has gained prominence in recent times and yet suffers from the severity of research linking it to financial distress are narrative disclosures within the annual reports of the firm (Elsayed & Elshandidy, 2020).

2.4 Narrative disclosure tone as a predictor of financial distress

The concept of narrative disclosure tone has rapidly risen to prominence in the fields of accounting and finance (Bassyouny et al., 2022; Elsayed & Elshandidy, 2020; Zhang et al., 2022; Zhao et al., 2022). Furthermore, it has also evolved into a highly demanded avenue for research (Bassyouny et al., 2022). From a strictly academic perspective, narrative disclosure tone can be linked to financial distress through signalling theory (Bassyouny et al., 2022; Elsayed & Elshandidy, 2020; Zhao et al., 2022).

From a signalling theory perspective, Elsayed & Elshandidy (2020) suggest that managers signal the future of the firm through the tone of textual content within annual reports, as they are concerned about mitigating reputational risks and information asymmetries. Consequently, they suggest that this can be used to predict ensuing distress within the firm. However, the empirical literature regarding narrative disclosure tone and financial distress is severely scarce (Bassyouny et al., 2022; Elsayed & Elshandidy, 2020; Zhang et al., 2022; Zhao et al., 2022).

For instance, Elsayed & Elshandidy (2020) utilize corporate failure-related disclosures by U.K. firms to predict failure. Consequently, they empirically provide evidence that these disclosures and their tone significantly increase the explanatory power in the prediction of distress. However, their study is limited to a singular definition of corporate failure, as they suggest that there could be various other reasons that are potentially not covered by their definition. In addition, Zhang et al. (2022) empirically prove that the tone of financial news provides incremental information regarding the prediction of financial crises within Chinese listed firms. However, their analysis is limited to a developed economy and specific to the prediction of financial crises. In another interesting analysis, Zhao et al. (2022) show that combining sentiment tones within the annual reports of a firm is an accurate indicator of future distress. However, their research is also limited to a developed economy and the dichotomy of the distress variable. Therefore, they suggest enhancing the robustness of the distress variable for a reliable prediction. Therefore, we hypothesize the following:

H2: Narrative disclosure tone improves the ability of traditional financial or quantitative indicators to predict financial distress.

2.5 A combination of narrative disclosure tone, corporate governance and financial indicators to predict financial distress

As discussed above, narrative disclosure tone and corporate governance indicators have previously been used to predict distress separately (Elsayed & Elshandidy, 2020; Liang et al., 2020; Zhang et al., 2022). In addition, their links with financial distress have been grounded in theory (Bassyouny et al., 2022; Mariano et al., 2021). However, there has been a dearth of studies that explore their effects together and compare their relative predictive power to predict distress.

In an interesting study, Elsayed & Elshandidy (2020) include corporate governance indicators in a model with narrative-related disclosures as a robustness test and find that they still have sufficient explanatory power. Grounded in the empirical and theoretical literature discussed in the previous sections, we can safely establish that both corporate governance indicators and narrative disclosure tone predict a certain degree of financial distress separately. In addition, we also find empirical evidence to support the notion that a model containing both corporate governance indicators and narrative disclosure tone will have predictive power (Elsayed & Elshandidy, 2020). Despite this limited evidence, no study has combined narrative disclosure tone and corporate governance indicators in the prediction of financial distress to compare their relative predictive power (Zheng et al., 2023). To address this gap, we hypothesize the following as an additional analysis:

H3: Corporate governance indicators improve the ability of both narrative disclosure tone and traditional financial or quantitative indicators to predict financial distress.

H4: Narrative disclosure tone improves the ability of both corporate governance indicators and traditional financial or quantitative indicators to predict financial distress.

3. Methodology

3.1 Sample and Data collection

The sample is drawn from a population of publicly listed firms within Pakistan. There are 551 publicly listed firms on the Pakistan Stock Exchange. First, we eliminate 129 financial companies from our population because their regulatory and governance requirements are distinct from those of nonfinancial companies. Second, we remove 272 firms from our sample because the relevant data are not publicly available. Finally, we eliminate 25 more firms because their annual reports are not machine-readable and cannot be converted into one. Therefore, our final sample consists of 125 nonfinancial firms in Pakistan. The sampling process is described in Table 1.

Table 1: Sampling Process

Particulars	Number of Companies
Panel A: Sampling process	
Total PSX population	551
Less: Financial, investment and banking companies	(129)
Less: Relevant data missing or incomplete	(272)
Less: Firms with annual reports not machine readable or not convertible	(25)
Final sample	125
Total number of firm-year observations (125*10)	1250
Panel B: Sample by sector	
Oil, gas, mining and refineries	14
Technology and communication	6
Power generation, distribution, cable and electric goods	11
Chemical and fertilizers	11
Construction, engineering and property	14

Food, sugar and personal care	15
Textile composite, spinning and weaving	20
Pharmaceuticals	5
Automobile parts, assemblers and transportation	9
Glass, ceramics, paper and board	5
Miscellaneous	15
Total	**125**

Sampling process and sector wise breakdown of final sample
Source: Authors own work

Furthermore, Pakistan is suitable because the COVID-19 crisis has had a magnified financial impact on it. Consequently, this has resulted in massive financial meltdowns (Khan & Ullah, 2021). Furthermore, its already unprecedented economic problems have been amplified by the political instability surrounding the country. Accordingly, investors in Pakistan have had their confidence shattered relevant to making investments in the country. Furthermore, publicly listed firms across Pakistan are selected between 2011 and 2022. This period is appropriate because it covers the aftermath of the global financial crisis of 2008-09 and the whole duration of the COVID-19 crisis (Khan & Ullah, 2021; Tahir et al., 2022). The annual reports are downloaded from the firm websites.

Therefore, our final sample consists of 1500 annual reports of Pakistani nonfinancial firms from 2011–2020.

3.2 Predictor variables or features

The features in the study include financial variables, corporate governance indicators and narrative disclosure tone. First, the study includes 19 quantitative features commonly associated with the prediction of distress discussed in the literature review above (Geng et al., 2015; Paule-Vianez et al., 2020). Second, we incorporate 7 corporate governance indicators based on a comprehensive literature review (Khurshid et al., 2018; Liang et al., 2020; Truong, 2022). Financial variables and corporate governance indicators are taken directly from the annual reports. Finally, scores for six narrative disclosure tones are computed based on a sentiment analysis performed on annual reports of the firms using natural language processing and the LM dictionary within the software R.

