DOCTOR OF PHILOSOPHY (PHD)

Analytical Methods of Predicting Corporate Bankruptcy: A Quantitative Meta-Regression and Comparative Analysis

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Award date:
2022

Awarding institution:
Glasgow Caledonian University

Analytical Methods of Predicting Corporate Bankruptcy:
A Quantitative Meta-Regression and Comparative Analysis.

By

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March 2022

Declaration Statement of Originality and Authenticity Format

I declare that this thesis is my own original work and has not been submitted elsewhere, wholly or partly, in the fulfillment of the requirements of this or any other award. Academic citation standards have been maintained and I have made due acknowledgment to the work of others where used in direct quotation and general references.

Madina Abdrakhmanova
March 2022

Acknowledgments

‘*It is during our darkest moments that we must focus to see the light*’ – **Aristotle.**

It was a long PhD journey for me, due to some unpredictable life circumstances that unfortunately I had to deal with while writing this dissertation. But no matter what life lessons you go through, you should keep going and never give up. Now I am standing here happy because it is finally the end of the exciting and amazing journey, where my life-long dream is coming true.

First and foremost, I am thanking Lord Almighty for giving me patience, strength and constant support. That is the very voice in my head that always said ‘you can do it, don’t give up, no matter what life throws your way’. Thank you, God, for your precious love.

Of course, this research dissertation would not have been possible without the support of very special people in my life. These people are two treasures, two beautiful caring souls, who are my parents, **Shuga Abdrakhmanova** and **Kuandyk Abdrakhmanov**. I would like to dedicate this thesis to them, to you mum and to you dad. Every single day you guys gave me massive support, care, love and optimism. This is your thesis too. You have been there for me, believing in me and filling me with confidence.

Я посвящаю этот тезис вам, мама и папа. Вы были моей опорой и поддержкой всегда. Я вас очень люблю!

I am massively thankful to my supervisory team, Dr. Chioma Nwafor, and Dr. Sanjukta Brahma. Dr. Brahma, we have started this research project together, you always supported me during bad times and good times. I am thankful for that, and always will be.

A truly special person without whom this research would not be possible is my director of studies, **Dr. Chioma Nwafor**. I am especially grateful to you; you are a strong powerful woman I am always looking up to you. I am particularly indebted to you, Dr. Nwafor, for your guidance, for your support and every single piece of advice that you have given me. Thank you for everything. Dr. Nwafor, I honestly appreciate you being there for me during my PhD journey.

I would like to end this part with an inspirational quote: '*The future belongs to those who believe in the beauty of their dreams*.' – **Eleanor Roosevelt**. Never stop fighting for your beautiful dreams: mine was achieving this special moment, my doctoral degree.

Abstract

The risk of going bankrupt is of significant interest to shareholders, creditors, employees of a firm and lenders. Following the financial crisis and the spate of corporate bankruptcies in recent times, bankruptcy prediction models are being used more than ever and for a variety of purposes, including monitoring the solvency of financial and non-financial firms by regulators, assessment of loan security, going-concern evaluations by auditors, the measurement of portfolio credit risk, and assessing securities exposed to credit risk. High episodes of corporate bankruptcies in the U.K. and elsewhere have precipitated a re-evaluation of the methods that underpin corporate bankruptcy prediction.

A plethora of literature is devoted to assessing the risk that corporate firms will go bankrupt. Two dominant tools used in developing bankruptcy prediction models are statistical and machine learning algorithms. The scope of this thesis is limited to reviewing some of the most frequently used bankruptcy prediction tools in the literature.

This thesis reviews the predictive abilities of two statistical bankruptcy predictive tools, namely Multi-Discriminant Analysis (MDA) and Logistic regression. Also, the following artificial intelligence tools were examined - Artificial Neural Network (ANN), Support Vector Machines (SVM), Rough Sets (RS), Case-Based Reasoning (CBR), Decision Tree (DT) and Genetic Algorithms (GA). We included the Hazard Model, a popular tool used in predicting a firm's time to default.

We provide a systematic review and quantitative meta-analysis of corporate bankruptcy prediction models. The systematic literature review (SLR) allows us to provide syntheses of

the state of knowledge in the bankruptcy prediction field to identify future research priorities. Our systematic literature review shows the Artificial Neural Network (ANN) to be the most popular machine learning algorithm used in bankruptcy prediction studies. Still, the results from the ANN studies differ in accuracy level and other performance evaluation metrics.

The use of systematic reviews to summarise and appraise the literature on bankruptcy predictive models is gathering pace. However, none of the previous systematic review studies in this knowledge domain has used a meta-regression to create a model describing the linear relationship between study-level covariates and the effect size. Also, the criteria used to assess the methodological qualities of the primary studies included in the reviews are unclear in previous studies. Moreover, most of these studies did not consider clustering in the analysis (e.g., intra-cluster correlation coefficient).

The present study differs from previous studies in two ways- first, we use meta-analysis to combine quantitatively the evidence from eligible studies identified from the systematic review of the literature and explore sources of between-study variations. Second, we use meta-regression to empirically examine the effects of the study characteristics such as *sample size, percentage of failed firms in the sample, model validation methods, and type of input datasets* on predicting bankruptcy event rate. The results from the quantitative meta-analysis reveal evidence of between-study heterogeneity. This result is not surprising because several factors such as *sample size*, t*ype of input data sets, percentage of bankrupt firms* in the sample and the type of *validation methods* used in the primary studies can influence the magnitude and direction of the effect size. Following the meta-analysis results, we empirically explored the potential sources of these variations using meta-regression.

The results from the meta-regression suggest that sample size has a statistically significant effect on the performance of the ANN model. Although we did not find a statistically significant relationship between the type of input datasets, the proportion of bankrupt firms and the event rate; however, our result shows that these variables, taken together, can explain approximately 77% of the variance in the event rate. Consequently, potential developers seeking to use the ANN model to develop bankruptcy prediction models should consider these variables.

The second empirical chapter of this thesis compares the predictive ability of two of the most commonly used algorithms in corporate bankruptcy prediction, namely the logistic regression (LR) and the Artificial Neural Network (ANN), while correcting for classification imbalance in the dataset. Using real-world bankruptcy prediction datasets with over six thousand observations and ninety-six attributes, we compare these two approaches using various performance criteria of sensitivity, specificity, accuracy, and area under receiver operating characteristics (AUC) curves.

The results of our empirical analysis indicate that the Logistic regression slightly outperforms the Artificial Neural Network techniques for specificity, accuracy and AUC performance evaluation metrics. After correcting for class imbalance in our dataset, the Operating Characteristic (ROC) Curve Analysis shows that the logistic regression model has a slight discrimination ability than the artificial neural network. Our findings confirm the *'accuracy paradox'* from previous studies. We can conclude that accounting for class imbalance in the dataset can improve the fit of logistic regression and the ability of ANN to predict the minority cases.

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Chapter One.

Introduction.

1.1 Research Background.

Insolvency is a major threat for many businesses today, irrespective of their size and the nature of their operations. Documentary evidence shows that business failures have occurred at higher rates in the past two decades than at any time since the early 1930s (Szmigiera, 2021; Neophytou et al 2000; Smid and Ciobica 2021). It is also worth noting that during the 1980's some sectors of the UK economy, such as small industrial businesses, experienced failure rates as high as 50% over five years (Rees, 1995). Data from the American Bankruptcy Institute suggests that around 24,000 U.S. businesses filed for bankruptcy between 2016 to 2018 (American Bankruptcy Institute, 2018).

In the U.K., company insolvency in England and Wales in Q3 of 2020 stood at 2,672. Out of this number, 1,920 were creditor voluntary liquidations, 292 were compulsory liquidations, and 460 were other company insolvencies[1] (The Insolvency Service 2021). These numbers are not surprising given a contraction of 3.7% in global GDP in 2020 because of the global COVID-19 pandemic. Specifically, the United Kingdom witnessed a deep recession in 2020 (-9.9% GDP) orchestrated by strict lockdown measures and Brexit uncertainties.

Global insolvencies are estimated to increase by 26% by the end of 2021 as COVID-19 continues to ravage many parts of the world (Smid and Ciobica 2021). The upward forecast is not surprising, because national governments have commenced the gradual phasing out of the

[1] For the remainder of this chapter, unless otherwise indicated, we use the terms bankruptcy, financial distress, default, and insolvency interchangeably.

temporary measures[2] that kept insolvencies unusually low in 2020, namely insolvency law amendments and fiscal support. Analysts predict that the level of bankruptcies at the end of 2021 will be higher in all markets than in 2019 (Smid and Ciobica 2021). For instance, bankruptcy moratoriums have expired in the first half of 2021 in most countries. The suspension of standard bankruptcy rules in Austria and Finland expired in Q1 of 2021, while Australia returned to standard bankruptcy procedures on 1 January 2021. The Netherlands' moratorium expired in April 2021 (Smid and Ciobica 2021).

It is expected that the continuous relaxation of the COVID-19 containment measures worldwide will end the fiscal supports and bankruptcy moratorium that were put in place to support businesses. The curtailment of these supports may throw more firms into bankruptcy in the coming years. We expect the Covid-19 crisis to trigger a significant acceleration in corporate insolvencies due to both the size of the economic shock and its long-term effects on businesses. Sectors that were already the most fragile pre-COVID-19 crisis are now among the sectors hit the hardest by measures to contain the pandemic (transportation, supply-chain, non-essential retail, hotels, and restaurants).

There are myriad factors that could lead businesses to bankruptcy. Extant literature attributes this phenomenon to high-interest rates, economic recessions, and heavy debt burdens, negative economic shocks (e.g., the global financial crisis and COVID-19 global pandemic) amongst others. Also, industry-specific characteristics, such as government regulation and the nature of operations can contribute to a firm's financial distress. Previous studies on patterns of business

[2] Most countries made changes to their insolvency regime to protect companies from going bankrupt. Governments the world-over took measures to counteract the COVID-19 adverse economic effects and to support businesses. In Europe, countries like France, Belgium, Italy, and Spain enacted laws in 2020 that temporarily froze bankruptcy proceedings or declare bankruptcies inadmissible. Outside of Europe, Australia increased the debt threshold for companies to declare bankruptcy (Smid and Ciobica 2021).

failures in the western world suggest that small businesses with weak control procedures and poor cash flow management and planning are more vulnerable to financial distress than large well established public firms (Star, 1990).

The economic and human cost of business failures is relatively large. A plethora of evidence shows that the market value of distressed firms declines significantly (Warner, 1977). Therefore, the suppliers of capital, investors, and creditors, as well as employees are severely affected by business failures. Other stakeholders, such as the distressed firm auditors, may also face the threat of a potential lawsuit if they fail to provide early warning signals about failing firms via the issuance of qualified audit opinions (Boritz, 1991; Zavgren,1983). Consequently, the need for reliable analytical models that predict corporate bankruptcy promptly and accurately is beneficial to enable the stakeholders to take either preventive or corrective action.

The timing of this thesis allows us to discuss the issue of systemic corporate financial distress/ corporate insolvencies/defaults triggered by the COVID-19 global pandemic and review, albeit briefly, the potential drivers of corporate insolvencies in 2021 and beyond.

1.2. Potential Drivers of corporate Insolvency in 2021 and Beyond.

As alluded to in section 1.1, the SARS-COV-2 virus (COVID-19 pandemic) creates an insolvency time bomb. The withdrawal of supportive policy measures by different sovereign governments may increase the surge in bankruptcies in the medium-to-long term. Although the Global GDP growth is estimated to grow at 5.6% in 2021, after a 3.7% contraction in 2020, there are risks to this estimate linked to the evolution of the COVID-19 pandemic and the possibilities of a third and fourth lockdowns in most countries (OECD 2021). If the global economy takes longer than expected to recover from the Covid-19 shock, there could be a rise in insolvencies/bankruptcies in different countries. Euler Hermes and Allianz report (2021) predicts a rise in bankruptcies in the following countries in 2021 compared to 2019 levels, U.S. (+57%), Brazil (+45%), China (+20%), U.K. (+43%), Spain (+41%), Italy (+27%), Belgium (+26%) and France (+25%).

The 2020 global insolvency report by Atradius (2021) shows a surprising decrease in business insolvencies for most markets. The global insolvencies in 2020 were estimated to have declined by only 14% with significant decreases recorded in Europe and Asia see table 1 below.

	Last point	**Year-on-Year**	**Year-to-Date**
U. S	Q1	4%	4%
Canada	May	-36%	-30%
Brazil	June	28%	-16%
Russia	May	-54%	-15%
Turkey	April	-1%	4%
Romania	April	-87%	-33%
Latvia	May	-49%	-39%
China	May	22%	10%
Japan	May	-55%	-1%
India	Q1	1%	1%
Australia	April	-42%	-18%
South Korea	May	-53%	-31%
Singapore	April	-84%	51%

Table 1a Business Insolvencies 2020- Globally. Source. Euler Hermes Allianz Research (2020).

	Last point	**Year-on-Year**	**Year-to-Date**
Germany	April	-13%	-6%
France	May	-62%	-36%
United Kingdom	March	-11%	-11%
The Netherlands	May	6%	2%
Switzerland	May	-23%	-16%
Sweden	May	2%	14%
Belgium	May	-72%	-30%
Austria	Q1	-9%	-9%
Denmark	May	-9%	-8%
Finland	Q1	14%	14%
Portugal	May	-12%	-2%
Ireland	Q1	-18%	-18%
Luxembourg	May	-45%	-32%

Table 1b Business Insolvencies 2020 Europe. Source. Euler Hermes Allianz Research (2020).

Table 2 above shows that many countries recorded significant monthly decreases in insolvencies over the March to May period bringing the year-to-date figures down. Massive decreases were recorded in Canada, Brazil, Australia, South Korea, France, with the U.S. and China as major exceptions. Practitioners attribute these decreases to the large government interventions[3] to prevent a liquidity crisis for corporate businesses. Furthermore, the temporary changes in insolvency regimes designed to give time and flexibility to companies before they resort to filing for bankruptcy also contributed to the decrease in insolvency in most parts of the world.

Countries like France, with a year-on-year insolvency rate of (-62%), and Belgium (-72%), enacted laws in 2020 that temporarily freeze bankruptcy proceedings or declare bankruptcies inadmissible. Australia (-42%) increased the debt threshold for companies to declare bankruptcy. All those countries witnessed a sharp decrease in insolvencies in 2020. As governments commence the gradual phasing of these fiscal stimuli, we expect to see a trend reversal that may gain traction, especially in the last quarter of 2021 in Europe and elsewhere.

The global pandemic is widening gaps in economic performance and recovery between countries and between sectors. Euler Hermes and Allianz report (2020) forecasts an increase of +35% in global business insolvencies by the end of 2021. According to the report, the most significant increase will be recorded in North America (+56% by the end of 2021), with Asia at +31%, Western Europe at +32%, Latin America at +33% and Central and Eastern Europe at +34% (see figure 1 below).

[3] Intervention measures such as the suspension of the obligation to file for bankruptcy under certain conditions, the extension of deadlines, a moratorium to prevent certain creditor actions against a company, the raising of the threshold limit of unpaid debt to initiate a bankruptcy and winding up application helped reduced the spate of bankruptcies in many countries.

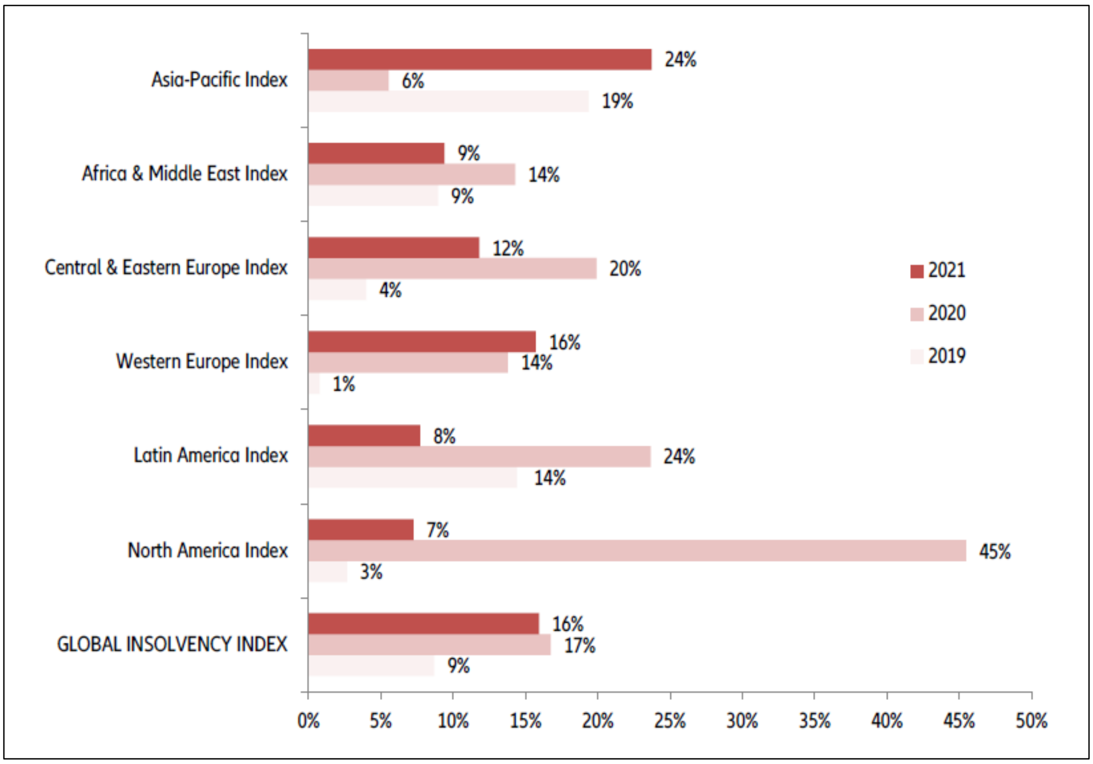


Figure 1.1: Euler Hermes Global Insolvency Index and Regional Indices.
Source. Euler Hermes Allianz Research (2020).