3.3 Dependent or Target variable – Financial distress

In our study, financial distress is operationalized through two different measures. First, the Altman Z score model specifically modified for emerging markets by Altman (1995) is used. According to this model, the Z score is calculated as a result of the following discriminant function based on four ratios.

$$Z\ score = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

where X_1 = working capital/total assets, X_2 = retained earnings/total assets, X_3 = EBIT and taxes/total assets and X_4 = market value of equity/book value of debt.

The computed Z score will be used to operationalize financial distress into a binary variable by using a cut-off point. According to Altman (2005), a good cut-off point when converting the said Z score into a binary variable is 4.15. Firms with a Z score above 4.15 are categorized as healthy firms and are assigned a value of 0. The firms that achieve a Z score of less than 4.15 are categorized as distressed firms and are assigned a value of 1.

In addition, we utilize the model proposed by Zmijewski (1984) because it is widely used in the context of emerging markets (Luqman et al., 2018). According to Bravo-Urquiza & Moreno-Ureba (2021), this model is a more reliable method for predicting financial distress than older models. All features and target variables employed in the study are described in Table 2.

Table 2: Variable definition

Symbol	Definition	Operationalisation	Source
Panel A: Target variable			
Z score	Emerging Markets Altman Z score	Firms are categorized as healthy (distressed) firms if Z score is greater (lesser) than 4.15	(Altman et al., 1995; Altman, 2005; Ninh et al., 2018)
Zm score	Zmijewski score	Firms are categorized as healthy (distressed) firms if Zm score is lesser (greater) than 0.5	(Zmijewski, 1984; Geng et al., 2015))

Symbol	Definition	Operationalisation	Source
Panel B: Predictor variables – Corporate Governance indicators (CGIs)			
BS	Board Size	The number of directors on the board	Annual Report
BI	Board Independence	The proportion of independent directors on the board	Annual Report
BGD	Board Gender Diversity	The proportion of female directors on the board	Annual Report
ACS	Audit Committee Size	The number of directors on the audit committee	Annual Report
ACI	Audit Committee Independence	The proportion of independent directors on the audit committee	Annual Report
ACGD	Audit Committee Gender Diversity	The proportion of female directors on the audit committee	Annual Report
FOWN	Foreign Ownership	The percentage of shares owned by managers	Annual Report
Panel C: Predictor variables – Narrative Disclosure Tone			
NEG	Negative	The ratio of negative words to total sentiment related words in an annual report	Annual Report
POS	Positive	The ratio of positive words to total sentiment related words in an annual report	Annual Report
UNC	Uncertain	The ratio of uncertain words to total sentiment related words in an annual report	Annual Report
LIT	Litigious	The ratio of litigious words to total sentiment related words in an annual report	Annual Report
SUP	Superfluous	The ratio of superfluous words to total sentiment related words in an annual report	Annual Report
CON	Constraining	The ratio of constraining words to total sentiment related words in an annual report	Annual Report
Panel D: Predictor variables – Financial or quantitative indicators			
EM	EBITDA Margin	EBITDA/Sales	Annual Report
OM	Operating Margin	Operating profit/Sales	Annual Report
NM	Net Margin	Net income/Sales	Annual Report
FCF	Financial capacity	Free cash flow/Sales	Annual Report

Symbol	Definition	Operationalisation	Source
ROE	Return on Equity	Net Income/Total equity	Annual Report
EPS	Earnings per Share	Net Income/Total outstanding shares	Annual Report
TIE	Times Interest Earned	EBIT/Interest Expense	Annual Report
ERR	Earnings Retention Ratio	Retained Earnings/Net Income	Annual Report
RInvR	Reinvestment Ratio	Capital expenditure/Net Income	Annual Report
QuickR	Quick Ratio	(Current Assets-Inventory)/Current Liabilities	Annual Report
ARTVR	Receivables Turnover	Net Credit Sales/Average accounts receivables	Annual Report
INTVR	Inventory Turnover	Cost of goods sold/Average Inventory	Annual Report
INDAYS	Inventory Days	(Average Inventory/Cost of goods sold) x 365	Annual Report
CCC	Cash Conversion Cycle	Inventory days – days sales outstanding – days payables outstanding	Annual Report
SIZE	Firm Size	Natural logarithm of Total Assets	Annual Report
AGE	Firm Age	The number of years the since the firm was formed	Annual Report
MB	Market to Book Value	Market Value of Equity/Book Value of Equity	Annual Report
TQ	Tobin´s Q	(Market Value of Equity and Liabilities)/(Book Value of Equity and Liabilities)	Annual Report

Variable definition, operationalization and source
Source: Authors own work

The Zmijewski (1984) model for distress prediction also uses a discriminant function to compute a score; however, in this case, the discriminant function is built on three ratios and is outlined below:

$$Zm\ score = -4.336 - 4.513X_1 + 5.679X_2 - 0.004X_3$$

where X_1 = net income/total assets, X_2 = total debt/total assets, and X_3 = current assets/current liabilities

Like the Z score, the Zm score also utilizes a cut-off point to operationalize financial distress into a binary variable. Specifically for the Zm score, companies whose values are greater than 0.5 are categorized as distressed companies and are denoted by 1, while those whose values are less than 0.5 are categorized as healthy companies and are denoted by 0 (Bravo-Urquiza & Moreno-Ureba, 2021; Luqman et al., 2018; Zmijewski, 1984).

3.4 Optimal feature selection using the Boruta algorithm

Feature selection is one of the most imperative steps to take before a machine learning classification problem (Xiaomao et al., 2019). This process is normally used to eliminate irrelevant predictor variables or features for the prediction of a particular target variable (Yeh & Chen, 2020). Therefore, this approach is crucial because it makes the model simple and easily interpretable by preventing overfitting. Feature selection will be conducted using the Boruta algorithm (Mousa et al., 2022).

The Boruta algorithm utilizes the random forest algorithm to eliminate features that are irrelevant for the prediction of a particular target variable (Mousa et al., 2022). Accordingly, we will run the Boruta algorithm on all four measures of financial distress separately to identify the most relevant variables for each. The Boruta algorithm will be run by using the *Boruta* package in R. Following this, we will split the narrowed dataset into training data and testing data.