In the face of a constrained global economic recovery, global corporate insolvencies in 2021 and beyond are expected to be higher than the insolvencies recorded during the 2007/09 financial crisis. The three key drivers of the growth in corporate bankruptcies from 2021 and beyond are the phasing out of fiscal support and lifting bankruptcy moratoriums in different countries. The second driver is the global economic recovery and how responsive insolvencies are to GDP growth. The final force shaping corporate defaults in 2021 and beyond is fiscal support. We discuss each of these factors in turn below.

Phasing out of fiscal support and lifting bankruptcy moratoriums in different countries: A first driver shaping corporate insolvencies in 2021 and beyond is the delayed effect of bankruptcies in 2020 due to the fiscal interventions and moratoriums extended to firms to reduce the economic impact of the COVID-19 pandemic. Since the onset of the global pandemic, extensive and timely fiscal support played a significant role in supporting incomes and preserving jobs and businesses. Various fiscal and monetary policy measures helped companies that would have defaulted due to the COVID-19 containment measures. We anticipate that parts of those bankruptcies will materialize in 2021 and beyond. Countries that delayed acceleration in business bankruptcies in 2020 may see a relatively substantial carry-over of corporate defaults into 2021 and beyond. Several markets that provided temporary adjustments to insolvency law and extensive fiscal support, such as Belgium, France, Austria, and Italy, are likely to experience a surge in insolvencies as the fiscal measures and insolvency law amendments are gradually unwounded.

Global economic recovery and insolvencies responsiveness to GDP: OECD projects a 5½ per cent growth in global GDP at the end of 2021 and 4% in 2022, with global output rising above the pre-pandemic level by mid-2021. Despite the improved global outlook, the level of economic recoveries differs across countries.

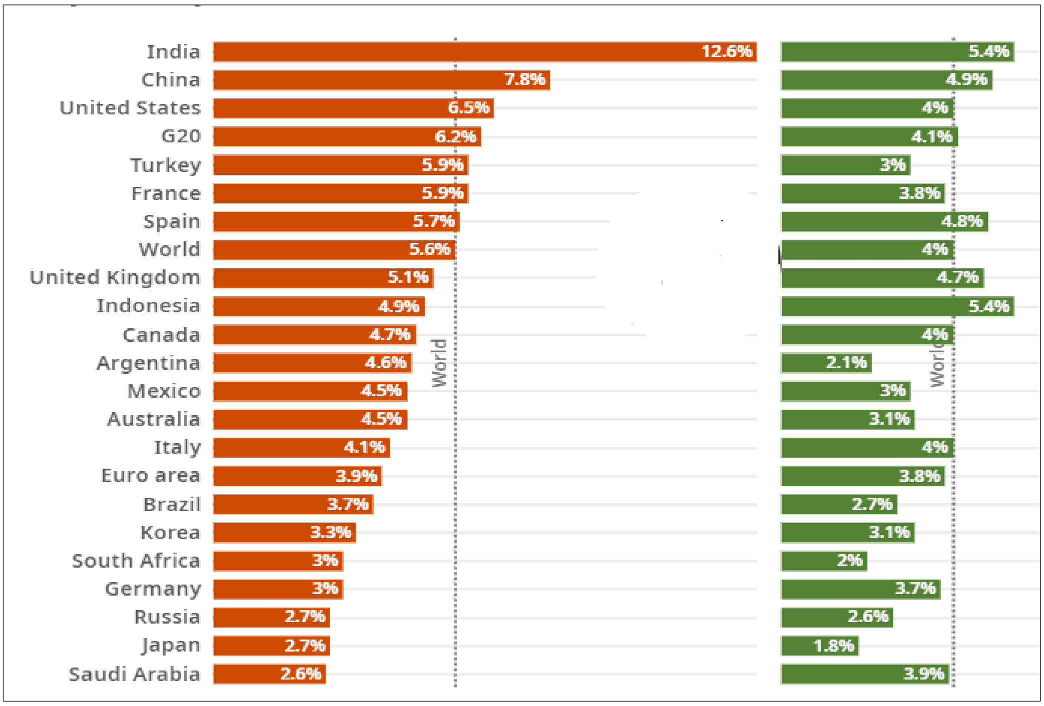


Figure 1.2 Real GDP Growth Projections for 2021 and 2022.

For instance, in Italy, Australia, and the United Kingdom, the estimated GDP growth is low compared to the globally outlook. This may lead to upward pressure on corporate insolvencies in these countries. In other countries, the economic recovery forecasts are relatively strong see-figure 2 (Turkey, China, and the United States).

Literature suggests a close correlation between the business cycle and insolvency figures (Euler Hermes, 2013). On average, it takes 2% to 3% GDP growth to stem the rise in insolvencies. And there is an extremely high elasticity of insolvencies to GDP growth in most countries. According to Euler Hermes (2013), a GDP growth reduction of 1 percentage point implies a 5% to 10% increase in insolvencies. Indeed, the financial constraints affecting businesses since the onset of the COVID-19 pandemic would lead to a rise in corporate defaults in 2021 and beyond. Furthermore, the high elasticity of insolvencies to GDP growth in some countries could result from the rigidity of the bankruptcy laws, which are very creditor friendly. It is expected that as countries continue to reform their bankruptcy procedures/laws, there could be changes to the elasticity of bankruptcies to GDP in the future.

Fiscal support: The third major driver that will shape corporate bankruptcies in 2021 and beyond is fiscal support. Fiscal support measures announced in several countries, including in the United States, Japan, Germany, Canada, and India at the peak of the pandemic in 2020, helped stem the spate of corporate bankruptcies. As of the time of writing, many countries have also extended existing income support schemes or planned for their reintroduction as in Brazil (Smid and Ciobica 2020). The level of insolvencies was particularly low in 2020 due to temporary insolvency freezes and fiscal support packages. However, fiscal policy and monetary policy may tighten in some countries as economies emerge from the COVID-19 pandemic. Considerable heterogeneity in near-term corporate bankruptcies is likely to persist, both between advanced and emerging-market economies. There is expected to be higher corporate defaults in countries with little fiscal support and weak economic recoveries. As governments commence a gradual withdrawal of these stimuli, the level of corporate bankruptcies is expected to increase. Consequently, the creation of reliable models of bankruptcy prediction is essential for various decision-making processes.

1.3 Motivation for the Study.

The effect of a high rate of corporate defaults can be devastating to the business owners, partners, staff members, the lending institution, and the economy. The corporate bankruptcy prediction knowledge domain continues to evolve with new predictive models developed using various statistical and artificial intelligence tools.

Following the seminal work of Beaver (1966) and Altman (1968), academics and practitioners have developed different bankruptcy prediction models to predict future bankruptcies better. For instance, Zmijewski (1984) developed a Probit model using accounting data, Shumway (2001) used a hazard model with accounting and market variables, and Hillegeist et al. (2004) developed a model based on the Black–Scholes–Merton option-pricing model (BSM-Prob model), which uses accounting and market variables.

One of the most prominent bankruptcy prediction models is the Altman (1968) $Z-score$ model. Altman's $Z-score$ model uses a multivariate discriminant analysis (MDA) based on accounting variables to predict future corporate bankruptcies. In 2015, Almamy, Aston and Ngwa came up with their so-called $J-UK$ model (Almamy, Aston, & Ngwa, 2015) to account for the flaws and limitations of the initial $z-model$. The authors contributed to Altman's original $z - score$ by adding a sixth variable, cash flow from operations/total liabilities. The $J - UK$ model was established to test the health of UK companies.

Previous studies have tested and compared the different failure prediction models in different countries. For example, Shumway (2001) compared the hazard model and z-model, Hillegeist et al. (2004) compared Ohlson's $O - score$, $Altman's\, z - score$, and the $BSM - Prob\, model$, Mossman et al. (1988) compared four different models. Wu et al. (2010) compared five bankruptcy prediction models. Agarwal and Taffler (2008) compare Taffler's Z-score model (Taffler (1983)) with the KMV-Merton-based models used by Hillegeist, Keating, Cram and Lundstedt (2004) and Bharath and Shumway (2008) using UK data. Recent studies compare the corporate bankruptcy predictive accuracy of Support Vector Machines (SVM) and artificial neural networks (Horak et al., 2020).

The scope of this thesis is limited to reviewing some of the most frequently used bankruptcy prediction tools in the literature; Following Alaka et al. (2018), we reviewed the predictive abilities of two statistical bankruptcy predictive tools, namely Multi-Discriminant Analysis (MDA) and Logistic regression. Also, the following Artificial intelligence tools were examined - Artificial Neural Network (ANN), Support Vector Machines (SVM), Rough Sets (RS), Case-Based Reasoning (CBR), Decision Tree (DT) and Genetic Algorithms (GA). We included hazard model which is a popular tool that is used in predicting time-to-default of a firm.

We also empirically compared the predictive abilities of two (Logistic Regression, and Artificial Neural Network) of the most commonly used bankruptcy predictive models correcting for class imbalance in the data. Class imbalance in the training dataset makes it very difficult to accomplish the objective of accurately predicting the positive class of interest (bankrupt firms). In addition, some evaluation metrics, such as accuracy, may mislead the analyst with high scores that incorrectly indicate good performance-the so-called **'accuracy paradox'**. This is an important line of enquiry as it sheds light on this less explored area in predicting corporate bankruptcy and the performance accuracy of the models.

A fundamental challenge facing both users and developers of corporate bankruptcy prediction tools is their inability to determine the right tools for different data sets, sample size and purpose. A model developer needs to understand the strengths and limitations of the widely used bankruptcy predictive models to ensure that a suitable model is used for the right data attributes and the right purpose.

1.4. Research Aim, Objectives, and Contributions to Literature.

The prediction of a firm's probability of default has been of considerable interest to academics and practitioners for many decades (Altman, 2001; Jones and Hensher, 2008). The development of theoretically robust and accurate corporate bankruptcy prediction models is critical to regulators, lending institutions and academics. The 2007-2009 financial crisis led to a resurgence of interest in bankruptcy prediction modelling (Jones and Hensher, 2008). For instance, poor estimates of default probabilities in the U.S. residential mortgage market caused a cascade effect through bond and equity markets, leading to the 2007-2009 global financial crises (Jones and Peat, 2008; Oliver 2013). High episodes of corporate bankruptcies in the U.K. and elsewhere has precipitated a re-evaluation of the methods which underpin the estimation of bankruptcy probabilities and the associated issuance of credit ratings.

Following the financial crisis and the spate of corporate bankruptcies in recent times, bankruptcy prediction models are being used more than ever, and for a variety of purposes, including monitoring of the solvency of financial and non-financial firms by regulators, assessment of loan security, going-concern evaluations by auditors, the measurement of portfolio credit risk, and assessing securities exposed to credit risk (Duffie and Singleton, 2003). Given the interest in bankruptcy prediction, improved modelling approaches can enhance the current knowledge in this field. They can also provide improved methodologies which researchers can apply in other areas of research.

Despite the plethora of studies using different statistical and artificial intelligence algorithms to predict corporate bankruptcy, there appears to be no consensus regarding the best models. Given the different techniques available for loan default prediction, it is crucial to understand these tools' uses, strengths, limitations, and predictive accuracy. In addition, none of the studies we reviewed addressed class imbalance problems in the dataset. Class imbalance is naturally inherent in many bankruptcy prediction models. Highly imbalanced data poses a significant challenge, as the training sample will exhibit bias towards the majority class and, in extreme cases, may ignore the minority class altogether.

The current study aims to evaluate the predictive accuracy as well as the limitations and strengths of the most widely used corporate loan default prediction tools using a systematic literature review and meta-analysis method. Also, we employed three data-level methods Namely-Synthetic Minority Over-Sampling Technique (SMOTE), Random Under-Sampling (RUS), and Random Over-Sampling (ROS) techniques to address the less explored area of class imbalance in corporate finance and banking literature.

Using the PICO[4] approach, we formulate the central research aim thus "**to assess the predictive accuracy of statistical and artificial intelligence tools in predicting corporate bankruptcie**s". The problem, or population ("corporate bankruptcy"), the intervention is ("bankruptcy predictive tools"), the comparison ("statistical versus artificial intelligence tools"), and the outcome is ("corporate default"). In addition, we test for the presence of statistical heterogeneity in studies that reported the ANN as the tools with the best predictive accuracy and empirically examines the effects of some confounding variables in the performance accuracy of the ANN models.

In pursing these aims we establish the extent to which existing research in corporate bankruptcy prediction has progressed and identify relationships, contradictions, gaps, and inconsistencies in the literature using a systematic review of literature methodology. The use of systematic reviews to summarise and appraise the literature on bankruptcy predictive models is gathering pace. Previous studies have employed a systematic review method in this knowledge area-(see Balcaen and Ooghe 2006; Aziz and Dar 2006; Appiah, Chizema, and Arthur 2015; and Alaka et al., 2018). However, none of these studies used a meta-regression which is used to create a model describing the linear relationship between study-level covariates and the effect size (Jakubowski 2015). Also, it is not clear the criteria used to assess the methodological qualities of the primary studies. Moreover, most of these studies did not take clustering into account in the analysis (e.g., intracluster correlation coefficient).

This thesis aims to use meta-analysis and meta-regression statistical techniques to combine data from Artificial Neural Network (ANN) studies on bankruptcy prediction models to test

[4] The formulation of a research question for a systematic review must follow the PICO approach or any other appropriate approach. The research aim and question should include information on the Population/problem (P), Intervention (I), Comparison (C), and Outcome (O) (Fagerland, 2015).

the presence of statistical heterogeneity and explore the possible sources of these variations. Our choice for focusing on ANN tools is that the ANN is the bankruptcy prediction tool with the highest prediction accuracy. In addition, the ANN machine learning model's ability to generalise and learn is one of the main advantages of the model over the traditional methods of corporate bankruptcy prediction tools.

Contributions to the extant Literature.

The present study differs from previous studies in two ways- first, we use meta-analysis to combine quantitatively the evidence from eligible studies identified from the systematic review of the literature and explore sources of between-study variations. Specifically, we quantify between-study heterogeneity and offer potential explanations for these heterogeneities. The research questions that we seek to address in this study are as follows:

1. Is there a presence of statistical heterogeneity in the ANN studies?
2. How much heterogeneity is present (what is the magnitude)?
3. What are the possible causes of the heterogeneity and their effect on the outcome variable (bankruptcy event rate)?
4. Does accounting for class imbalance in the dataset affect the predictive accuracy of LR and ANN.

The following objectives will assist us in achieving the aim of this study-

1. Conduct a systematic review of the literature between 2016 to 2020.
2. Extend the systematic literature review of Alake et al. (2018) by conducting quantitative meta-analytics.
3. Provide implications for practice and policy,
4. Compare the predictive accuracy of LR, and ANN after accounting for class imbalance in the dataset.

5. Describe direction for future research.

In pursuing these objectives, this thesis makes the following contributions to existing studies in this area—first, the thesis updates existing systematic reviews on this topic. It has been almost five years since the last systematic review on this topic (Alake et al., 2018), and the literature has rapidly expanded. Secondly, most of the reviews were narrative and summary of findings reviews (see Balcaen and Ooghe 2006; Aziz and Dar 2006; Appiah, Chizema, and Arthur 2015). The thesis uses meta-regression to investigate between-study heterogeneity and provide a detailed quantitative synthesis of the sources of these heterogeneities. Finally, the study shows that accounting for class imbalance in bankruptcy dataset affects the predictive accuracy of the model.

1.5. Summary of findings.

A fundamental assumption of meta-analysis and meta-regression is that studies included in the analysis must address identical/similar research question(s). To achieve this aim and adhere to the assumption, we used findings from comparative bankruptcy prediction studies that reported the Artificial Neural Network as the method with the best forecast accuracy. Specifically, the meta-analysis allows us to address the abovementioned research questions.

In addition, a meta-regression is used to explore the potential sources of between-study differences in the pooled ANN studies. We used a multivariate meta-regression model to address the following research questions:

1. Can the sample size, percentage of failed firms, and type of input datasets explain between-study differences?

2. What percentage of unexplained between-studies variance and the proportion of variance are explained by the regression model?
3. To what extent does class imbalance affect the predictive ability of logistic regression and the artificial neural network?

The results from the analysis reveals that the quantitative tests of heterogeneity statistics - the $chi - square$ test for heterogeneity is significant at a level of less than 10%, and the I^2 value for the ANN studies is 98%. These quantitative results suggest there is between-study variability (i.e., heterogeneity). We explored some moderators of effect sizes using meta-regression as part of the review's secondary outcomes. The results from the meta-regression suggest that sample size has a statistically significant effect on the performance of the ANN model. Although we did not find a statistically significant relationship between the type of input datasets, the proportion of bankrupt firms and the event rate; however, our result shows that these variables taken together can explain approximately 77% of the variance in the event rate.