3.5 Training and testing split

The splitting of data into training and testing data represents a crucial step in all machine learning classification problems (Yeh & Chen, 2020). Training data are a part of the entire dataset that the algorithm utilizes to learn and identify patterns within the dataset. The test data are part of the data the algorithm has never seen and are used by the algorithm to predict the outcome values of a target variable based on the input values of predictor variables. As we predict the future from the past values of certain variables, the training data always precede the testing data (Mousa et al., 2022). Accordingly, we split our dataset into a 2011-2021 time period for training, and the year 2022 is used for testing. Finally, since our study is restricted to a binary dependent variable, we apply machine learning-based supervised logistic regression for the purpose of predicting financial distress. According to Bao et al. (2019), logistic regression is a suitable supervised learning algorithm for solving binary classification and prediction problems.

4. Empirical Framework

4.1 Logistic Regression

One of the few methods that machine learning has borrowed from traditional statistical methods is logistic regression (Bao et al., 2019). According to Osisanwo et al. (2017), supervised machine learning enhances the ability of traditional logistic regression to efficiently discriminate between classes of a binary variable. Its main advantage over other machine learning methods is that it's easy to understand and it´s high explanatory power (Tran et al., 2022). Most machine learning prediction problems use logistic regression as a benchmark model for comparison with other machine learning algorithms (Osisanwo et al., 2017; Bao et al., 2019; Tran et al., 2022).

4.4 Hypothesis testing

For hypothesis testing, we build different predictive models, each with distinct sets of features. A comparison of the predictive performance of these models is performed to test our hypotheses.

4.4.1 Model 1

Model 1 is our benchmark or base model containing a set of financial features that predict financial distress. The features in Model 1 are used to predict financial distress using logistic regression.

4.4.2 Model 2

In addition to the features in Model 1, Model 2 also contains corporate governance indicators as predictors of financial distress. Similar to Model 1, the features in Model 2 are also used to predict financial distress utilizing logistic regression. For hypothesis testing, the predictive performances of models 1 and 2 are compared. If Model 2 performs better than Model 1 in terms of evaluation metrics, H1 is supported.

4.4.3 Model 3

In addition to the features in Model 1, Model 3 also includes narrative disclosure tones as predictors of financial distress. Similar to Model 1, the features in Model 3 are used to predict financial distress utilizing logistic regression. For hypothesis testing, the predictive performances of models 1 and 3 are compared. If Model 3 performs better than Model 1 in terms of evaluation metrics, H2 is supported.

4.4.4 Model 4

Finally, we build model 4 containing all the features used in this study to predict financial distress. Accordingly, Model 4 contains both corporate governance indicators and narrative disclosure tones, in addition to features in Model 1. Consequently, if Model 4 has a better predictive performance relative to Model 3, H3 is supported. Similarly, if Model 4 has a better predictive performance than Model 2, H4 is supported.

4.4.5 Evaluation metrics

We utilize certain metrics after a comprehensive literature review to evaluate the predictive performance of the abovementioned models (Mousa et al., 2022; Petropoulos et al., 2020)

Table 3: Evaluation metrics

Metric(s)	Definition	Reference
Accuracy	The proportion of acceptance or correct classification and prediction	Petropoulos et al. (2020); Mousa et al. (2022)
Kappa Coefficient	Frequency of the model performing when it is compared with itself by chance	Petropoulos et al. (2020); Mousa et al. (2022)
Sensitivity	The percentage of acceptance of a correct classification (class specific)	Petropoulos et al. (2020); Mousa et al. (2022)
Specificity	The percentage of rejection of an incorrect classification (class specific)	Petropoulos et al. (2020); Mousa et al. (2022)
Positive Predicted Value (PPV)	The percentage of acceptance of a correct prediction (class specific)	Petropoulos et al. (2020); Mousa et al. (2022)
Negative Predicted Value (NPV)	The percentage of rejection of an incorrect prediction (class specific)	Petropoulos et al. (2020); Mousa et al. (2022)

Evaluation metrics used in the prediction of financial distress
Source: Authors own work

For the purpose of hypothesis testing, we employ accuracy, the kappa coefficient and significance test measures (Mousa et al., 2022). In the literature, these metrics refer to the overall prediction and classification of a model based on a specific algorithm; we use their comparison for the testing of hypotheses. Moreover, to gain insight into class-specific prediction, we follow Petropoulos et al. (2020) and utilize sensitivity, specificity, negative predicted value (NPV) and positive predicted value (PPV). These metrics are generated using the *caret* package in R. A summary of these evaluation metrics can be found in Table 3.

In addition, we identify the contributions of each variable to the overall prediction by employing a measure of relative importance within the *caret* package in R.

5. Results

5.1 Descriptive Statistics

Table 4 shows the descriptive statistics

Table 4 – Descriptive Statistics

Variable	Obs.*	Mean	SD*	1st Quartile	Median	3rd Quartile
Z score	1500	8.49	32.55	4.55	6.315	9.61
Zm score	1500	-1.34	2.16	-2.53	-1.512	-0.47
EM	1500	14.38	13.47	5.57	12.38	20.62
OM	1500	10.22	12.44	2.67	8.82	16.50
NM	1500	11.6	7.93	0.67	5.46	11.96
FCF	1500	0.01	0.17	-0.04	0.01	0.09
ROE	1500	13.78	18.72	0.38	11.72	23.55
ROIC	1500	12.38	18.46	0.11	8.42	17.75
EPS	1500	13.37	16.78	0.87	6.16	20.62
TIE	1500	12.76	21.93	0.77	2.93	10.58
ERR	1500	0.32	5.75	0.37	0.71	1
RInvR	1500	6.28	35.48	0.01	6.23	13.92
QuickR	1500	1.03	1.96	0.41	0.72	1.15
ARTVR	1500	9.58	9.04	3.04	6.68	12.85
INTVR	1500	7.21	7.56	3.2	4.47	7.78
INDAYS	1500	81.08	67.42	45.77	81.08	111.72
CCC	1500	115.91	84.59	51.7	103.38	155.97