Our recommendations for practice are to pay attention to the sample size used in developing a bankruptcy prediction model and the validation method. The Artificial Neural Network (ANN) model seems to be very sensitive to the number of data points used in the model. A small sample size may negatively impact the performance ability of the model. Developers should also pay attention to the class imbalance inherent in bankruptcy data and take relevant steps to address them.

1.6. Structure of the Thesis.

The rest of the thesis is structured as follows; Chapter 1 discusses the research background and provides motivation for the research topic. Also, we discuss the potential drivers of corporate bankruptcy in 2021 and beyond and provide a summary of the findings from the meta-analysis. Chapter two discusses bankruptcy prediction studies and the popular models. The mathematical theory and the intuitions behind the following models Multi-Discriminant Analysis (MDA) (Z-Score Model and J-UK Model), Logistic regression, Artificial Neural Network (ANN), Support Vector Machines (SVM), Rough Sets (RS), Case-Based Reasoning (CBR), Decision Tree (DT) and Genetic Algorithms (GA) were also discussed in chapter two.

Chapter three reviews the main bankruptcy theories, including the Modigliani-Miller theory, trade-off theory, and value-based theory. Also, some of the main methods of resolving financially distressed firms were discussed and the challenges of private reorganisation. Chapter four is the systematic review and meta-analysis chapter. This chapter discussed the rationale for a systematic review and reviewed some of the major steps in conducting a systematic review.

Also, we presented and discussed in detail our search strategy, inclusion and exclusion criteria, data extraction, quality assurance, and the meta-regression findings. Chapter five addresses class imbalance issues in the dataset and shows that not accounting for the inherent difference in the number of bankrupt and none-bankrupt firms in the dataset could lead to an accuracy paradox. Chapter six is the summary and conclusion chapter. This chapter discussed the key findings from this thesis and areas for future research.

Chapter Two.

Bankruptcy Prediction Studies and Review of Models.

2.0. Introduction.

The discussions in chapter one reveal the high number of corporate insolvency in the UK and elsewhere. Recent studies estimate global insolvencies to increase by 26% by the end of 2021 as national governments commence the withdrawal of COVID-19 fiscal support. Consequently, lending institutions must rethink their use of predictive algorithms in classifying good and bad credit risks. Good knowledge of the relative performance of the commonly used predictive algorithm can provide a guideline and subsequently aid lending institutions in their credit decisions.

In this chapter, we review the literature on the bankruptcy prediction model and the commonly used statistical and machine learning algorithms used in this area. We aim to summarize and analyze the extant literature while highlighting the historical evolution of this knowledge domain and facilitating future research in this area. To put the analysis into context, we define failure following (Beaver, 1966) as "the inability of a firm to pay its financial obligations as they fall due. According to Beaver (1966), a firm is said to have failed when any of the following events have occurred: bankruptcy, bond default, an overdrawn bank account, or nonpayment of a preferred stock dividend.

Altman (1968) developed one of the most widely known bankruptcy prediction models using the Multivariate Discriminant Analysis (MDA). Since Altman's MDA, the bankruptcy prediction research domain has evolved with many different predictive models developed. We analyzed over a hundred bankruptcy prediction studies published from 1965 to the present and discussed the trends in model development. For example, the literature on bankruptcy prediction dates as far back as the 1930s with the use of ratio analysis in predicting future bankruptcy (FitzPatrick, 1932).

In the 1960s, the focus was on the use of univariate -single factor analysis. Beaver (1966) is one of the widely used univariate models. In the later part of the 1960s, Alman published the first multivariate study - (multivariate discriminant analysis), which is still being used today. There are significant variations in the bankruptcy prediction models developed between the 1960s to early 2000s. These variations include the number of factors/variables used to the type of statistical methods/algorithms employed in developing the models. For instance, while Altman's (1968) model is a five-factor multivariate discriminant analysis model, Boritz and Kennedy's (1995) model was a 14-factor neural network. The number of variables considered in other models ranges from one to fifty factors.

In addition, some of the bankruptcy prediction models in the 1960s to early 2000s were narrowly focused. Altman's (1968) model was for manufacturing companies, Sinkey's (1972) model targeted predicting bank failures, and Wang (2004) developed models for predicting technology (internet) firms in the U.S. Recent studies have used artificial intelligence tools, including artificial neural networks, support vector machines, rough sets, case-based reasoning, decision tree and genetic algorithm.

The rest of this chapter is structured as follows. Sections 2.1 summarizes the Bankruptcy prediction studies—section 2.2 reviews bankruptcy prediction tools, including MDA, Logistic regression, and Artificial neural networks amongst others. Sections 2.3 and 2.4 present discussions on the model factors/variable and validation methods, while section 2.5 analyses the model's predictive accuracy and 2.6 is the conclusion.

2.1 Bankruptcy Prediction Studies a Survey of Previous Literature.

Most bankruptcy prediction models in the early 1930s focused on using financial ratios to predict or discriminate financially strong from non-financially strong firms. Consequently, it is essential to provide a brief review of the theory of ratio analysis. The theory of ratio analysis is best described through the lens of the Cash Flow model (Walter 1957). Under this model, a firm is seen as a liquid asset reservoir supplied by cash inflows and liquidated/drained by cash outflows. The reservoir serves as a cushion or buffer against variations in the flows. The firm's solvency can be defined as the probability that the reservoir will be exhausted/depleted. At which point, the firm will be unable to pay its obligations as they mature, leading to the firm's failure (Beaver 1967).

Following this notion, Beaver (1967) made the following propositions: 1) The larger the reservoir, the smaller the probability of failure. (2) The larger the net liquid-asset flow from operations (i.e., cash flow), the smaller the probability of failure. (3) The larger the amount of debt held, the greater the probability of failure. (4) The larger the fund expenditures for operations, the greater the probability of failure. These four propositions are used in the selection of ratios in most corporate bankruptcy prediction studies.

The early studies in bankruptcy predictions mainly used univariate ratio analyses to evaluate the creditworthiness of firms. For instance, the Bureau of Business Research (BBR) in 1930 published a study of ratios of failing industrial firms. The BBR study analyzed 24 ratios of 29 firms to determine standard features of failing firms. According to the study, the failing firms displayed specific similar characteristics or trends. Specifically, the study found eight ratios that the authors considered good indicators of a failing firm. According to the BBR studies, the standard ratios were *Working Capital to Total Assets*, *Surplus and Reserves to Total Assets*, *Net Worth to Fixed Assets*, *Fixed Assets to Total Assets*, the *Current Ratio*, *Net Worth to Total Assets*, *Sales to Total Assets*, and *Cash to Total Assets*. It is worth mentioning that the Current Ratio was first cited in the literature as early as 1908 by William M. Rosen- dale (1908).

In 1932, FitzPatrick (1932) analyzed 13 ratios of 19 pairs of failed and non-failed firms and found that the successful companies' financial ratios were more robust while the failed firms had weak ratios. Evidence from Fitz (1932) indicated that there were remarkable differences in the ratios of failed and non-failed firms for at least three years before failure. The author suggests that the two significant ratios were Net Worth to Debt and Net Profits to Net Worth. FitzPatrick (1932) opines that the *Current Ratio* and *Quick Ratio* should not be the focus of analysis for companies with high long-term liabilities. Following the BBR's 1930s publication,

Smith and Winakor (1935) analyzed the mean ratios of 183 failed firms across different industries for ten years prior to failure. They found a significant deterioration in the mean values with the rate of deterioration increasing as the firms' approach failure. Specifically, the authors found significant weaknesses in the *Current Assets to Total Assets* ratio as a firm approached bankruptcy. Their study revealed that *Working Capital to Total Assets* was a superior predictor of financial problems than *Cash to Total Assets* and the *Current Ratio*.

The study of Merwin (1942) focuses on small manufacturers. He reported that when comparing successful with failing firms, the failing firms displayed signs of weakness as early as four or five years before failure. Merwin's study also found three ratios that were significant indicators of business failure - *Net Working Capital to Total Assets*, the *Current Ratio*, and *Net Worth to Total Debt*. Jackendoff (1962) compared the ratios of profitable and unprofitable firms in his study. His study reveals that profitable firms have higher *Current Ratio* and *Net Working*

Capital to Total Assets. Also, profitable firms had lower *Debt-to-Worth* ratios than unprofitable firms.

From the discussion so far, it is clear that not all ratios do predict equally well. For example, four of the studies we reviewed indicated that Working Capital to Total Assets and current ratio were important indicators of financial distress. At the same time, two of the studies showed that the Current Ratio was not as valuable as Working Capital to Total Assets in predicting financial distress. These early studies formed the bedrock for the studies on corporate bankruptcy. Bankruptcy prediction models began to develop with Beaver's [1966] univariate study and have continued to evolve since then.

The 1930s saw the use of financial ratios by financial institutions to determine the creditworthiness of their borrowers. In the 1970s, logit and probit methods became widespread. Then, in the 1990s, artificial neural networks and genetic algorithms began to emerge. In the 21st century, along with the development of information technology, various techniques used for forecasting bankruptcy were developed. This section evaluates the evolution of bankruptcy prediction models from 1966 to the present.

The study of Beaver (1966), in which he compared the mean value of 30 ratios of 79 failed and 79 non-failed companies in 38 industries brought another perspective to the bankruptcy predictive models literature. His study tested the individual ratios' predictive abilities in classifying bankrupt and non-bankrupt firms, and found that *Net Income to Total Debt* had the highest predictive ability (92% accuracy one year before failure), followed by *Net Income to Sales* (91%) and *Net Income to Net Worth*, *Cash Flow to Total Debt*, and *Cash Flow to Total Assets* (each with 90% accuracy). Beaver's suggestion on areas of future research indicated the possibility that multivariate models with financial ratios as explanatory variables may have higher predictive ability than single ratios. His suggestions kicked off the evolution of multivariate models in bankruptcy predictions literature.

Altman (1968) published the first multivariate discriminant five-factor model (referred to as the Z-Score model) to predict the bankruptcy of manufacturing firms. Altman's Z-Score model is a numerical measurement that indicates the chances of a firm going bankrupt in the next two years if the firm's score fell within a certain range. Altman's Z-score model had a high predictive ability one year before the failure of the sample firms (95% accuracy). However, the model's predictive ability tapers off considerably from there with only 72% accuracy two years before failure, down to 48%, 29%, and 36% accuracy three, four, and five years before failure, respectively. The model's predictive ability when tested on a hold-out sample was 79%.

The need for reliable corporate bankruptcy prediction models is critical, especially in the current climate of financial uncertainty. The literature on corporate bankruptcy prediction models has continued to evolve since Altman's multivariate discriminant Z-Score model. There have been significant improvements in methodologies and statistical techniques to forecast corporate financial distress accurately. Altman, Haldeman and Narayanan (1977) developed a revised version of Altman (1968) Z-Score model called the $ZETA$ Credit Risk model. The authors justified modifying the original model based on changes in accounting reporting standards since the 1960s.

The resulting linear $ZETA - Score$ discriminant model was highly accurate in predicting financial distress up to 5 years before the actual occurrence of corporate financial distress. The study included 53 bankrupt and 58 existing manufacturing and retailer companies between

1969 and 1975. The $Zeta$ Credit Risk model can predict insolvency up to five years before the bankruptcy. The model was more than 90% successful in classifying bankruptcy one year before the firm became bankrupt and 70% five years before the default.

The model classifies a company as bankrupt with a negative score, a score larger than zero is classified as non-bankrupt. Altman, Haldeman and Narayanan (1977) compared their ZETA model with Altman's z-score. Both models show almost the same accuracy of bankruptcy prediction one year prior to bankruptcy, but two and more years prior to bankruptcy, the ZETA model gives a better prediction. Five years before the default, the ZETA model gives a correct prediction of 70%, whereas the z-score is only 36% accurate (Altman, Haldeman, & Narayanan, 1977).

Studies in the 2000s used different methods to predict corporate bankruptcy. The majority of studies compared the prediction accuracy of the various prediction models. For instance, the study of (Chen, Yang et al. 2011) reported the Artificial Neural Network (ANN) and Support Vector Machine (SVM) as being more accurate than the Genetic Algorithm (GA). In their contribution, (Chen, Ribeiro, Vieira, Duarte and Neves 2011) compared a hybrid of GA and K-nearest neighbour (KNN) with other tools, including ANN and SVM and concluded that the hybrid model outperforms the standalone models in predicting bankruptcy.

Other studies have used novel methods to predict bankruptcy. Divsalar et al. (2011) used Linear Genetic Programming (LGP), Divsalar et al. (2012) proposed a novel version of GA called Gene Expression Programming (GEP) and showed that the model was more accurate than the other models. Kasgari et al. (2013) used the Artificial Neural Network. The majority of the studies reviewed showed the Artificial Neural Network (ANN) and the Support Vector

Machine (SVM) to be the more accurate tools for developing a bankruptcy prediction model (Iturriaga & Sanz, 2015; Virág & Nyitrai, 2014).

The ultimate purpose of these models is to warn company managers and shareholders of the possible impending danger of financial distress of the firms in which they are stakeholders. We will evaluate the efficacy of the most common methods of predicting bankruptcy in chapter four of this thesis using a meta-regression and correlation analysis.

2.2.0 Bankruptcy Prediction Tools.

So far, we have discussed the different bankruptcy prediction models from 1965 to the present. What is evident is that various researchers have developed different models for predicting the bankruptcy of companies across the world. Our review clearly shows that these models differ in terms of the tools and attributes/factors used. For instance, the Multiple Discriminant analysis and Logistic regression use statistical tools. The Artificial Neural Networks (ANN), Support Vector Machines (SVMs), Genetic Algorithms (GA), and Rough Sets (RS) use Artificial Intelligence tools.

In addition, these models differ in terms of their information contents. For instance, while the traditional models like Altman's Z-score models use accounting information (Altman, 1968), the hazard models assess bankruptcy risk using accounting and market data (e.g. Shumway, 2001). The purpose of this section is to discuss a variety of bankruptcy prediction models and their differences. This section will review ten tools used to develop bankruptcy prediction models, including Multiple Discriminant Analysis (MDA) (Z-Score and J-UK Models), Logistic Regression (LR), Artificial Neural Network (ANN), Support Vector Machines (SVM), and Decision Tree (DT) Algorithm.

2.2.1 The Multivariate Discriminant Analysis.

Most multidiscriminant bankruptcy prediction models use accounting data to filter relevant information from publicly available financial statements to assess bankruptcy risk. In a way, these models can be regarded as a structured fundamental analysis using published financial statements and are typically developed by searching for the linear combination of ratios that best differentiates between (matched) samples of non-failed and failed firms through discriminant or logit models. Coefficients are estimated based on sample observations.

A discriminant score is developed by summing up the products of the ratios and their coefficients. MDA applies a linear combination of variables, usually financial variables and ratios, that best differentiate between failing and healthy firms to classify firms into one of the two groups. The equation below is a mathematical specification of a multidiscriminant model.

$$Z = C_1X_1 + C_2X_2 + \cdots + C_nX_n \qquad (1)$$

Where $C_1, C_2, C_3 \ldots C_n$ are discriminant coefficients $X_1, X_2, \ldots X_n$ are independent variables. MDA estimates the discriminant coefficients. The function is applied to estimate a Z-score. A cut-off score is chosen based on status of sample firms.

One of the most known and the oldest bankruptcy prediction models is the Altman z-score by NYU Stern Finance Professor Edward Altman (1968). The Z-score model uses a multivariate discriminant analysis (MDA) based on accounting variables. Almamy, Aston and Ngwa came up with their so-called J-UK model (Almamy, Aston, & Ngwa, 2015). The authors contributed to Altman's original z-score model by adding a sixth variable, cash flow from operations/total liabilities. The J-UK model aims to test the health of UK companies. We will provide a review of both models in this section of this thesis.

Altman's z-score is a model used to predict the likelihood of a company becoming bankrupt. Altman used a multiple discriminant analysis (MDA) with which he analyzed 66 manufacturing U.S companies. 33 Out of these 66 companies became bankrupt between 1946-1965, and the other half were existing companies in 1966. The original z-score formula given in equation 2 below focuses on five financial ratios:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \qquad (2)$$

$$X_1 = Working\ capital/total\ assets$$

$$X_2 = Retained\ earnings/total\ assets,$$

$$X_3 = Earnings\ before\ interest\ and\ taxes/total\ assets$$

$$X_4 = Market\ value\ of\ equity/book\ value\ of\ total\ debt$$

$$X_5 = Sales/total\ assets$$

$$Z = Overall\ Index$$

Companies with a $Z - Score < 1.81$ are more likely to face financial distress. A $Z - Score \geq 2.99$ or higher indicates no potential danger of bankruptcy. The zone between 1.81 and 2.99 is called the *Zone of Ignorance*[5] or a grey area due to the predisposition of errors. The first ratio in the model $working\ capital\ to\ total\ assets$ measures the net liquid assets relative to the total capitalization. The $retained\ earnings\ /\ total\ assets$ ratio measures the cumulative profitability of a company over time. The third ratio,

[5] The zone of ignorance suggests a possibility of the company going bankrupt within the next two years.

$earnings\ before\ interests\ and\ taxes\ (EBIT)\ /\ total\ assets,$ measures the actual productivity of a company's assets. X_4 is the $market\ to\ book$ ratio, which measures how much a company's assets can decline in value before the liabilities exceed the assets and the company becomes bankrupt. The final ratio, the $total\ asset\ turnover$, emphasizes the sales generating ability of the company's assets (Altman, 1968).