SIZE	1500	9.76	1.58	8.63	9.79	10.8
AGE	1500	41.47	18.94	26	38	57
MB	1500	1.99	2.43	0.55	1.12	2.31
TQ	1500	1.01	1.91	0.21	0.45	0.99
BSIZE	1500	8.39	1.82	7	8	9
BI	1500	0.21	0.22	0.13	0.14	0.29
BGD	1500	0.10	0.22	0.00	0.09	0.14
ACS	1500	3.61	0.87	3	3	4
ACI	1500	0.33	0.21	0.25	0.33	0.4
ACGD	1500	0.09	0.15	0.00	0	0.2
FOWN	1500	0.17	0.28	0.00	0.01	0.24
NEG	1500	0.30	0.04	0.27	0.30	0.33
POS	1500	0.20	0.07	0.15	0.18	0.24
UNC	1500	0.18	0.03	0.16	0.18	0.20
LIT	1500	0.18	0.05	0.15	0.18	0.21
SUP	1500	0.01	0.03	0.01	0.01	0.01
CON	1500	0.13	0.02	0.12	0.13	0.14

Descriptive statistics of all features and target variables used in the prediction of financial distress
Obs = Observations; SD = Standard deviation
Source: Authors own work

Furthermore, based on the calculation of the Z and the Zm score and their respective cut-off points, the number of observations categorized as healthy and distressed are described in Table 5.

Table 5 – The number of healthy and distress firm observations

Target Variable	Healthy	Distressed	Total
Z score	1186	314	1500
Zm score	1283	217	1500

The number of healthy and distressed firm observations as calculated by the Z and Zm score
Source: Authors own work

Accordingly, 314 out of 1500 observations have identified financial distress within the firm as calculated by the Z score. This represents a sizeable proportion. Regarding the Zm score, it calculated 217 out of 1500 observations as distress. Therefore, this establishes a considerable difference between the two target variables. This will enable us to test whether our prediction of financial distress is robust to different definitions of financial distress which capture different degrees of distress.

5.2 Boruta Algorithm

Table 6 shows the results of the Boruta algorithm when we predict the Z score, while Table 7 shows its results when we predict the Zm score.

Table 6 – Boruta algorithm for the prediction of Z score

Feature	meanImp*	medianImp*	minImp*	maxImp*	normHits*	decision
EM	13.81668	13.77705	12.59101	15.25557	1	Confirmed
OM	14.27483	14.30392	13.31034	15.3955	1	Confirmed
NM	19.97318	19.70711	18.57511	21.99891	1	Confirmed
FCF	5.226466	5.090039	4.083681	6.895559	1	Confirmed
ROE	15.02369	14.83994	14.03934	16.20158	1	Confirmed
ROIC	16.19665	16.0143	15.35409	17.87594	1	Confirmed
EPS	22.58556	22.70431	21.14026	24.36948	1	Confirmed
TIE	13.89306	14.18213	12.51002	15.10216	1	Confirmed
ERR	13.13105	13.35908	11.30653	13.78959	1	Confirmed
RInvR	11.33819	11.05502	10.43758	12.51607	1	Confirmed
QuickR	29.49906	29.71668	28.04701	30.83029	1	Confirmed
ARTVR	9.687288	9.713292	8.689342	10.7305	1	Confirmed
INTVR	11.42566	11.51126	9.895945	12.21426	1	Confirmed
INDAYS	12.44494	12.28313	11.52396	14.17563	1	Confirmed
CCC	20.58807	20.7454	19.157	21.99403	1	Confirmed
SIZE	8.867864	8.804347	7.515359	10.83336	1	Confirmed
AGE	8.31712	8.132421	7.083665	9.551134	1	Confirmed
MB	8.267316	8.529085	6.799864	9.707448	1	Confirmed
TQ	21.74621	21.7309	20.46466	23.48435	1	Confirmed
BSIZE	8.737043	8.865135	7.006902	10.16627	1	Confirmed
BI	6.380096	6.492133	4.109099	8.480185	1	Confirmed
BGD	7.280145	7.10783	6.164339	8.744543	1	Confirmed
ACS	4.983644	5.065194	3.628802	6.035583	1	Confirmed
ACI	6.631664	6.450083	5.423406	8.724055	1	Confirmed
ACGD	6.008018	6.139243	4.807389	7.393182	1	Confirmed
FOWN	9.856433	10.01356	8.426744	11.18623	1	Confirmed
NEG	5.421883	5.49441	2.757636	7.227022	1	Confirmed
POS	8.747484	8.943078	7.230173	10.17696	1	Confirmed
UNC	10.05018	10.39151	8.462886	11.61382	1	Confirmed
LIT	4.45257	4.255307	3.403948	6.139814	1	Confirmed
SUP	4.904143	4.938668	4.127279	5.873713	1	Confirmed
CON	8.323926	8.123956	7.073401	10.17128	1	Confirmed

Optimal feature selection for the prediction of Z score using Boruta algorithm
meanImp = mean importance; medianImp = median importance; minImp = minimum importance; maxImp = maximum importance; normHits = normal hits
Source: Authors own work