Altman's Z-score had a high predictive ability for the initial dataset one year before failure with 95 % accuracy. Unfortunately, the model's predictive ability fell significantly to 72% accuracy two years before the bankruptcy, 48% three years before, 29% four years before and 36% five years before failure. When tested on a hold-out sample, the model's predictive ability was 79%. (Altman, 1968).

Altman revised his original Z-Score model in 2000 and came up with Z'-score prime for private companies by changing X_4 the $market\ value\ of\ equity$ to the $book\ value\ of\ equity$. In this revised model, the high financial distress score changed from 1.81 to 1.23 (Altman, 2000). The adjusted formula for the $Z' - Score$ is specified as follows:

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5 \quad (3)$$

Altman revised the Z'prime to get the Altman's Z'' Score Model for Non-Manufacturing firms in 2002. The industry sensitive Asset Turnover Ratio (Sales/Total Assets) was removed from the model and the coefficients for the weighted ratios was changed (Altman,2002). The revised four-factor model is specified as follows:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (4)$$

Almamy, Aston and Ngwa (2015) developed the J-model based on UK companies. The authors tested the financial health of companies in the UK before, during and after the 2007 global financial crisis. They extended Altman's first Z-Score model (1968) and added a sixth variable $cash\ flow\ from\ operations/total\ liabilities$. The model specified is of this form:

$$J = 1.484J_1 + 0.043J_2 + 0.39J_3 + 0.004J_4 + 0.424J_5 + 0.75J_6 \tag{5}$$

With

$$J_1 = \ working\ capital/total\ assets$$

$$J_2 = \ retained\ earnings/total\ assets$$

$$J_3 = \ earnings\ before\ interest\ and\ taxes/total\ assets$$

$$J_4 = \ market\ value\ equity/total\ liabilities$$

$$J_5 = \ sales/total\ assets$$

$$J_6 = \ cash\ flow\ from\ operations/total\ liabilities$$

The sixth ratio, $cash\ flow\ from\ operations\ /\ total\ liabilities$, measure the time it takes a company to repay its debts using the cash flow from operations. Almamy, Aston and Ngwa (2015) used total liabilities instead of the book value of total debt as used by Altman.

The researchers used Altman's z-score on their dataset and compared their findings of both models. They found that companies were classified correctly 51,5% before the crisis using Altman's z-score and 64,1% using the J-model. The Z-Score model classified 67,4% of firms correctly and the J-UK model 79,2% during the financial crisis. After the crisis, the classification was the best, with 71,5% for Altman's z-score and 81,2% for the J-UK model.

The authors concluded that the J-UK model had a higher accuracy of predicting bankruptcy in all cases, before, during and after the financial crisis (Almamy, Aston, & Ngwa, 2015).

Despite the broad use of the accounting-based bankruptcy prediction models in the literature, they are criticized for their lack of theoretical underpinning. Some researchers argue that the historical nature of accounting data and the going concern assumption that underpins financial statements make their use in predicting the future fundamentally flawed (Hillegeist et al. 2004). Others suggest that accounting numbers are subject to reporting standards (such as conservatism and historical cost accounting) that might hinder an accurate representation of the economic value of assets. In addition, a firm's management can manipulate accounting numbers to some extent, thus making their use in predicting bankruptcy inadequate (Agarwal and Taffler 2008a).

2.2.2 The Logistic Regression (LR).

Logistic Regression can be seen as a process of modelling the probability of a discrete outcome given input variables. Despite its name, the Logit model is a classification model rather than a regression model. It is a simple and more efficient method for binary and linear classification problems. The model uses a logistic function to model a binary dependent variable in its basic form, although many more complex extensions exist. A binary logistic model has a dependent variable with two possible values, such as *Bankrupt*/*No-Bankrupt* represented by an indicator variable, where the two values are labelled "0" and "1".

Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable. We consider a logistic regression with 2 predictors (x_1, x_2) and one Bernoulli response variable Y, which we denote $p = P(Y = 1)$. In line with previous in this area, we assume a linear relationship between the explanatory variables and the log-odds or logit of the event that $Y = 1$. The linear relationship can be written in this reduced functional form:

$$\theta = log_e \frac{p}{1-p} = \beta_o + \beta_i x_i \dots + \beta_n x_n \qquad (6)$$

Where θ is the log-odds, e is the base of the logarithm and β_i are the parameters of the model. The odds can be recovered from equation 6 by exponentiating the log-odds as:

$$\frac{p}{1-p} = e^{\beta_o + \beta_i x_i \dots + \beta_n x_n} \qquad (7)$$

Applying algebraic manipulation to equation 7 the probability that $Y = 1$ is:

$$p = \frac{e^{\beta_o + \beta_i x_i \dots + \beta_n x_n}}{e^{\beta_o + \beta_i x_i \dots + \beta_n x_n} + 1} = \frac{1}{1 + e^{-e^{\beta_o + \beta_i x_i \dots + \beta_n x_n}}} = S_e\left(e^{\beta_o + \beta_i x_i \dots + \beta_n x_n}\right) \qquad (8)$$

Where p is the probability of bankruptcy, $\beta_i (i = 0, \dots, n)$ are the coefficients and n is the number of explanatory variables x_i $(i = 1 \dots, n)$.

Where S_e is the sigmoid function with base e. Equation (8) suggests that once the parameters are fixed, we can compute either the log-odds that $Y = 1$ for a given observation, or the probability that $Y = 1$ for a given observation. Essentially, the logistic regression (LR) is a transformation of a linear regression using the Sigmoid function[6].

[6] A sigmoid function is a mathematical function having a characteristic "S"-shaped curve or sigmoid curve.

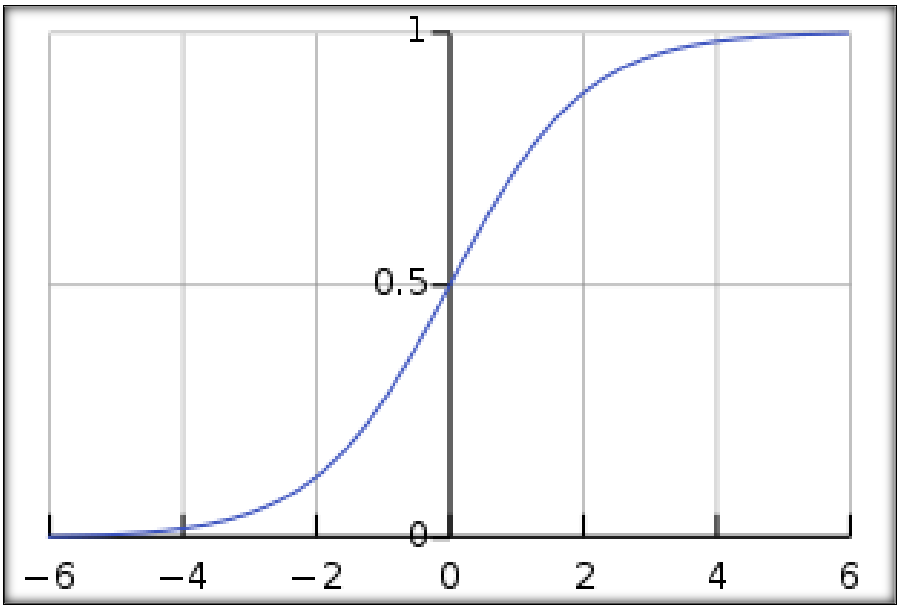


Figure 2.1 The Logistic Regression Sigmoid Curve

The vertical axis in figure 2.1 above stands for the probability for a given classification and the horizontal axis is the value of x. The logistic function applies a Sigmoid function to restrict the Y value from a large scale to within the range 0–1.

2.2.3 Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) model is a nonrestrictive and nonparametric alternative to bank failure prediction (Van der Ploeg, 2010). ANN was first proposed by McCulloch and Pitts (1943) and inspired by how the biological nervous systems work. The model consists of several homogeneous processing units, referred to as nodes or neurons, interconnected in a network. Each neuron can be described by a mathematical function transforming input signals into output signals. The output signals are then directed, depending on the structure and topology of the model, as input signals of nodes in the following layer, Van der Ploeg, 2010).

Essentially, ANNs are complex systems for mapping the relationship between the input (explanatory) variables and output (dependent) variable. The derivation/interaction of the relationship between the input variables is accomplished via a series of one or more hidden layers between the input and output variables, which are referred to as the input and output layers, respectively (Khashman 2010). In these layers, the algorithms use several multiple regression-like models whose outputs are transformed and used as inputs in the subsequent layers. The most frequently used ANN is the multilayer perceptron (MLP).

Artificial Neural Network model development is a three-phased process. The first phase (Phase 1) is known as the training phase. The inputs are processed through the network in phase 1. This phase is commonly called the feedforward phase. In phase 2, commonly referred to as the backpropagation phase, the output errors are sent back through the network (Khashman 2010). The connection weights are adjusted throughout the process to minimize the associated errors. Phases two and three will repeat until a predetermined stopping criterion is achieved. This criterion is mostly the point at which the error in a validation dataset ceases to improve (Fausett, 1994).

These predetermined criteria are set to avoid overfitting the model to the training data. We specify the algorithm for training the network as follows: first the connection weights W_{ih} are initialized to small random values. At the beginning of the feedforward phase, the input vector is populated with the independent variables x_i. Each of these inputs are sent to the neurons in the hidden layer h_j where they are associated with their respective connection weights between the neurons. Each neuron performs the following steps in parallel in the hidden layer: i) the inputs and their associated weights are summed:

$$h_j = z_j + \sum_{i=1}^{n} x_i w_{ih} \tag{9}$$

Where z is the value for the bias (errors) for the hidden neuron h_j. The rest of the notations are as previously defined. A sigmoidal activation function[7] computes the output for the neuron. The two frequently used activation functions in financial literature are the logistic function specified in equation 10 and the hyperbolic tangent function specified in equation 11.

$$h_j' = \frac{1}{1+e^{-h_j}} \tag{10}$$

$$h_j'' = \frac{e^{h_j}-e^{-h_j}}{e^{h_j}+e^{h_j}} \tag{11}$$

The outputs $\left(h_j' or h_j''\right)$ from the hidden layer are associated with connection weights and passed to the output layer o_k. The weighted input signals (equation 12) are summed in the output layer, and the outcome is expressed as a probability. A logistic activation function (equation 13) is used to generate the model's output. This ends the feedforward phase.

$$o_k = z_k + \sum_{h=1}^{n} h' v_{hk} \tag{12}$$

$$o_k' = \frac{1}{1+e^{-ok}} \tag{13}$$

Where z is the value for the bias for output neuron o_k, v_{hk} is the connection weight between hidden neuron h_j and output neuron k, and the other notations are as previously defined. Like in regression models, the output from the ANN model is compared with the dependent variable, and the error is computed. The computed error is passed back through the network, and the connection weights are adjusted to minimize the error. For a detailed understanding of the

[7] The sigmoid activation function is also referred to as the logistic function. It is the function used in the logistic regression classification algorithm. The function takes any real value as input and outputs values in the range of 0 to 1. The larger the input (more positive), the closer the output value will be to 1.0, whereas the smaller the input (more negative), the closer the output will be to 0.0 (Nwafor 2022).

different techniques available for adjusting the connection weights in an ANN see Fausett (1994).

ANN models provide an analytical alternative to traditional failure prediction models due to their nonrestrictive characteristics. Conventional econometrics models can be limited by assumptions on variable independence and the relationship between the probability of default and its predictors. Furthermore, ANN models can approximate numerous statistical models without hypothesizing certain relationships between variables because of their nonrestrictive nature. The relationships between variables are instead determined during the iterative learning process of the model.

A weakness inherent to the flexibility of ANN models is that the underlying process of determining the relationship between the independent and dependent variables is not easily interpretable, Trinkle and Baldwin (2016). Artificial Neural Network may not be handy if the central focus is to understand the empirical relationship between the dependent and independent variables. On the other hand, when interpreting the underlying relationships between variables is not essential, ANN models might be preferred due to their nonrestrictive characteristics.

ANNs are sophisticated artificial intelligence techniques for building predictive models because they are very adept at recognizing underlying patterns in nonlinear data. Many authors have used supervised machine learning algorithms to classify loan customers into default and non-default groups within the field of credit scoring. These algorithms attempt to predict the probability of default for new loan customers, conditional on the observed characteristics of previously defaulted customers (Khemakhem and Boujelbene, 2015 and Gante et al., 2015).

For a broader review of the credit scoring literature and credit models, see Abdou and Pointon (2011).

Given the importance of customer selection in credit risk management, many researchers have compared the classification and prediction performance of different machine learning algorithms. For instance, Boguslauskas and Mileris (2009) apply various machine learning models to analyze the credit risk of 50 cases of successful and 50 cases of insolvent firms in Lithuanian. Their results show the neural network to be an efficient method of credit risk estimation. Khashman (2010) applied the neural network algorithm on 1000 German credit datasets; their results show 99.25% and 73.17% accuracy rates for the training and test data, respectively. Gante et al. (2015), using the same German credit dataset, compares the performance of 12 neural network models on different input neurons. Their results show that the network topology with 20 input neurons, 10 hidden neurons and one output neuron outperforms the other 11 models.

The study of Khemakhem and Boujelbene (2015) also reveals that the neural network model outperforms discriminant analysis in predicting credit risk. Witkowska (2006) studied the predictive abilities of ANNs and radial basis functions (RBFs) using the data of approximately 300 Polish corporate credit applications. The study had 13 independent variables and four credit rating classes; the RBF predicted the lowest error rates on the classes. However, the ANN correctly classified a more significant percentage of the firms correctly overall. Blanco et al. (2013) used multilayer perceptron (MLP) neural networks to create credit scoring models for the Peruvian microfinance industry. Their study provided the first applications of ANNs to microfinance in emerging markets.

Most of these studies report that neural networks are flexible and robust and allow the characteristics[8] of the loan applicant to interact in several different ways. For instance, a single characteristic can be connected to more than one characteristic, which make-up the whole network structure. It is clear from the literature outlined above that few studies have used recent U.K datasets in the area of corporate bankruptcy prediction. The current study addresses this gap by using a sample of U.K solvent and insolvent firms over the period 2008 to 2020 in evaluating the performance accuracy of ANN, Hazard and Logistic regression models.

2.2.4. Discrete Hazard Model.

Despite the successful application of neural network in credit risk evaluation, Shumway (2001) suggests that ignoring information about the length of time a solvent firm has survived produces biased and inconsistent estimates of the model's parameters. To adequately address this, Shumway (2001) uses a discrete-time hazard model. In the hazard model, the hazard rate is the firm's probability of going bankrupt at time t conditional upon having survived until time t. Therefore, in a hazard model, the likelihood of bankruptcy changes over time. This allows the probability of bankruptcy to change as a function of a vector of explanatory variables that also change over time. We discuss the general form of the hazard model in line with Charalambakis, Espenlaub and Garrett (2009) in this section.

The general form of the hazard model is:

$$Ln\left[\frac{h_i(t)}{1-h_i(t)}\right] = \alpha(t) + \beta' x_{it} \qquad (14)$$

[8] Characteristics in a scorecard model are the lists of questions for a loan applicant. The applicant then provides his/her answers based on a set of possible answers- called attributes (Khashman, 2010).

Where $h_i(t)$ represents the hazard of bankruptcy at time *t* for firm *i*, conditional on survival to *t*; $\alpha(t)$ is the baseline hazard; β is a vector of coefficients and $x_{i,t}$ is a $k \times 1$ vector of observations on the ith covariate at time t.

According to Shumway (2001), the discrete-time hazard model can be regarded as a dynamic logit model where each period that a firm survives is included as a non-failing firm. Therefore, the probability of bankruptcy is estimated as:

$$P_{t-1}(Y_{it} = 1) = \frac{1}{1+exp(-\alpha-\beta' x_{it-1})} \tag{15}$$

Where Y_{it} is a is a variable that equals one if firm *i* goes bankrupt in year *t*, and zero otherwise. β and x are as defined before. In estimating the probability of bankruptcy, we use data dated $t-1$. This ensures that we use data that is available at the beginning of the year in which bankruptcy occurs.

Most hazard models combine accounting and market data in simple discrete-time logit models (Shumway, 2001). Chava and Jarrow (2004) used a mixture of accounting and market base ratios of profitability, liquidity, and market volatility or market price to predict corporate bankruptcy. Campbell et al. (2008) integrated accounting and market information using ratios containing accounting variables in the numerator and the market value of total assets in the denominator.

The second strand of literature tests the performance of hazard models against accounting-based models. Shumway (2001) compares a hazard model to the accounting-based alternatives and finds that the majority of previously used accounting variables from Altman (1968) and Zmijewski (1984) have little power in forecasting bankruptcy. Campbell et al. (2008) is the only study that compares hazard and contingent claims-based models. They show that not only does their hazard model outperform the contingent claims-based model of Moody's KMV in information content tests, it also subsumes the bankruptcy-related information of the contingent claims-based model.

2.2.5 Support Vector Machines (SVMs).

A Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification, regression, and outlier detection purposes (Vapnik, 1998). Since the current thesis focuses on classifications, we will discuss the SVM as a classification algorithm. SVMs are based on the idea of finding a hyperplane that best divides a dataset into two classes. Support vectors are the observations/data points nearest to the hyperplane. Removing these points of a data set would alter the position of the dividing hyperplane. Because of this, they can be considered the critical elements of a data set.