Table 7 – Boruta algorithm for the prediction of Zm score

Feature	meanImp	medianImp	minImp	maxImp	normHits	decision
EM	14.37062	14.36045	12.3536	15.7037	1	Confirmed
OM	14.59878	14.62656	12.69102	16.17436	1	Confirmed
NM	16.2647	16.37046	14.17888	17.85841	1	Confirmed
FCF	8.941688	8.991252	6.555602	10.9459	1	Confirmed
ROE	17.98606	17.94681	16.07211	20.01453	1	Confirmed
ROIC	16.79637	16.80715	14.88819	19.33741	1	Confirmed
EPS	13.21229	13.26118	12.14727	14.45427	1	Confirmed
TIE	11.57547	11.59795	10.03062	12.95254	1	Confirmed
ERR	7.76678	7.795569	6.372117	9.325976	1	Confirmed
RInvR	17.0619	17.04755	15.47846	18.85213	1	Confirmed
QuickR	16.98873	16.99683	15.13827	19.18984	1	Confirmed
ARTVR	9.945752	9.941523	7.903282	11.85704	1	Confirmed
INTVR	7.505572	7.388316	5.321974	9.549548	1	Confirmed
INDAYS	8.254169	8.223812	6.304733	9.777997	1	Confirmed
CCC	18.08265	18.0644	15.1492	20.33045	1	Confirmed
SIZE	12.42858	12.36174	10.8487	14.38096	1	Confirmed
AGE	7.204418	7.124111	5.319962	9.598084	1	Confirmed
MB	11.87851	11.97235	10.02894	13.83194	1	Confirmed
TQ	14.02149	13.98992	12.43602	15.62475	1	Confirmed
BSIZE	12.10665	12.16107	10.34616	13.84531	1	Confirmed
BI	2.78996	2.738298	0.348247	4.812554	0.575758	Tentative
BGD	4.148169	4.088236	2.182893	6.283202	0.909091	Confirmed
ACS	3.348807	3.299406	1.276825	5.507265	0.787879	Confirmed
ACI	1.662171	1.583205	0.333144	2.924255	0.020202	Rejected
ACGD	0.847573	0.834075	-0.76287	2.498238	0.010101	Rejected
FOWN	7.804054	7.787528	5.07394	10.3386	1	Confirmed
NEG	6.681331	6.71175	4.748529	9.476586	1	Confirmed
POS	8.070746	8.060264	6.122458	10.17171	1	Confirmed
UNC	8.652109	8.554615	7.05967	10.82674	1	Confirmed
LIT	6.038144	6.076274	4.083209	8.003274	1	Confirmed
SUP	1.678271	1.802116	-0.4237	4.054207	0.040404	Rejected
CON	3.951855	3.971701	1.176143	6.467033	0.848485	Confirmed

Optimal feature selection for the prediction of Zm score using Boruta algorithm
meanImp = mean importance; medianImp = median importance; minImp = minimum importance; maxImp = maximum importance; normHits = normal hits
Source: Authors own work

Based on the results, we can confirm that the Boruta algorithm has the desired confidence to deem all variables confirmed as optimal for the prediction of both the Z score (Kursa and Rudnicki, 2010). Regarding the prediction of the Zm score, ACI, ACGD and SUP are rejected and confirmed as unimportant. As for, BI the decision is tentative. Accordingly, we follow Kursa and Rudnicki (2010) and peform the *TentativeRoughFix* function of the Boruta package. After performing this function, BI is confirmed as important. Therefore, we eliminate SUP, ACI and ACGD from the list of features pertaining to the prediction of the Zm score. Finally, we predict the Z and the Zm score using logit regression using important variables regarding their prediction.

5.3 Logit Regression

The results for all four models regarding the prediction of the Z score using logit regression are shown in Table 8. Model 1 achieves an accuracy of 88.33% and a kappa coefficient of 61.96 and is significant, with a p-value of 0.00. The accuracy is indicative of the ability of the model to successfully classify and predict the Z score, with a success rate of 88.33%. Furthermore, the kappa coefficient is indicative of the reliability of the model´s prediction. Accordingly, if the model´s predictive performance is compared to itself by chance, it will have a 61.96% probability of performing. In addition, the sensitivity indicates that the model can correctly classify 95.36% of the observations, while the model specificity shows that the model can appropriately reject incorrect classifications within 61.9% of the observations. The PPV and NPV values indicate that the model can successfully accept correct and reject incorrect predictions within 90.4% and 78% of the observations, respectively. Finally, the balanced accuracy of Model 1 is 78.63%.

Table 8 – Logit Regression

Panel A: Z Score				
Parameters	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Accuracy	88.33	89	91.67	93.33
Kappa	62.96	65.44	73.16	78.93
p-value	0.00	0.00	0.00	0.00
Sensitivity	95.36	94.51	91.75	97.47
Specificity	61.90	68.25	71.43	77.78
PPV	90.40	91.80	92.74	94.29
NPV	78.00	76.79	86.54	89.09
Balanced Accuracy	78.63	81.38	84.24	87.62
Panel B: Zm Score				
Accuracy	87.33	88.67	88	88.67
Kappa	35.02	39.43	36.95	39.43
p-value	0.11	0.02	0.06	0.02
Sensitivity	98.03	99.21	98.82	99.21
Specificity	28.26	30.43	28.26	30.43
PPV	88.30	88.73	88.38	88.73
NPV	72.22	87.50	81.25	87.50

Balanced Accuracy	63.15	64.82	63.54	64.82

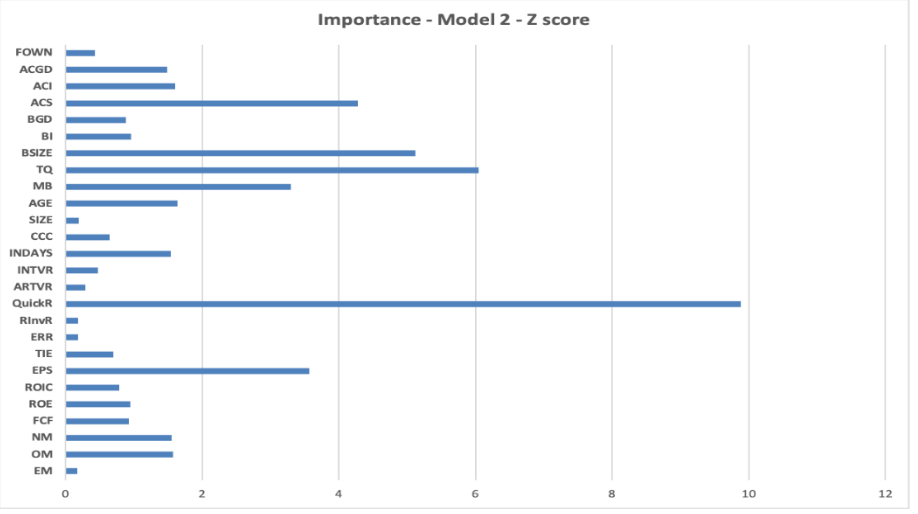
Logit classification
Panel A: Z score prediction for all three models
Panel B: Zm score prediction for all three models
Source: Authors own work

The comparison of models 1 and 2 lends support to H1, suggesting that corporate governance indicators significantly enhance the prediction of Z score. This is evident because Model 2, which includes corporate governance indicators and financial features as predictors, achieves an accuracy of 91.67%, which is greater than that of Model 1 (89.33%). This trend of improvement can also be observed in the kappa coefficient, as Model 2 achieves 73.16% reliability compared to Model 1's 61.96%. Finally, Model 2 is also significant, with a p-value of 0.00. Therefore, adding corporate governance indicators to a model that includes financial features as predictors significantly improves the ability to predict the Z score. Similarly, model 3 performs relatively better than Model 1 as well, lending support to H2. This is evident as Model 3 achieves an accuracy of 89% and a Kappa coefficient of 65.44%, relative to Model 1's 88.33% and 61.89%, respectively. In addition, both models are significant, with a p-value of 0.00. This suggests that the addition of narrative disclosure tone in a model containing financial features alone significantly improves the prediction of distress, as proxied by the Z score.