In the case of bankruptcy prediction, an SVM algorithm creates the boundary using binary class. The variables closest to the hyperplane- support vectors are used to define the binary outcome, either the firm is solvent or insolvent. All other data points are not used to decide the binary class boundaries (Louzada et al., 2016; Zhou et al., 2009; 2010; and Ling et al., 2012). The SVM views a data point as a $p - dimensional$ vector and the idea in the case of a linear classifier is to separate such points with a $(p - 1)\ dimensional$ hyperplane.

The best hyperplane is the one that represents the largest separation, or margin, between the two classes. Hyperplane is chosen so that the distance from it to the nearest data point on each side is maximized. According to Cortes and Vapnik (1995) if such a hyperplane exists, it is known as the *maximum-margin* hyperplane and the linear classifier it defines is known as a *maximum-margin classifier*.

Assume a linear SVM (LSVM) with a training datasets of n points of the form: $(x_1, y_1), \dots, (x_n, y_n)$, if we take the y_i as either healthy firms 1 or failing firms -1, each indicating the class to which the point x_i belongs. We want to find the maximum-margin hyperplane that divides the group of points x_i for which $y_i = 1$ from the group of points for which $y_i = -1$. The idea is to maximize the distance between the hyperplane and the nearest point x_i from either group. The LSVM algorithm will select a line that not only separates the two classes but stays as far away from the closest samples as possible. Any hyperplane can be written as the set of points x satisfying:

$$w^T x - b = 0 \tag{16}$$

Where w in equation 16 is the normal vector to the hyperplane. The parameter $\frac{b}{\|w\|}$ determines the offset of the hyperplane from the origin along the normal vector w.

We have assumed in the discussion so far that the training dataset is linearly separable. Therefore, we can select two parallel hyperplanes that separate the two classes (healthy and failing firms) so that the distance between them is as large as possible. The region bounded by these two hyperplanes is called the *margin*, and the *maximum-margin* hyperplane is the hyperplane that lies halfway between them. If the dataset is normalized or standardized, we can describe these hyperplanes by the following equations:

$$w^T x - b = 1 \tag{17}$$

Equation 17 implies that data points on or above this boundary belongs to the healthy firms.

$$w^T x - b = -1 \tag{18}$$

Data points on or below this boundary belongs to the class of failing firms. The distance between these two hyperplanes is $\frac{2}{\|w\|}$, consequently to maximize the distance between the planes we want to minimize $\|w\|$. To prevent data points from falling into the margin, we add the following constraint: for each i either

$$w^T x_i - b \geq 1,\ if\ y_i = 1 \tag{19}$$

Or $w^T x_i - b \leq -1 = \ -1$ (20)

Equations 19 and 20 state that each data point must lie on the correct side of the margin. This can be written in reduced form equation as:

$$y_i(w^T x_I - b) \geq 1,\ for\ \ all\ 1 \leq i \leq n \tag{21}$$

The optimization problem can be described by equation 22 below.

$$Minimize \|w\|\ subject\ to\ y_i(w^T x_i - b) \geq 1\ for\ i = 1, \ldots, n \tag{22}$$

The w and b that solve equation 22 determines our classifier. the maximum-margin hyperplane is completely determined by those $\vec{x}_i$ that lie nearest to it. These x_i are called Support Vectors. Authors that have applied this technique in their research, such as (Gestel et al. 2006; Xiao and Fei 2006; Yang 2007; Zhou et al. 2009; 2010; and Ling et al.2012), found it to be robust even in the presence of biased training sample. The main advantages of the SVM model include its flexibility in terms of the threshold separating solvent firms from insolvent firms, and SVMs provide a good out-of-sample generalization.

2.2.6. Decision Tree.

The Decision Tree algorithm belongs to the family of supervised learning algorithms. It is used to solve both regression and classification problems. A Decision Tree aims to create a training model that can predict the class or value of the target variable by learning simple decision rules inferred from preliminary data (training data), (Nwafor 2022). The model uses a decision tree to go from observations about an item (represented in the branches) to conclusions about the item's target value (represented in the leaves).

Tree models where the target variable can take a discrete set of values are called classification trees; in these tree structures, leaves represent class labels, and branches represent combinations of features that lead to those class labels, (Nwafor 202). Decision trees where the target variable can take continuous values are called regression trees.

The decision tree algorithm aims to estimate a set of if-then logical conditions that allow predicting or classifying cases (Louzada et al., 2016). The following studies have applied this statistical model: Kao et al. (2012), John et al. (1996), and Bijak and Thomas (2012). The following studies have applied decision tree algorithm in bankruptcy predictions: Kao et al. (2012), John et al. (1996), and Bijak and Thomas (2012). The main advantage of this model is that it allows the consideration of as many outcomes of a decision as possible. Decision tree models can also help to weigh the likely consequences of one decision against another. In some cases, they can assist in estimating the expected payoffs of decisions.

2.3. Review of Model Factors and Variables.

Following the seminal work of Beaver (1966), who showed the ability of financial ratios to serve as reliable proxies for measuring risk of financial failure, and of Altman (1968), who first measured the usefulness of multivariate statistical techniques to design forecasting rules, a plethora of studies have studied the variables that are effective in determining financial failure, (Agarwal and Taffler, 2008; Wilson and Sharda,1994; Guan, 1993; Nour 1994). Other studies focus on the factors that may influence the accuracy of a model (Karels and Prakash, 1987; du Jardin, P., 2009). The most common factors are sample size, the relative size of each group (bankrupt vs non-bankrupt) in a sample, the data collection horizon, misclassification cost, and the forecast period.

In this section, we discuss some of the common variables used in bankruptcy prediction studies. Our review shows that most Bankruptcy Prediction studies use quantitative variables, usually in the form of financial ratios. The table below shows the common ratios that are used.

Net income/Total assets	54
Current ratio	51
Working capital/Total assets	45
Retained earnings/Total assets	42
Earnings before interest and taxes/Total assets	35
Sales/Total assets	32
Quick ratio	30
Total debt/Total assets	27
Current assets/Total assets	26
Net income/Net worth	23
Total liabilities/Total assets	19
Cash/Total assets	18
Market Value of Equity/Book Value of Total Debt	16
Cash Flow from Operations/Total Assets	15
Cash Flow from Operations/ Total liabilities	14
Current liabilities/Total assets	13
Cash Flow from Operations/ Total Debt	12
Quick Assets/ Total Assets	11
Current Assets/Sales	10
Earnings before Interest and Taxes/Interest	10

Table 2.1 Most Common Financial Ratios Used in Bankruptcy Prediction Studies.

Various authors highlighted the need for qualitative macroeconomic variables in bankruptcy prediction models (Alaka et al., 2016; Argenti, 1980; Keasey and Watson, 1987). A firm's economic environment via general indicators such as interest rates, level of inflation, or the business cycle can affect the firm's financial stability. Therefore, some authors include economic indicators as proxies for the business cycle in the model[9].

2.4 Classification Forecast Accuracy Evaluation

While examining the performance of the classification models in bankruptcy prediction modelling, the selection of performance evaluation measures plays a vital role in the final evaluation result. Consequently, the selected evaluation measures should be able to reflect the overall classification performance of the model. A conventional approach to assessing the performance of a default classification model is to consider the number of predicted defaults (or no-defaults) and compare this with the actual number of defaults (or no-defaults) experienced by the lending institution.

2.4.1 Confusion or Error Matrix.

A common means of representing this is a confusion matrix or error matrix, (Stehman, 1997). The confusion matrix comprises four different combinations of predicted and actual values. The first is the true positives (TP) which indicate that the prediction result of the sample is good credit (fully paid) and is consistent with its actual class; false negatives (FN) means that the predicted result of the sample is bad credit (charged-off) but its observed class is good credit.

[9] Some of these studies are discussed in the systematic literature review chapter.

Likewise, false positives (FP) are predicted as good credits but they are actually bad credit while bad credit samples with a predicted result of bad credit are denoted as true negative (TN). The confusion matrix is useful for calculating other performance evaluation matrices including accuracy, recall, precision, specificity, and the area under the receiver operating characteristic curve (AUC-ROC). Accuracy is defined as the correct prediction sample size divided by the total testing sample size, as is shown in equ (23).

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \tag{23}$$

Previous studies suggest that the accuracy performance evaluation metric is sensitive to the composition of the portfolio. It also does a poor job of monitoring scoring models over time when there is a change in the composition of credit portfolios and for comparing classification performances of rating models across different portfolios, (Calabrese 2014). To overcome this shortcomings, the current study uses four additional evaluation measures namely: $F - Measure$, precision, specificity, sensitivity-recall, as well as three visual aids for evaluating the performance of a classification model. The $F - measure$, precision, recall and specificity are calculated as shown in equations (24), (25), (26) and (27).

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{24}$$

$$Precision = \frac{TP}{TP+FP} \tag{25}$$

$$Recall = Sensitivity = TPR = \frac{TP}{TP+FN} \tag{26}$$

$$Specificity = \frac{TN}{TN+FP} \tag{27}$$

2.4.2 Area Under the Curve (AUC).

The visual performance evaluation measures used in this study are the receiver operating characteristics curve (ROC) and its performance index known as area under the curve (AUC), the decile chart and the lift chart. The ROC Curve is used to assess the discriminatory accuracy of the fitted models. The Curve summarizes classifier performance over a range of trade-offs between true positive (TP) and false positive (FP) error rates. It is a plot of sensitivity (the ability of the model to predict an event correctly) versus 1-specificity[10] for the possible cut-off points. In other words, the curve plots the true positive rate versus the false positive rate as the discriminative threshold is varied between 0 and 1, (Sirignano et al, 2018).

The discriminatory ability of the fitted models are used to calculate the fitted probabilities $P(Y = 1|x_1, \ldots, x_P)$. The current paper choses a cut-off point $\pi = 0.5$ this in line with previous studies and classify those observations with a fitted probability above π as positive and those at or below it as negative. The sensitivity is estimated as $sensitivity = P(\hat{y} = 1|y = 1)$ and **Specificity** as $specificity = P(\hat{y} = 0|y = 0)$. A model with good discriminatory ability has an ROC curve which goes closer to the top left hand corner of the plot, where the True Positive Proportion (TP) is 1.0 and the False Positive proportion (FP) is 0. The higher the value of the AUC, the higher the ability of the classifier to discern between the two classes.

2.4.3 Prediction/Classification Errors.

There are two types of errors that may occur in bankruptcy prediction: Type I and Type II errors. Type I error involves predicting a bankrupt company as a non-bankrupt one

[10] The **Sensitivity** is defined as the probability of the prediction rule or model predicting an observation as 'positive' given that in truth $(Y = 1)$. In other words, the **Sensitivity** is the proportion of truly positive observations which is classified as such by the model or test. Conversely the **Specificity** is the probability of the model predicting 'negative' given that the observation is 'negative' $(Y = 0)$.

(misclassifying a failed firm), and Type II error predicting a non-bankrupt company as a bankrupt one (misclassifying a healthy firm). The classification error is specified as:

$$Classification\ Error = \sum_{i=1}^{N} \frac{e_i}{N} \tag{28}$$

Where e_i is the classification error of the company i and N is the sample size.

$$Type\ 1\ Error = \sum_{j=1}^{N_F} \frac{e_j}{N_F} \tag{29}$$

$$Type\ II\ Error = \sum_{k=1}^{N_H} \frac{e_k}{N_H} \tag{30}$$

Where e_j is the classification error of failed company j, N_F the number of failed firms, e_k the classification error of healthy company k and N_H the number of healthy firms. Although both types of prediction errors entail a certain amount of financial loss, Type I errors can result in a more significant financial loss than Type II errors. Therefore, prediction requires a cut-off score, which classifies a company into either the bankrupt or non-bankrupt group with a minimum cost of classification errors.

The goal of supervised machine learning algorithm is to find a model that accurately assigns data to predefined classes. Selecting a classifier that performs optimally requires a set of trade-offs (the so called ‘bias-variance’ trade-off) in model complexity. Using simple parameters may lead to under-fitting while too complex parameters may lead to over-fitting. To test different assumptions most researchers, divide a data set into two parts- a training and validation set. The prediction accuracy is tested on the validation data set.

2.5 Conclusion.

This chapter reviews different bankruptcy prediction models from the earliest days of Altman's Z-Score model. The discussion shows that various authors have developed different bankruptcy prediction models. The Logistic regression that overcomes some of the constraints that discriminant analysis imposes on data is one of the most common models.

An artificial neural network, like discriminant analysis or logistic regression, is also a frequently used classification method in the literature. The neural network does not require distributional assumptions of the explanatory variables and can model all types of non-linear functions between the input and the output of a model. The chapter also presented some of the standard variables used within this knowledge domain and discussed the prediction accuracy tools used in model evaluation. A formal comparison of the logistic regression and the artificial neural network is discussed in chapter 5 of this thesis. The next chapter will review some common bankruptcy prediction theories and the different methods of resolving financially distressed firms.

Chapter 3

Review of Theoretical Developments on Financial Distress and Bankruptcy

3.0 Introduction.

The post-world war great depressions (1920-24) and those that happened after them resulted in failure and reorganization for many corporations around the world (Gordon 1971). The topic of financial distress and corporate bankruptcy resurfaced in the public domain following the 2007 global financial crisis that saw many vulnerable institutions got rescued by the government or file for bankruptcy. The run on the British Bank Northern Rock despite the liquidity support from the Bank of England on the 14th of September 2007 was the first UK bank run for over 140 years (Bank of England). Literature suggests that failure and bankruptcy are preceded by financial distress, and our aim in this chapter is to review the theory of financial distress and bankruptcy.

A review of bankruptcy theories is essential for stakeholders involved in resolving bankrupt firms. Stakeholders engaged in bankruptcy issues need to be aware of the best way to deal with it. Onakoya and Olotu (2017) provided an excellent review of bankruptcy theories. We discussed three main bankruptcy theories:

- Modigliani-Miller theory
- Trade-off theory
- Value-based theory
- Creditors' bargaining theory
- Risk-sharing theory

We will briefly analyse how some of these theories relate to a firm's capital structure. Given that this thesis focuses on corporate bankruptcy, we will also discuss the different methods of resolving financially distressed firms and the associated problems. We highlight the resolution mechanisms in the private domains using corporate finance paradigms to interpret some of the far-reaching developments in financial distress of systemic nature. The rest of the chapter is structured as follows, in section 2, we discuss the institutional features of financial distress and bankruptcy in the UK and U.S. Section three reviews the theories of corporate bankruptcy and distress and examines the challenges of private reorganization.

3.1 Institutional Features of Financial Distress and Bankruptcy.

In the years leading up to the 2007 global financial crisis, the British Bank Northern Rock had expanded aggressively, turning to international money markets to fund its rapid growth. But when problems in the U.S. sub-prime mortgage market began to spread to Europe and other parts of the world in the summer of 2007, this source of financing dried up, and Northern Rock faced a severe liquidity crisis.

The global financial crisis's panic led most national governments to step in and bail out systemically important financial institutions in the U.K. and elsewhere. The determination on the part of the government to prevent a repeat of such bailouts led to the Dodd-Frank Wall Street Reform and Consumer Protection Act (hereafter Dodd-Frank Act) in the U.S.A (Senbet and Wang 2012). and the Banking Act 2009 (the Act), covering England, Scotland, Northern Ireland and Wale, (HM Treasury 2020).

The U.K. banking Act provides for a special resolution regime (S.R.R.), providing the Bank of England, the Prudential Regulation Authority (P.R.A.), the Financial Conduct Authority

(F.C.A.) and Her Majesty's Treasury (the authorities) with tools to protect financial stability by effectively resolving banks, building societies, investment firms, banking group companies and central counterparties that are failing while protecting depositors, client assets, taxpayers and the broader economy. The Dodd-Frank Act in the U.S. purports to overcome the taxpayer bailouts and facilitate orderly distress resolution.

This section reviews the institutional features of financial distress and bankruptcy in the U.K. and the U.S.A. A good understanding of these frameworks is essential to lending institutions and other stakeholders involved in the credit business.

The legal process of dealing with corporate financial distress and bankruptcy in the United States is governed by the Bankruptcy Reform Act of 1978. While in the U.K., the statutory processes available to insolvent companies are set out in the Insolvency Act 1986. Unlike the U.S., U.K. insolvency proceedings are mainly conducted out of court and are heavily regulated. Licensed 'insolvency practitioners' (IPs) are usually appointed to lead the insolvency process. The role of a formal bankruptcy proceeding is to provide a collective procedure for the resolution of impaired contractual claims held against the firm. A bankruptcy filing in the U.K or U.S may be voluntary or involuntary, depending on whether the procedure is initiated by the incumbent management or by the firm's creditors.

3.1.1 Features of UK Insolvency and Bankruptcy.

The four principal types of insolvency proceedings applicable to corporations in the UK are administration, receivership, liquidation and company voluntary arrangements and schemes (Kelly et.al, 2020). We will briefly discuss each of these proceedings in turn below.

Administration. Administration under UK insolvency law is analogous to a Chapter 11 proceeding in the US (to be discussed in the next session). The administration is an insolvency process by which a company is placed under the control of an insolvency practitioner. It is the most prevalent procedure used in UK corporate insolvencies since 2003, taking over from receivership (discussed next). The first objective[11] of any administration is to rescue the company to continue trading as a going concern (Salerno et al 2010).