Regarding H3 and H4, we compare the performances of Model 4 with those of Models 2 and 3. First, Model 4 performs relatively better than both models 2 and 3, providing partial support for both H3 and H4. However, Model 4 shows a greater improvement than Model 3, whereas it shows a slight improvement compared with Model 2. Accordingly, Model 4 achieved an accuracy of 93.33% and a kappa coefficient of 78.93%, with a p-value of 0.00. Therefore, Model 4 improves Model 2 by less than 2% in terms of accuracy and almost 5% in terms of the kappa coefficient. In contrast, Model 4 improves the accuracy of Model 3 by 4.33% and the kappa coefficient by almost 14%. Therefore, these comparisons indicate that adding corporate governance indicators to a model containing both narrative disclosure tone and financial indicators improves the prediction of distress by 4.33%. However, adding narrative disclosure tone to a model containing both corporate governance indicators and financial indicators improves the prediction of distress by less than 2%. Therefore, these results indicate the superiority of corporate governance indicators relative to narrative disclosure tone as predictors of distress.

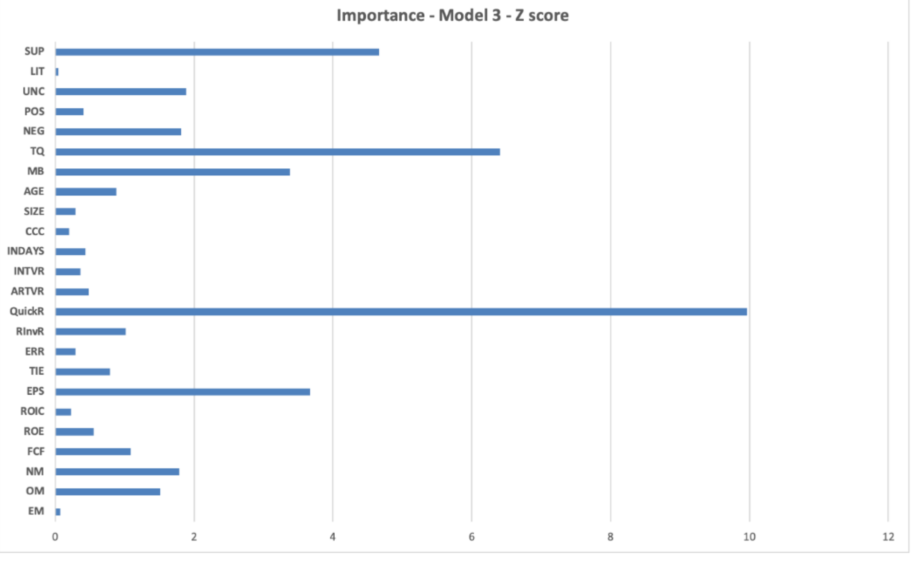
The results for the prediction of the Zm score are similar to those for the prediction of the Z score. The results are shown in panel B of Table 7. Model 2 performs best, as it achieves an accuracy of 88.67% and a kappa coefficient of 40.45%. In addition, Model 2 is significant, with a p-value of 2%. Although Model 1 achieves an accuracy of 87.33% and a kappa coefficient of 35.02%, its prediction is not significant, with a p-value of 11%. Therefore, the comparison of models 2 and 1 supports H1. Similarly, the comparison of models 3 and 1 supports H2. This is evident, as Model 3 achieves an accuracy of 88% and a kappa coefficient of 36.95% with a p-value of 0.06, indicating that it is significant. In contrast, Model 1 is not significant. This provides support for H2. The results regarding the prediction of the Zm score suggest that both corporate governance indicators and narrative disclosure tone enhance predictive performance. Interestingly, the prediction of Zm score by Model 4 was not significantly different from Model 2´s. However, Model 4 achieves 88.67% accuracy relative to Model 3's 88%. Furthermore, this trend of improvement is also evident in the kappa coefficient, as Model 4 achieves 40.45% relative to Model 3's 36.95%. Furthermore, Model 4 achieves greater statistical significance relative to Model 1. Therefore, the results regarding the prediction of Zm score provide more clarity relevant to H3 and H4. Specifically, they provide support for H3 and against H4, suggesting that corporate governance indicators enhance the prediction of distress when added to a model containing narrative disclosure tone and financial features. In addition, they suggest that narrative disclosure fails to improve the prediction of distress when it is added to a model containing corporate governance indicators and financial features. Therefore, these results highlight the superiority of corporate governance indicators over narrative disclosure tone in the prediction of distress.

Figure 1- Variable Importance for Model 2´s prediction of the Z score



Source: Authors own work

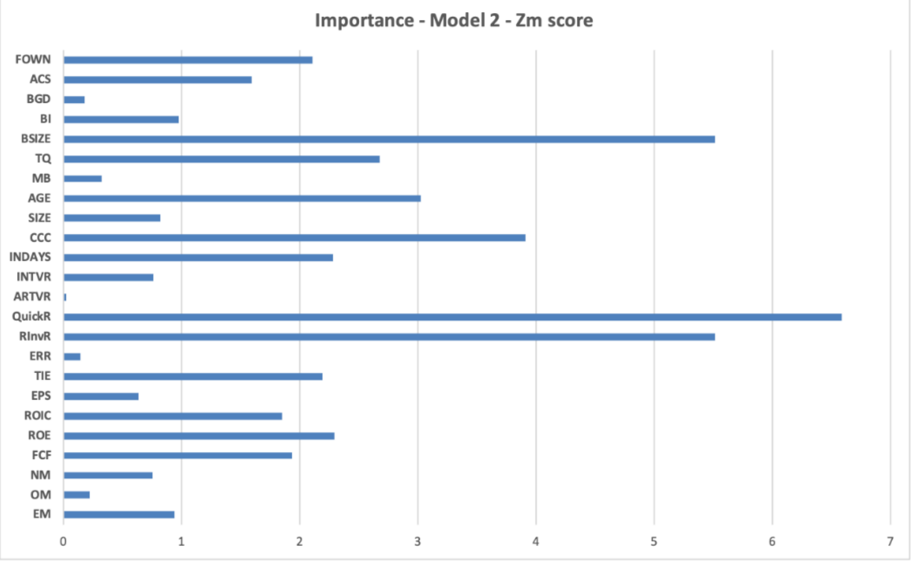
Figure 2 - Variable Importance for Model 3´s prediction of the Z score



Source: Authors own work

The variable importance for the prediction of the Z score is shown for models 2 and 3 in figures 1 and 2, respectively. QuickR is the most important variable for the prediction of Z score in both models. However, in Model 2, all the corporate governance indicators outrank most of the financial indicators, indicating their superiority. The most important corporate governance indicator is BSIZE, followed by ACS. In Model 3, SUP, NEG, UNC and POS outrank certain financial indicators. This indicates that the improvement in the prediction of Z score was mostly because of these tones. However, LIT is the least important tone, whereas CON is automatically due to issues of multicollinearity.

Figure 3 - Variable Importance for Model 2´s prediction of the Zm score



Source: Authors own work

Figure 4 - Variable Importance for Model 3´s prediction of the Zm score

Source: Authors own work

The variable importance for the prediction of Zm score using models 2 and 3 is shown in figures 3 and 4, respectively. Similar to the prediction of Z score, QuickR is the most important predictor of the Zm score using both models. However, in Model 2, BSIZE is the second most important predictor overall and the most important governance indicator. In Model 3, all five tones, barring LIT, outrank certain financial predictors in the prediction of the Zm score, and the most important tone is CON, followed by NEG, UNC and POS.

5.5 Additional Analysis – Random Forest and Stochastic Gradient Boosting

As an additional analysis, following Alfaro et al. (2019), we expand the degrees of distress captured by our dependent variables by categorizing the emerging market Altman Z score into three categories, namely, safe, grey and distress. Therefore, we classify firms in the safe zone if the Z score is above 5.85, in the grey zone if it is between 4.15 and 5.85 and in the distress zone if the score is lower than 4.15 (Ninh et al., 2018). However, because of a lack of well-established cut-off points to capture three degrees relevant to the Zm score, we only the Z score for the additional analysis. Due to the limitation of logit regression regarding the use of a binary target variable, we utilize alternative machine learning algorithms, such as random forest and stochastic gradient boosting, for this analysis.

Random forest (hereafter referred to as RF) is one of the most robust methods of supervised and ensemble learning normally utilized for classification and prediction purposes (Chen et al., 2020). RF classification is an iterative process that utilizes a multitude of decision trees. It uses various tests to filter out the features in a decision tree at each node until all nodes have elements of a single class (Chen et al., 2020). Another commanding machine learning ensemble technique that we employ is stochastic gradient boosting (hereafter referred to as SGB) (Halteh et al., 2018). In SGB, decision trees are generated in sequence and then combined to identify the most accurate model. With the addition of each tree, the SGB algorithm learns new information about the data. Therefore, we use the same training and testing split to predict three degrees of the emerging market Altman Z score using RF and SGB. The results are shown in Table 9.

Table 9– Additional analysis: Random Forest and Stochastic Gradient Boosting

Panel A: Random Forest				
Parameters	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Accuracy	84	85	85.33	85.67
Kappa	71.49	73.43	73.93	74.34
p-value	0.00	0.00	0.00	0.00
Panel B: Stochastic Gradient Boosting				
Accuracy	84.33	85.33	87	85.67
Kappa	72.9	74.38	77.3	75.5
p-value	0.00	0.00	0.00	0.00

Panel A: Random forest prediction of 3 factor Z score
Panel B: Stochastic gradient boosting prediction of 3 factor Z score
Source: Authors own work

Model 1 achieved 84% accuracy and a kappa coefficient of 71.49%, with a p-value of 0.00, rendering it significant. However, both models 2 and 3 perform relatively better than model 1 in terms of both accuracy and the kappa coefficient. This is evident because Model 2 achieves 85% accuracy with a kappa coefficient of 73.43%, while Model 3 achieves 85.33% accuracy with a kappa coefficient of 73.93%. These results lend support to H1 and H2, suggesting the ability of both corporate governance indicators and narrative disclosure tone to significantly enhance the prediction of distress. This is consistent with our main analysis. However, the results regarding H3 and H4 as predicted using RF are inconsistent with our main analysis. This is apparent as model 4 performs better than both models 2 and 3. Specifically, Model 4 achieves an accuracy of 85.67% and a kappa coefficient of 74.74%. This finding lends support to both H3 and H4, but shows the superiority of narrative disclosure tone over corporate governance indicators as predictors of distress. This is because adding narrative disclosure tone to a model containing corporate governance and financial indicators as predictors shows greater improvement. In contrast, the performance of a model containing narrative disclosure tone and financial variables as predictors is not enhanced as much by the addition of corporate governance indicators.

However, regarding SGB´s prediction of the Z score, our results are completely consistent with the main analysis. This is evident as both models 2 and 3 perform relatively better than model 1 in terms of both accuracy and the kappa coefficient, lending support to H1 and H2. In addition, the prediction of Z score using SGB shows support for both H3 and H4, as Model 4 performed better than both models 2 and 3. However, consistent with our main analysis, the comparisons of Model 4 with models 2 and 3 show the superiority of corporate governance indicators relative to narrative disclosure tone. This is evident, as Model 4 performs worse relative to Model 2 as it decreases in accuracy by almost 1.5% and the kappa coefficient by 2%. In contrast, Model 4 improves the accuracy of Model 3 by 1.67% and the kappa coefficient by almost 2%.

5.6 Robustness Analysis

We perform a robustness check by converting the Z and Zm scores into their continuous forms and performing a panel regression (Ikpesu, 2019; Farooq et al., 2022). Furthermore, as this is a panel regression, we select tones most commonly associated with distress or negative financial outcomes based on a thorough analysis of the literature (Li et al., 2020; Doshi et al., 2023; Zhang et al., 2022). We skip this step for corporate governance indicators because all governance variables used in the study have a strong empirical association with distress (Khurshid et al., 2018; Yousaf et al., 2021; Sarker and Hossain, 2023).