Suppose the rescue of the company is not possible. In that case, the administrator must aim to achieve a better result for the company's creditors as a whole than would be likely if the company were put into liquidation (paragraph 3(1)(b), Schedule B1). The administrator may pursue a third objective of realising the company's property to make a distribution to the company's secured or preferential creditors (paragraph 3(1)(c), Schedule B1). In the U.K, filing in court of a notice of intention to appoint an administrator triggers a moratorium on creditors' legal actions, which continues even when the company goes into administration. Studies suggest that most U. K administrations result in a sale of the business or liquidation rather than a restructuring (Kelly et.al, 2020).

Receivership: This could be seen as an out-of-court enforcement mechanism used by a secured creditor rather than a restructuring method. The U.K law differentiates between two types of receiverships- Administrative[12] receivership and Fixed-charge receivership (Salerno et al 2010). Administrative Receivership is a process initiated by a secured creditor who doubts a company's ability to repay the sums owed. Administrative receivership allows a secured

[11] The administrator must follow this objective unless he considers that to do so is not reasonably practicable.
[12] Administrative receivership is a remedy available only to a secured creditor of a limited company or a PLC, who has a floating charge over the company's assets and a fixed or floating security over all, or substantially all, of those assets. The security is usually in the form of a debenture

creditor to appoint an administrative receiver in circumstances where they are holding security – most commonly a debenture[13].

Fixed-charge receivership (also known as the Law of Property Act (LPA) is used when a lender has a fixed charge such as a mortgage over property or other assets like intellectual property or the goodwill of a business. The lender can appoint a Receiver to take control of the asset and sell it on behalf of the lender to repay its debt (Kelly et.al, 2020).

Liquidation is a formal process of bringing a business to an end and distributing its assets to the creditors. Liquidation is similar to a US Chapter 7 proceeding (Kelly et.al, 2020). A liquidator is appointed to take control of the company and to collect, realise and distribute its assets. Liquidation can be compulsory or voluntary. A compulsory liquidation is a liquidation by order of the court and is the only method by which a creditor can initiate liquidation. Creditors' voluntary liquidations (insolvent) and members' voluntary liquidations (solvent) require shareholder approval. The company is dissolved once the liquidation is completed.

A *Company Voluntary Arrangement* (CVA) can help a company escape debt by negotiating a formal payment plan with creditors that allows reduced monthly repayments, (Kelly et.al, 2020). The company's directors retain complete control of their company during a CVA, and the business is allowed to continue trading throughout the process. Unsecured debts can be included in the arrangement. The CVA is an option for companies experiencing temporary financial problems and are expected to recover in time and can support the monthly payments.

[13] A debenture is a common method of obtaining security, under which a lender is typically granted both fixed and floating charges over all of a company's assets and undertakings.

The arrangement becomes legally binding for all parties as long as the company maintains the new repayment schedule for the duration once it is approved.

A licensed insolvency practitioner (IP) is appointed to analyse the company's financial position and advise the creditors. The creditors then vote on the CVA, and 75% in value of the unsecured claims of creditors voting in person or by proxy need to be in favour before it's approved.

A major change to the U. K's insolvency regime came into force on the 26th of June 2020. The Corporate Insolvency and Governance Act[14] is the largest change to the UK's corporate insolvency regime in more than 20 years (GOV.UK). The Act introduced new corporate restructuring tools and temporary easements to allow financially distressed businesses the space to get advice and seek possible rescue. One of its major provisions is introducing the new role of a Monitor[15] to oversee the corporate moratorium – an extendable 20 working day period giving businesses protection from creditor action while they seek professional restructuring advice. The Act also introduced restrictions on the termination of contracts for the supply of goods and services. Finally, the ACT includes temporary measures in response to the COVID-19 pandemic[16].

3.1.2 Features of US Insolvency and Bankruptcy.

In the United States, the legal process of dealing with corporate financial distress and bankruptcy is different from that of the United Kingdom. The majority of bankruptcy filings

[14]The Act had a rapid passage through the UK parliamentary process, making its way from first publication on 20 May 2020 to Royal assent on 25 June 2020

[15] A monitor must be a licenced insolvency practitioner.

[16] Interested reader can vist GOV.UK at https://www.gov.uk/government/news/major-changes-to-insolvency-law-come-into-force. For details of the change.

by U.S. businesses are voluntary. The Bankruptcy Reform Act of 1978 provides a liquidation process (Chapter 7) and a reorganization process (Chapter 11) (Senbet and Wang 2012).

Chapter 7 liquidation is similar to the U. K's liquidation process discussed in the previous section. In Chapter 7, liquidation, the court appoints a trustee who closes the firm. The trustee liquidates the firm's assets, and the proceeds are given to the court for distribution to the firm's claimants. The seniority of payment distribution is defined according to the absolute priority rule[17]. In Chapter 7, payoffs to the firm's creditors depend directly on the value that the trustee obtains by liquidating the firm's assets and the assigned seniority of the claim. Chapter 11, on the other hand, deals with the rehabilitation of a financially distressed but economically viable firm. This is analogous to the U. K's Administration.

Once a business enters Chapter 11, the incumbent management prepares a reorganization plan. The plan will propose an allocation of firm value among the existing claimants. Chapter 11's automatic stay provision prevents secured creditors from seizing their collateral and stops all principal and interest payments due to creditors. The provision precludes creditors from cancelling contracts and halts lawsuits against the firm. The automatic stay provision gives the distressed debtor some much-needed breathing room and time to work out a solution.

The voting process for approving a reorganization plan may favour the incumbent management and the shareholders. The Bankruptcy Reform Act of 1978 impacts the balance of power among managers, equity holders, and the firm's remaining stakeholders in economically important and identifiable ways. Given that both the financial distress and bankruptcy regime of both the U.K.

[17] The principle of bankruptcy law that requires the claims of a dissenting class of creditors to be paid in full before any class of creditors junior to such dissenting class may receive or retain any property in satisfaction of their claims.

and the U.S. specifies the set of rules under which claimants bargain for their entitlements, they also influence the behaviour of the various stakeholders outside of the formal bankruptcy process. The next section reviews some of the bankruptcy theories in corporate finance literature.

3.1.3 Theory of Corporate Bankruptcy and Distress.

The bankruptcy problem is essentially an entitlement distribution system involving the distribution of a given asset, which is inadequate to meet all the creditors' demands. The bankruptcy of a corporate impinges upon a diversity of interests, including that of creditors, employees, customers and the community. The most important questions relate to whose interests are more important to safeguard, or should all the stakeholders be treated equally? It is also a fact that all creditors may not recover their claims when a company becomes bankrupt because the assets are insufficient to satisfy all the demands. The theories underpinning bankruptcy is discussed in this section.

We start with the *Modigliani-Miller bankruptcy irrelevance theory*. The seminal work of Modigliani and Miller (1958, 1963) suggests that in perfect and frictionless capital markets, firm value is unaffected by financial policy. It follows that corporate bankruptcy is irrelevant to the value of firms since the investment decisions are entirely separable from the financing decisions. The bankruptcy irrelevance theory suggests that a firm's capital structure determines how the total cash flow is allocated between equity holders and debt holders and thus the risk borne by each class of capital providers. This theory views bankruptcy as a 'transfer' of ownership from equity holders to debt holders when the value of assets drops below the value of debt.

3.1.4. The Trade-off Theory.

Modigliani and Miller (1963) argue that the tax code favours debt over equity financing by allowing interest expenses to be deducted from gross income for corporate tax purposes. An additional pound of debt generates the marginal benefit of a tax deduction without any offsetting cost in this framework. The firm value is maximized by utilizing as much debt as possible to finance corporate investment decisions.

Economists, such as Scott (1976), and Kim (1978), opine that the costs of bankruptcy might cause businesses to consider limits on the usage of debt and the predictions of the tax-adjusted Modigliani-Miller analysis of financial policy. The debt capacity of businesses is limited because they trade-off the tax savings generated by the deductibility of interest payments against the expected value of the costs incurred in the event of bankruptcy.

The *trade-off theory* states that the optimal capital structure is a trade-off between interest tax shields and the cost of financial distress (Kraus and Litzenberger 1973, Scott 1976, and Kim 1978). An essential purpose of the theory is to explain the fact that corporations usually are financed partly with debt and partly with equity. The theory states that there is an advantage to financing with debt, the tax benefits of debt, and there is a cost of financing with debt, the costs of financial distress including bankruptcy costs of debt.

Leland (1994) developed a unified analytical framework with closed-form solutions to understand the value of corporate debt and optimal capital structure. His model shows that the trade-off between the tax benefit of debt and the bankruptcy costs determines the value of the corporate bond, the bond yield, the optimal leverage ratio, and the optimal timing of bankruptcy. Leland's model also provided essential insights about the trade-off between the tax benefit of debt and the agency cost of debt.

According to the author, when firms face financial distress and bankruptcy, equity holders may have an incentive to increase the firm's risk via asset substitution- that transfers wealth from bondholders to equity holders. Corporate bonds should come with covenants that prohibit equity holders from profiting by increasing firm risk to mitigate this agency problem. Consequently, protected debt may be the preferred form of financing for firms more exposed to the agency cost of debt.

Potential direct bankruptcy costs include-court fees involving third party advisors to the firm, such as lawyers, tax accountants, trustees, etc. Indirect bankruptcy costs may be in the form of inefficient investments induced by the reorganization process and costly disruptions in the firm's relationship with stakeholders, such as capital providers, customers, suppliers, and employees. Senbet and Wnag (2012) argue that if there are market mechanisms that allow firms to escape the costs of bankruptcy, then bankruptcy has no impact on corporate capital structure decisions, even in an imperfect world. But if bankruptcy costs are not easily avoidable, then almost all dimensions of the firm's financial contracting decision are impacted.,

Consequently, in deciding on an optimal capital structure, the firm needs to balance between the potential cost of becoming bankrupt and the cost of equity capital. If the bankruptcy cost far outweighs the cost of equity capital, then the company will use more equity in financing its operations.

3.1.5. Value-Based Theory.

The value-based theory was propounded by Korobkin (1991). This theory suggests that a mere economic account of bankruptcy may be flawed and needs to be understood in terms of all its facets. The theory views the emergence of the bankruptcy law as a system with wide-ranging forms, proportions and magnitudes. According to Korobkin (1991), bankruptcy law should consider the distributional impact of winding up a corporate entity on those not technically creditors and who may not have formal legal rights to the business's assets. In other words, bankruptcy law should consider and resolve the multidimensional, social and political issues arising from the financial stress of a firm. Given that each claimant would necessarily possess a conflict of interest, the law should allow them to derive optimum value. The value-based theory focuses on the value maximisation aspect of bankruptcy law and how it should strive to distribute the value most efficiently amongst the stakeholders.

3.1.6 Creditors' Bargaining Theory.

The Creditors' Bargain theory of bankruptcy was developed by Jackson (1982). The theory postulates that the main objective of bankruptcy law is to maximise the collective return to creditors through a compulsory collective system. According to the theory, the central aim of the bankruptcy process is to regulate the inherent conflicts among different groups having separate claims against a debtor's assets and incomes. The theory posits that secured and unsecured creditors may act differently, preferring liquidation or reorganisation to suit their interests and maximum recovery. The theory, therefore, suggests that bankruptcy law should provide incentives for creditors such that each of them finds it optimal either to wait or to collect their share immediately with the central objective of maximising the total welfare of the group as a whole.

Indeed, the creditors' bargain conception focuses on maximising group welfare through collectivisation. According to Shekar and Guru (2020), the theory is based on the idea that bankruptcy law generally reflects the hypothetical creditors' bargain that creditors would reach if they were to bargain before their extensions of credit. The essential point from our discussion is that when companies cannot pay their debts, they may have limited options in the future. One of such options is bankruptcy. Bankruptcy in the U.S and the U.K frees a company from its debts and other obligations while giving creditors an opportunity for repayment. Lending institutions should consider the level of debt in a company's capital structure in addition to using the bankruptcy/credit scoring model.

3.1.7. Risk-sharing theory.

Jackson and Scott (1989) modified the Creditors' Bargain theory considering the gap that presumes that creditors would agree to change pre-existing contractual priorities. The risk-sharing theory argues that all types of investors in a business entity, including bondholders, equity investors and creditors, need to be compelled to share the risk of loss from the debtor's insolvency to maximise the value of available assets and resources of the debtors. Miles (2011) suggests that the two types of such risks include *economic-wide/industry-specific/government policy risks* which are exogenously determined and are outside the control of the management, and *company-specific risks* relating to endogenous sources. According to Shekar and Guru (2020), the creditors can bargain and choose to bear one or other type of risk. The bankruptcy law can provide a manner in which this sharing of the risk of bankruptcy is managed so that all participants can obtain optimum value.

3.2 Methods of Resolving Financial Distress/Bankrupt Firms.

The critical role of exit mechanisms for businesses was first highlighted by Joseph Schumpeter, the 20th-century economist, who argued that innovation by entrepreneurs leads to what he described as '*creative destruction*. Schumpeter (2003) suggests that Capitalist reality is first and last a change process. For this change to be facilitated, entrepreneurs need to be provided with easy entry and exit opportunities from the markets, Schumpeter (2003). The essential purpose of bankruptcy law is to provide an orderly process for such an exit.

This section reviews different methods of financial distress resolutions outside the bankruptcy system. Corporate managers facing financial distress could use- debt restructuring, asset sale, and infusion of new capital from outside sources. According to Haugen and Senbet (1978), these private reorganisation mechanisms provide a more cost-efficient method for resolving financial distress. We discuss the three ways in turn below.

3.2.1. ***Debt restructuring*** allows a financially distressed debtor company to renegotiate with its creditors to modify an outstanding debt contract's term(s) to reduce its debt obligations and improve its overall financial conditions (Katchova and Dinterman 2017). It is noteworthy that publicly and privately-held debt contracts are subject to different disclosure and regulatory constraints. Consequently, the set of feasible debt restructuring techniques outside of formal bankruptcy proceedings largely depends on whether the debt obligation is public or private.

The majority of debt restructurings involve corporate firms that are over-leveraged and unable to service current debt levels. Restructuring plans may prevent value erosion in the form of formal insolvency/bankruptcy procedure and ensure that a fundamentally viable business continues to comply with its debt obligations. Debt restructurings may involve one or more of the following approaches: a covenant waiver and reset; a debt rescheduling; a new debt injection; a refinancing by new lenders; a debt for equity swap, amongst others, (Baker 2020). Whether one of these approaches is acceptable to the lender will depend on the circumstances. For them to be possibilities, the lender will need to recognise that the distressed position of the borrower is a temporary one.

3.2.2. ***Sale of Assets***: As discussed in chapter one of this thesis, the COVID-19 pandemic has resulted in an unexpected and unprecedented disruption for many companies. As a result of the economic downturn, some affected companies face a liquidity crunch that could threaten the viability of their businesses in the future. Since companies are required to commence the payment of their debt obligations, illiquid companies may be required to consider formal reorganization proceedings such as Chapter 11 bankruptcy filings to preserve going concern values of their business and assets. Companies may decide to sell assets as an alternative to a debt restructuring to relieve their financial distress.

Selling assets can help distressed companies eliminate unprofitable business divisions and sell properties that no longer fit into the company's goals, transforming those assets into cash at a time when other sources of liquidity may be unavailable. Indeed, a partial sell-off of the existing assets can generate some money that can be used to reduce outstanding debt or to look for new investment opportunities.

It is important to note that the firm's weak financial situation/position may severely weaken its bargaining position in an asset sale. In addition, if the sale is conducted under duress from the firm's creditors, the outcome may be that the price received is less than the asset's value under current management by the distressed firm. Lenders tend to favour asset sales because it effectively accelerates the future cash flow stream from the assets. Therefore, the net result of the transaction would be a wealth transfer from equity holders to debt holders in addition to a reduction in the aggregate firm value.

3.2.3. ***Infusion of New Capital from Outside Sources***: This is the final method of financial distress resolutions outside the bankruptcy system. Myers (1977) suggest that in the event of financial distress, seeking funding from outside sources may be challenging to obtain due to the high risk involved in lending to the distressed firm and the problem of "debt overhang". According to Myers (1977), the debt-overhang problem arises because a disproportionate amount of the economic gain from the incremental investment accrues to the existing senior financial claimants, making it difficult for the distressed firm to attract new junior funding sources.

According to Stulz and Johnson (1985), a financially distressed firm that suffers from a lack of liquidity may consider asset-based and secured debt financing. Although, the feasibility of this approach would depend on the availability of collateral to pledge and an understanding of the additional restrictions imposed by the new creditors.

Given the abovementioned challenges, Senbet and Wnag (2012) suggest an alternative financing method- debtor-in-possession financing (DIP financing). According to the authors, DIP financing is a unique form of financing provided for companies under Chapter 11 bankruptcy protection. DIP financing is more senior than debt, equity, and any other securities issued by the distressed firm. It gives the distressed firm a new start under stringent conditions.

3.3 Private Workouts and The Bankruptcy Costs.

Haugen and Senbet (1978), in their theoretical analysis of the link between private workouts, bankruptcy costs, and firms' financial policy decisions, posit that the costs of financial distress are insignificant to the theory of capital structure. Their idea was based on Modigliani and Miller's no-arbitrage approach. According to the author's, the present value of the transaction costs associated with an informal reorganization are insignificant at the time of the firm's initial capital structure decisions.