Finally, we choose the top four financial indicators, commonly occurring in the variable importance of our main analysis, as controls. On this list of variables, we perform a 2SLS and a random effect panel regression. The results are shown in Tables 10 and 11 for the Z and Zm scores, respectively.

Table 10 – 2SLS and Random Effect Model with continuous Z score

	Z score	
VARIABLES	**2SLS**	**RE**
NEG	-19.4	-22.6
POS	18.2	17.7
UNC	72.9**	71**
BSIZE	-0.14	-0.13
BI	14.61**	14.71**
BGD	-15.2**	-15.25**
ACS	1.01	1.02
ACI	8.1	8.04
ACGD	-1.42	-1.36
FOWN	7.01**	7.03**
QuickR	0.98**	0.98**
SIZE	-1.95***	-1.91***
RInvR	0.04*	0.04**
AGE	0.004	0.005
Constant	7.01	8.90
Observations	1,500	1,500
R-squared	0.04	33.79

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: Authors own work

Table 11 – 2SLS and Random Effect Model with continuous Zm score

	Zm score	
VARIABLES	**2SLS**	**RE**
NEG	7.7***	5.32***
POS	-2.1*	-1.89*
UNC	-10.9***	-3.26**
BSIZE	0.04	0.03
BI	-0.35	-0.5
BGD	0.35	-0.79**
ACS	-0.08	-0.02
ACI	0.09	0.41*
ACGD	0.28	0.52
FOWN	-0.66***	-0.37

QuickR	-0.24***	-0.1***
SIZE	-0.11***	-0.04***
RInvR	-0.01***	-0.004***
AGE	-0.006**	-0.001
Constant	0.51	-1.56
Observations	1,500	1,500
R-squared	20.56	0.19

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Source: Authors own work

Regarding the impact on Z score, UNC is statistically significant in both the 2SLS and the random effect models. For governance indicators, BI, BGD and FOWN are statistically significant within both model specifications. In contrast, all three tones employed have a statistically significant impact on the Zm score under both model specifications. For the governance variables, FOWN is significant in the 2SLS model, while BGD and ACI are significant within the random effect model.

These results show that certain types of tones and corporate governance indicators have a role in impacting the Z and Zm scores. Therefore, the results of our main analysis are robust to the continuous forms of both Z and Zm scores using panel data regression.

6. Discussion

The results of the study provide some interesting insights. Specifically, they show that both corporate governance indicators and narrative disclosure tone are important predictors of financial distress. These results are consistent with both theory and empirical literature. Furthermore, they offer some interesting implications.

From an academic standpoint, the results regarding corporate governance indicators are consistent with agency theory (Jensen & Meckling, 1976; Mariano et al., 2021). According to Mariano et al. (2021), agency theory posits that good corporate governance helps reduce informational asymmetry and agency costs, resulting in a healthy firm. Furthermore, these results receive sufficient empirical support (Liang et al., 2020; Truong, 2022; Khurshid et al., 2018). For instance, in an analysis specific to Vietnamese firms, Truong (2022) find a statistically significant impact of certain corporate governance indicators on financial distress. Furthermore, Khurshid et al. (2018) achieve similar results for Pakistani firms. In another interesting study similar to ours, Liang et al. (2020) use machine learning algorithms to prove that the addition of corporate governance indicators to financial predictors significantly enhances the prediction of distress.

Regarding narrative disclosure tone, our results are theoretically justified by signalling theory (Bassyouny et al., 2022; Elsayed & Elshandidy, 2020; Zhao et al., 2022). For instance, Bassyouny et al. (2022) and Elsayed & Elshandidy (2020) posit that managers use the tone of narrative disclosures to signal the current and future state of a firm to investors and shareholders. Furthermore, Zhao et al. (2022) suggest that linguistic tone in annual report narratives can signal an upcoming crisis. In terms of empirical literature, Zhao et al. (2022) provide evidence of narrative disclosure sentiments indicating distress. Furthermore, Zhang et al. (2022) provide evidence of narrative disclosure having incremental information regarding the prediction of distress by utilizing machine learning algorithms.

7. Conclusion

The purpose of the present study is to test whether the prediction of financial distress is improved by incorporating nonfinancial information, such as corporate governance indicators and narrative disclosure tone, into financial predictive models of distress. The study utilizes a sample of 125 nonfinancial firms in Pakistan for the period of 2011-2022. Four models are built, each based on a separate set of predictors. Financial distress is then predicted based on logit regression using each model separately, and their performances are compared for hypothesis testing. The results show that both corporate governance indicators and narrative disclosure tone significantly improve the prediction of distress. The study contributes to the literature in a myriad of ways.

First, they establish nonfinancial disclosures, such as narrative disclosure tone, as reliable predictors of financial distress by utilizing machine learning-based logit regression in our analysis (Liang et al., 2020; Shahwan, 2015). Second, they contribute by amalgamating corporate governance with machine learning literature (Di Vito & Trottier, 2022). In doing so, they establish the reliability of corporate governance indicators as predictors of distress. Third, we contribute by incorporating two alternate measures and different degrees of distress in our analysis (Miglani et al., 2015; Tron et al., 2022). Finally, the study contributes by employing an emerging economy setting plagued by unprecedented economic and political instability (Ullah & Saqib, 2018). This is important, as in such settings, investors look towards nonfinancial information for their investment decision-making (Aly, et al., 2019). Therefore, the study's results have several implications for investors and regulators.

Specifically, they urge regulators and policymakers to strengthen the transparent and accurate disclosures of nonfinancial information, such as narrative disclosures and corporate governance indicators. Furthermore, the study offers implications for investor confidence by establishing these disclosures as reliable tools for predicting financial distress. This is especially important in an economy with heightened economic uncertainty.

This study is not without its limitations. First, the study is limited to narrative disclosures within annual reports, whereas there are other sources of narrative disclosures, such as earnings press releases. Second, the study is limited to the use of board and audit committee data as corporate governance indicators, and future research could employ other governance indicators, such as that of the risk committee, in the prediction of distress.

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