Therefore, rational claim holders will agree to restructure via a private workout to avoid the costlier formal bankruptcy procedure. Given that informal restructuring represents a cost-efficient alternative to formal bankruptcy proceedings, claim-holders tend to favour private workouts over the traditional court system. Authors such as (Roe 1983; and Jensen 1989) supports the notion of privatization of bankruptcy. Academic literature has identified three major impediments to private resolution of financial distress to include- holdout problem, information asymmetry and conflicts of interest, Senbet and Wnag (2012). We will discuss these three factors in turn below.

3.3.1 Holdout Problem: A holdout problem occurs when a bond issuer is in default or nears default and launches an exchange offer in an attempt to restructure debt held by existing bondholders. Such exchange offers require the consent of holders of a minimum portion of the total outstanding debt, often over 90%. Unless the bond terms provide otherwise, non-consenting bondholders will retain their legal right to demand repayment of their bonds at par or the full face amount. Claimholders who retain their right to seek the full repayment of original bonds may disrupt the restructuring process by seeking the full payment through the threat of litigation, creating the so-called holdout problem (Tamura 2004). According to Senbet and Wnag (2012), Some bondholders may choose to holdout in the expectation that the post-offer value of their claim will exceed the value of participating in the exchange.

Financially distressed firms may use coercive techniques to mitigate the potential holdout problems and enhance the chance of a successful exchange offer. The coercive methods include offering new bonds with higher priority or shorter maturity than the existing debt. Current bondholders may be willing to participate in an exchange offer because they fear that holding out will make their claims junior to the new securities.

It is important to note that the covenants in existing debt contracts may limit the ability of the financially distressed firm to issue new securities. A distressed firm may solicit exit consent to eliminate restrictive bond covenants. Such distressed firms can design financial restructuring programs that strip the protection of existing bond indentures and coerce participation in tender or exchange offers.

3.3.2. Information Asymmetry: Information failure or asymmetric information exists in any transaction where one party knows more about the asset's true value than another party. Corporate managers are assumed to possess private information about the actual economic value of the firm than outside investors. Firm insiders may be incentivized to misrepresent the firm value to convince bondholders to agree to exchange their existing claims for lower-valued securities.

The asymmetric information problem suggests that a more significant proportion of fixed income securities offered in a distressed exchange offer should contain contingent payment features. Since the future values of contingent payment securities will adjust readily to the revelation of information about the firm's true value. According to Giammarino (1989) the presence of asymmetric information distressed firms may forgo an informal debt restructuring and incur high bankruptcy costs by entering the formal reorganization process to resolve financial distress. The presence of asymmetric information may cause debt holders to prefer the uncertain allocation outcome of a legal bankruptcy procedure rather than corporate managers in an informal reorganization.

3.3.3 Conflicts of Interest. The bankruptcy of Eastern Airlines in 1989 is a typical example of how the conflicting interests between creditors and equity holders can severely distort the distress resolution process (Weiss and Wruck 1998). The conflicting incentives of various claim holder classes make the reorganization difficult. The allocation of wealth across different claimants in a private reorganization of a financially distressed firm is an outcome of a bargaining process. The estimates of a financially distressed company's going-concern value are used to set the payoffs to each class of claimants during the process of distress resolution.

Consequently, the debate over the estimate of the firm's value reflects differing information and conflicting interests of different classes of claimants. Each of the claimants may have an incentive to present a biased estimate of the value of the business depending on the priority of their claims. For instance, junior claimants may favour upwardly biased estimates of the firm value because this increases the proportion of their value. On the other hand, the senior claimants may prefer downwardly biased estimates because this allows them to retain a more significant portion of the firm if the firm subsequently performs well. In addition, the managers may be incentivised to value the firm above its liquidation value to protect their jobs.

The study of Brown (1989) examines how conflicts of interest among claimholders can distort the resolution of a financially distressed firm in an informal reorganization. According to Brown (1989), inter-group conflicts arise because allocation to one claimant class under any given reorganization plan can be increased at the expense of another claimant class. It is essential to mention that the abovementioned impediments of private reorganization do not necessarily render bankruptcy costs significant to the theory of optimal capital structure, since there are ways of mitigating them.

This chapter reviews the main bankruptcy theories, including the Modigliani-Miller theory, the trade-off theory, and the value-based theory, amongst others. Also, we discussed some of the main methods of resolving financially distressed firms and the challenges of private reorganisation. The next chapter focuses on the systematic literature review and meta-analysis of the analytical tools in predicting corporate bankruptcy.

Chapter Four

Chapter Four Systematic Literature Review and Meta-Regression

4.1. Introduction.

The year 2018 marked the 50th anniversary of the publication of Prof. Edward Altman's landmark article that uses multidimensional discriminant analysis to forecast corporate bankruptcy. Fifty-three years after his publication, predicting corporate bankruptcy is still an essential issue in corporate finance literature. The ability to predict business failure is crucial in financial decision-making, and is particularly important to lending institutions, rating agencies, and other corporate stakeholders (Altman et al. 2017). Given the importance of bankruptcy prediction in lending and credit risk analytics, numerous researchers have researched the predictive abilities of different tools used in empirical literature to predict corporate bankruptcy[18].

A large body of literature is devoted to predicting the risk that corporate firms will go bankrupt. The two popular approaches are statistical tools (Ohlson 1980); and machine learning tools (Balcaen & Ooghe, 2006; Jo & Han, 1996). The common statistical tools are the Multiple Discriminant Analysis (MDA) and the Logit models. And the standard machine learning tools are the Artificial Neural Networks (ANN) and the Support Vector Machines (SVM) (Aziz & Dar, 2006; Tseng & Hu, 2010; Kim et al. 2018; Vochozka and Machová 2018; Machová and Vochozka 2019; Krulický 2019; Horak, Vrbka, Suler 2020). The ability of these machine

[18] We discussed the literature on some of the bankruptcy prediction models in chapter two of this thesis.

learning models (SVM and ANN) to generalize and to learn is one of their main advantages to traditional methods of corporate bankruptcy prediction tools.

The literature on the methodological issues and the comparative predictive ability of various corporate bankruptcy prediction models is well-documented in many studies. For instance, Taffler (1984) analysed the UK Z-score models and suggested the need for accurate validation samples in assessing the models' predictive performance. Zmijewski (1984) highlights the problem of sample selection biases, while O'Leary's (1998) suggests that the proportion of bankrupt firms in the data could influence the quality of the results. Perez (2007) reviewed thirty studies that used Neural Networks to discriminate between healthy and failing firms. Ravi Kumar and Ravi (2007) provided a comprehensive review of the work done during 1968–2005. Lin et al. (2011a) provided a statistical survey of papers predicting bankruptcy and credit scoring published between 1995 and 2010.

The plethora of statistical and machine learning models within this field and the apparent lack of consensus regarding model development's methodological issues led to adopting a systematic literature review (SLR) methodology. For example, (Appiah, Chizema, and Arthur, 2015) employed the SLR to review the methodological challenges highlighted in the existing literature to improve our understanding of these issues. The systematic literature review of Alaka et al. (2017) reviewed 8 popular tools that previous studies used to develop Bankruptcy Prediction Models between 2010 and 2015.

These tools include multiple discriminant analysis (MDA) and Logistic regression (LR), Artificial Neural Network (ANN), Support Vector Machines (SVM), Rough Sets (RS), Case-Based reasoning (CBR), Decision Tree (DT) and Genetic Algorithm (GA); and concluded that no single tool is primarily better than other tools in relation to the 13 evaluation criteria they employed in the study. However, their study showed the ANN and SVM to be the most accurate while MDA appears to be the least accurate. Kirkos (2015) presented a review of forty-two papers published between 2009 and 2011 and highlighted the difficulties in comparing the performance of different models, given that several factors can affect their accuracy levels. The author suggested that an accuracy rate between 81% and 90% would reflect a realistic average performance of the models proposed by the studies.

Our systematic literature review shows the Artificial Neural Network (ANN) to be the most popular machine learning algorithm that is used in bankruptcy prediction studies. Still, the results from the ANN studies differ in accuracy level and other performance evaluation metrics. This chapter aims to use meta-analysis and meta-regression statistical techniques to combine data from ANN studies on bankruptcy prediction models to test the presence of statistical heterogeneity and explore the possible sources of these variations. Specifically, the research questions that we seek to answer in this chapter are as follows:

1. Is there a presence of statistical heterogeneity in the ANN studies?
2. How much heterogeneity is present (what is the magnitude)?
3. What are the possible causes of the heterogeneity and their effect on the outcome variable (bankruptcy event rate)?

In doing this, the thesis makes the following contributions to the extant literature. First, this is the first study to the best of our knowledge that uses meta-analysis to combine data and summarize the findings of several corporate bankruptcy prediction studies that used the ANN machine learning algorithm. Using meta-analysis is beneficial because it can provide a single numerical value of the presence of systematic heterogeneity and the level of such heterogeneity. Second, given the substantial differences in study event rates observed from the meta-analysis, we empirically explored the potential sources of these variations using meta-regression analysis.

This thesis extends the systematic literature review of Alaka et al. (2018) in the following ways; first, we included bankruptcy prediction studies published between 2016 to 2021; second, we pooled results from studies that met our inclusion criteria and tested for heterogeneity in the studies using meta-analysis. The meta-analysis allows us to quantify an estimate of the pooled event rates of the ANN corporate bankruptcy studies. Given the evidence of significant heterogeneity as reported in the I^2 and chi-square $p-value$, we conducted a meta-regression to explore possible sources of these variations.

Finally, we used meta-regression to empirically examine the effects of the study characteristics such as: *sample size, percentage of failed firms in the sample* and *type of input datasets* on predicting bankruptcy event rate. The findings from the analysis hold practical implications for academic researchers and practitioners alike.

The meta-regression will allow us to evaluate how sample sizes, types of input datasets, validation methods and percentage of failed firms in the samples affect the performance of the Artificial Neural Networks in predicting corporate bankruptcy. These factors can influence a model's performance. Consequently, understanding the percentage of unexplained between-studies variance and the proportion of variance explained by the model will improve our understanding of the between-study differences in bankruptcy prediction studies.

The rest of this chapter is structured as follows; in section 4.2, we discussed the rationale for the systematic literature review (SLR) and the different steps in conducting an SLR. Section 4.3 is our methods and materials section. This section discusses our search strategy and article selections, inclusion and exclusion criteria, data extraction, quality assurance, and narrative synthesis—section 4.4 presents a discussion of the results from the meta-analysis and meta-regression techniques. While section 4.5 presents the conclusions and practical implications for policy and practice.

4.2 Rationale for a Systematic Literature Review (Review Questions).

The rationale for systematic literature reviews (SLR) is grounded firmly in several premises. First, policymakers, researchers and practitioners need to reduce large quantities of information into manageable chunks to aid decision making. Second, decision analysts use systematic reviews to estimate the variables and outcomes that are included in their evaluations. Systematic reviews can also enhance our understanding of between-study variations in a particular knowledge domain. Finally, researchers use SLR to keep abreast of the primary literature in a specific field and to understand covariates that warrant consideration in future studies.

The past four decades have seen a plethora of research around bankruptcy prediction models, often with conflicting results. These between-study variations may be due to study differences or chance (sampling variation). Given the conflicting results, it is not always clear what the overall picture is or which results are most reliable and should be used as the basis for practice and policy decisions. Systematic reviews aim to address the challenges of between-study differences by identifying, critically evaluating and integrating the findings of all relevant individual studies addressing similar research questions. Figure 4.1. below presents the steps in a systematic review of literature.

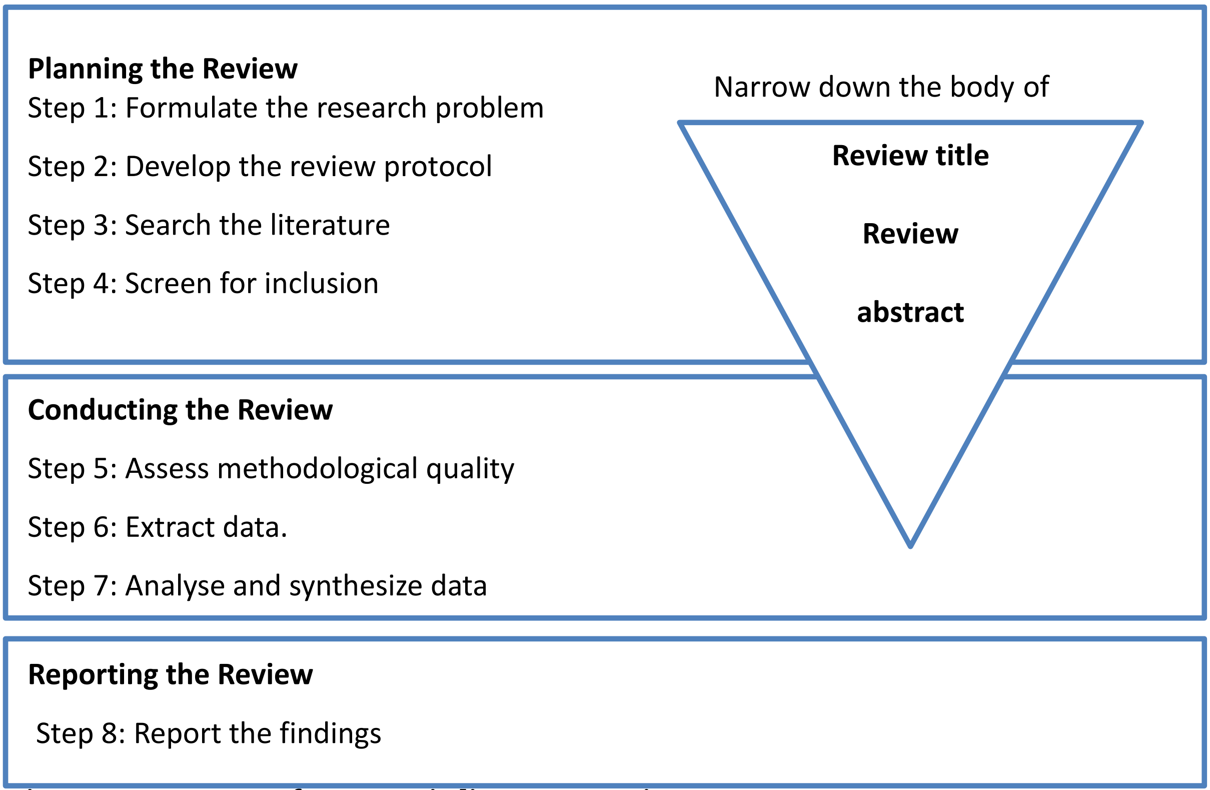


Figure 4.1: Process of systematic literature review

This systematic literature review (SLR) allows us to provide syntheses of the state of knowledge in the bankruptcy prediction field for the purpose of identifying future research priorities. A systematic review can address questions that individual bankruptcy prediction studies may not answer and recognise problems in primary research that researchers should address in future studies. Also, SLRs can generate or evaluate theories about how or why phenomena occur. According to Higgins et al. (2019), a systematic review uses explicit, systematic methods to collate and synthesise findings of studies that address a research question.

A systematic review is a piece of research and, by its nature, can address much broader questions than a single empirical study. For instance, a systematic review can identify connections/relationships among many empirical findings (Baumeister & Leary, 1997). Indeed, systematic reviews are above all other research designs at the top of the 'hierarchy of evidence' because they can provide the most important practical implications. The explicit methods used in systematic reviews limit bias and improve conclusions' reliability and accuracy.

In this thesis, we used a systematic literature review for the following purposes-

1. To evaluate the extent existing research has progressed in using statistical and machine learning tools in developing models that can predict corporate bankruptcy.
2. To identify study characteristics that could influence model performance.
3. To evaluate the performance ability of different bankruptcy prediction models using the percentage accuracy levels and type I and type II errors in their models.

In doing so, we provide implications for practice and discuss directions for future research.

We used a meta-analysis to provide quantitative evidence of the presence of systematic heterogeneity. A meta-analysis is a statistical assessment of the data provided from multiple studies that attempt to address a similar research question (Page et al. 2020). Unlike conventional research methods, a meta-analysis uses the results or summary statistics from individual studies as the data points (Page et al. 2020). The present research uses meta-analysis to present potential readers with the estimate of heterogeneity in existing studies-thus extending the scope of earlier reviews that have attempted to evaluate evidence using a narrative synthesis and summary of findings approach (Kirkos 2015; Appiah, Chizema, and Arthur, 2015; and Alaka et al. 2018).

4.2.1. Formulation of the Study Hypotheses.

Predicting corporate bankruptcy is one of the most critical problems facing lending institutions the world over. The 2007-2009 global financial crisis is an example where bankruptcies cost the United Kingdom billions of pounds. The International Monetary Fund estimated that large U.S. and European banks lost more than $1 trillion on toxic assets and bad loans from January 2007 to September 2009 (Gomez 2011). The effect of a high rate of corporate defaults can be devastating to the business owners, partners, staff members, the lending institution, and the economy.

The corporate bankruptcy prediction knowledge domain continues to evolve with new predictive models developed using various statistical and artificial intelligence tools. Nevertheless, there appears to be no consensus on the best statistical algorithm for predicting corporate bankruptcy. To ensure that a loan default model performs well regarding the performance evaluation criteria of preference, users and modellers alike need to understand the strengths and weaknesses of the most commonly used techniques.

The previous studies suggest Artificial Neural Networks as one of the most commonly used machine learning algorithms in bankruptcy prediction models. However, very few papers have tested these studies for the presence and sources of statistical heterogeneities, except for the study by Leary (1998) that compared fifteen Neural Network studies for their formulations, including aspects such as the impact of using different percentages of bankrupt firms, the input variables, training and testing and statistical analysis of results.

The study extends the findings from previous studies in this area by conducting a Meta-Regression to test the impact of the proportion of bankrupt firms, sample size, validation methods and type of input variables, amongst others, on the model.

A fundamental assumption of meta-analysis and meta-regression is that studies included in the analysis must address identical/similar research question(s). To achieve this aim and adhere to the assumption, we used findings from comparative bankruptcy prediction studies that reported the Artificial Neural Network (ANN) as the method with the best forecast accuracy. Specifically, the meta-analysis allows us to address the following research questions-

1. Is there a presence of statistical heterogeneity in the ANN studies?

We formulate the first hypothesis for the study as follows:

$H_0 =$
$There\ is\ no\ evidence\ of\ statistical\ heterogeneity\ in\ ANN\ studies\ given\ no\ relationships\ in\ the\ studies.$

$H_1 = There\ is\ evidence\ of\ statistical\ heterogeneity\ in\ ANN\ studies.$

Anecdotally, we expect to find some level of between studies heterogeneity given that different studies use different datasets, different input variables and different sample sizes. If we reject the null hypothesis of no between studies heterogeneity, we would proceed to test the size /magnitude of the study variations. Therefore, the second research question addresses the magnitude of the heterogeneity in the studies included in the meta-analysis.

2. If there is statistical heterogeneity, what is the magnitude of heterogeneity?

We formulate the second hypothesis as follows:

$H_0 = \ The\ magnitude\ of\ the\ heterogeneity\ is\ zero.$

$H_1 \neq \ The\ magnitude\ of\ the\ heterogeneity\ is\ not\ zero.$

In addition, a meta-regression is used to explore the potential sources of between-study differences in the pooled ANN studies. We used a multivariate meta-regression model to address the following research questions:

3. Can some of the ANN studies' characteristics, including sample size, percentage of failed firms, and type of input datasets, explain between-study differences?
4. What percentage of unexplained between-studies variance are explained by the regression model?

To answer the above research questions, we specified the equation model below:

$$Event\ Rate_i = \alpha_i + \beta_i' X_i + \varepsilon \tag{31}$$

Where,

$Event\ Rate$ denotes the Effect Measure (number of bankrupt firms), α is the regression intercept, and $X_i's$ is a vector of the covariates in the model including: $sample\ size,$ $input\ data\ type,\ model\ validation\ method,\ proportion\ of\ failed\ firms.$ and ε is the error term.

And tested the additional hypothesis:

$$H_0 = Sample\ size, percentage\ of\ failed\ firms, and\ type\ of\ input\ datasets\ do\ not\ explain\ variations\ in\ the\ prediction\ accuracy\ of\ ANN\ models$$

$$H_0 = 0$$

The null hypothesis above suggests that there is no statistical relationship between the study characteristics listed in equation 31 and the prediction of the event (bankruptcy). While the null hypothesis postulates a significant statistical relationship.

$$H_1 = Sample\ size, percentage\ of\ failed\ firms, and\ type\ of\ input\ datasets\ do\ not\ explain\ variations\ in\ the\ prediction\ accuracy\ of\ ANN\ models$$

$$H_1 \neq 0$$

The results from these analyses will help future developers of bankruptcy prediction tools using the Artificial Neural Network algorithm to pay close attention to the study characteristics that could have the highest impact on the model's performance ability and also understand the limitations of the model.

4.3. Methodology.

Relevant studies in bankruptcy prediction studies were obtained by systematically searching several online databases. In line with Alaka et al. (2018), we limited our search to studies that used the following tools, logistic regression, artificial neural network (ANN), support vector machines (SVM), rough sets (RS), case-based reasoning (CBR), decision tree (DT) and genetic algorithm (GA). The review adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009).

In this section, we discuss the search strategy, search terms/string and limits used, inclusion/exclusion criteria, how studies were screened, data extraction, how disagreement of inclusion was decided between reviewers, and quality assessment method. We also provide a flow diagram that describes the identification, screening, eligibility and inclusion stages, with the number of studies included and excluded at each stage, along with reasons for exclusion during the eligibility full-text versions of articles.

4.3.1. Inclusion and Exclusion Criteria.

This study uses meta-analysis to test for the presence of statistical heterogeneity and meta-regression to explore the sources of these heterogeneities in studies that found the artificial neural network to have superior predictive accuracy. Given the large numbers of statistical and machine learning tools used in bankruptcy prediction studies, we limited our search to articles that used the multiple discriminant analysis (MDA), Logistic regression (LR), artificial neural network (ANN), support vector machines (SVM), rough sets (RS), case-based reasoning (CBR), decision tree (DT) and genetic algorithm (GA). Studies were included if they used or compared any of the aforementioned tools.

Figure 4.2 below presents a PRISMA flow diagram for the eligibility of studies included in the narrative synthesis. Only peer-reviewed articles were considered in line with previous reviews. The inclusion of peer-reviewed articles would enhance the validity of the studies, Alake et al. (2018). Although language constraint is not encouraged in a systematic review, the inability of the researchers to pay for translation services meant that we had to restrict our search to studies published in the English language (Smith et al., 2011).

Search Strategy: Electronic databases, including Wiley Interscience; Science Direct; Web of Science UK (WoS); ProQuest and Business Source Complete (BSC). Google Scholar was not used because it produced an almost endless result and did not have the required filters to remove irrelevant articles. In line with Alake et al. (2018), we used the Engineering Village (EV), Web of Science UK (WoS) and Business Source Complete (BSC) in our final searches.

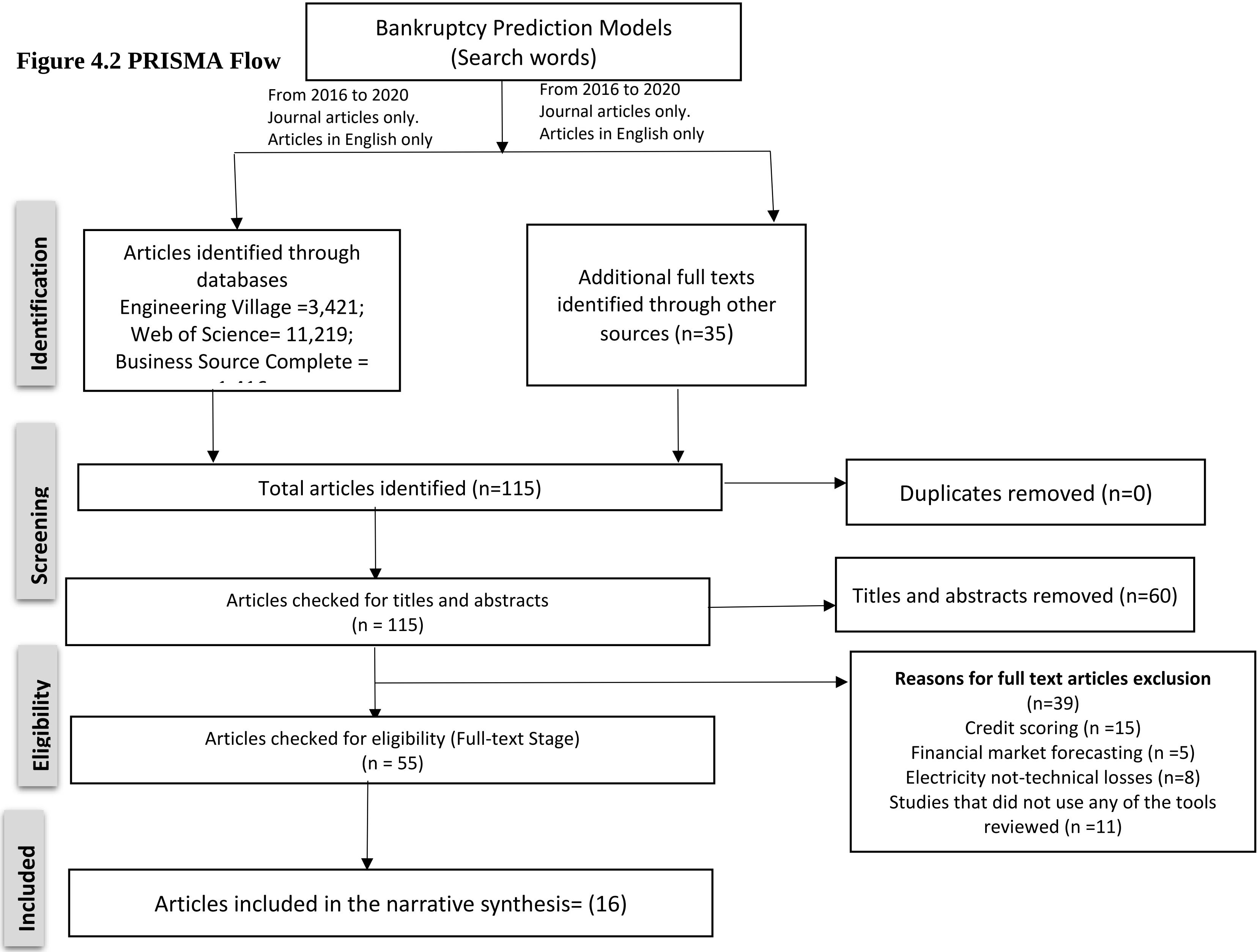
In extending the systematic literature review of Alake et al. (2018), we restricted our searches to studies published between 2016 to 2021. Previous studies use bankruptcy, insolvency and financial distress as synonyms for company failures. We designed a search framework that captured all these words with the following defined string ("Forecasting" OR "Prediction" OR "Predicting") AND ("Bankruptcy" OR "Insolvency" OR "Distress" OR "Default" OR "Failure"). Titles and abstracts were screened for potentially eligible studies in the initial phase. In the second phase, we read full texts of the remaining articles to determine if they meet the inclusion and exclusion criteria (the student and the supervisor did all the screening).

We found Three Thousand Four Hundred and Twenty-One studies from the Engineering Village database. For the Web of Science, we found Eleven Thousand, Two Hundred and Nineteen articles, and for the Business Source Complete, we found One Thousand Four Hundred and Sixty articles. Based on screening titles, irrelevant articles were removed. Studies such as Botchey et al. (2020), Lee and wang (2020) and Yeom et al. (2019) were removed based on titles. After eliminating studies based on title, we scanned the remaining studies for abstract relevance. Studies such as Herzog et al. (2020), Mitrovic et al. (2020) and Fu et al. (2020) were removed based on abstract relevance. One hundred and fifteen articles were left after removing irrelevant studies.

The topics of papers that emerged after our screening looked okay to determine which ones were fit for this analysis. We uploaded the remaining articles into RefWorks a reference management tool used for creating database by importing references from text files or online databases to remove all duplicates. The final number of articles relevant to the research question was sixteen. There were no duplicates found in RefWorks, so the sixteen articles were exported to excel. There were no disagreements regarding the eligibility of studies, as these were agreed upon before commencing the review. Figure 5.2 below shows the PRISMA flow diagram for studies eligibility for the narrative synthesis and table 1 shows the study characteristics.

We included studies that reported the ANN as the best bankruptcy prediction accuracy tool. To qualify for inclusion in the meta-analysis and regression, studies need to meet our methodological quality assessment criteria. None of the final sixteen studies published between 2016 and 2021 reported these criteria. Consequently, we extracted data from Alake et al. (2018) study. First, we discuss the methodological appraisal tool we used in this thesis and present the study characteristics in the next section.

Figure 4.2 PRISMA Flow



4.3.2 Narrative Synthesis 2016 to 2021 Studies

This section aims to provide a narrative synthesis of some of the sixteen studies from the systematic literature review from 2016 to 2021 to facilitate future research in this area. The summary of the reviewed studies aims and the types of bankruptcy prediction tools used are presented in table 4.1. For this narrative synthesis, we focus our discussion on the following, study objective, input datasets used, model validation method and findings.

Khoja et al. (2016) examine the predictive ability of 28 financial ratios using the logistic regression model in the Gulf region. Using a sample of 112 firms, the authors show that profitability ratios, leverage ratio and cash flow ratio can predict insolvency with accuracy rates of 84.8%, 95.6% and 73.9% respectively. DuJardin (2016) compares the bankruptcy predictive ability of single and ensemble models in a sample of bankrupt and non-bankrupt French firms. The author reveals that the ensemble models have better predictive power than the single models.

Singh & Mishra (2016), using a sample of 208 Indian manufacturing companies, tested the predictive accuracy of the Multiple Discriminant model (MDA), Probit and Logit models. And found the MDA has an accuracy rate of 88.462%, probit has a rate of 76.923% and the logit model has a rate of 64.103%.

Barboza et al. (2017) tested machine learning models, particularly support vector machines, to predict bankruptcy one year before the event and compare the results with discriminant analysis, logistic regression, and neural networks. The study analysed more than 10,000 firm-year observations based on North American firms. This study concluded that machine-learning techniques show approximately 10% accuracy more than the traditional models.

Fallahpour et al. (2017) tested the predictive accuracy of Sequential Floating Forward Selection (SFFS) and Support Vector Machine (SVM) technique to predict corporate bankruptcy using 29 financial ratios as input variables. The authors used firms listed on Tehran Stock Exchange. The findings demonstrated that SFFS combined with SVM yields higher accuracy (95% on average) than any other feature selection algorithm. Also, SVM yields 83.33% accuracy on average as a model to predict distress.

Halteh et al. (2018), in their contributions, used data set comprising 101 international publicly listed Islamic banks to test the bankruptcy predictive power of some financial ratios using decision trees, stochastic boosting and random forests models. This paper found that variables such as working capital/total assets, current ratio, debt ratio and retained earnings/total assets were most significant for the decision tree model. Germano (2018) proposes an improved Bayesian approach to regularize feed-forward neural networks. The author used corporate and retail firm's datasets. The paper found that the improved Bayesian approach performed well when compared to the classical regularization approach for neural networks.

The 2019 studies we found tested the predictive accuracies of different bankruptcy prediction tools in Pakistan firms Ahraf et al. (2019), Greek firms (Charalambakis and Garrett, 2019), Spanish firms (Munoz-Izquierdo 2019), and (Korol 2019) European firms. Ahraf et al. (2019) compare the prediction accuracy of traditional bankruptcy prediction models for the companies at early and advanced stages of failure in Pakistan. Their results suggest that the Z-score model more accurately predicts insolvency for both types of firms, those at an early stage and those at an advanced stage of financial distress.

The study by Charalambakis and Garrett (2019) applies an extensive data set of 31000 Greek private firms to examine the determinants of the probability of corporate financial distress. The authors use a multi-period Logit model and the following input variables; profitability, leverage, the ratio of retained earnings-to-total assets, size, liquidity ratio, an export dummy variable, tendency to pay dividends and the growth rate in real GDP to predict financial distress. Their results suggest that these variables performed well in classifying bankrupt firms in their out-of-sample model.

Munoz-Izquierdo (2019) examines the explanatory power of the external audit report in predicting corporate bankruptcy. The author employed the PART algorithm, random forest and support vector machines on 808 private non-financial Spanish companies. The study reported an 81% Classification accuracy results for PART algorithm model. Robustness checks to ensure reliability of the empirical evidence, were performed using the random forests and SVM algorithms. According to these machine learning techniques the ability to anticipate bankruptcy for the audit report variables of this study was robust.

Korol (2019) aimed to develop and evaluate dynamic bankruptcy prediction models for European enterprises. The author used fuzzy sets, recurrent and multilayer artificial neural networks and decision trees algorithms and found that the Fuzzy sets have the highest bankruptcy predictive ability. Horak et al. (2020) created a model for predicting the potential bankruptcy of companies using SVM and ANN. The study's findings showed that SVM gives a relatively high accuracy level of 99.39% compared to ANN, which showed 82.79% accuracy.

However, the research in this study showed that neural networks could resolve some of the defined problems – the algorithm can adapt to a new environment by retraining it on a dataset sample of a given market. Due to its ability to meet the requirements for changing the setting of its internal parameters, the neural network can thus be considered flexible and widely applicable. Zizi et al. (2020) took a slightly different approach by studying the determinants and predictors of bankruptcy in 90 SMEs using logistic regression. Their findings show that autonomy ratio, interest to sales, asset turnover, days in accounts receivable and duration of trade payables increase the probability of default while return on assets and repayment capacity decrease the likelihood of failure. These variables give an overall classification of 84.44% two years and one year before failure.

The study by Shrivastav et al. (2020) analyses the survival probability of the financial firms using the SVM. The study uses a two-step feature selection technique on a sample of 59 private and public sector banks in India. The results reveal that SVM with linear kernel shows 92.86% forecasting accuracy, while an SVM with radial basis kernel function shows 71.43% accuracy. More recent studies, such as Voda et al. (2021), uses the MDA to predict corporate bankruptcy and insolvency risk amongst 80 Romanian firms. The authors used 37 financial indicators and showed that the MDA had an 88.75% accuracy in predicting bankruptcy.

The study of Zulkifli et al. (2021) compares the classification accuracy of corporate bankruptcy predictive models using deep learning models on financial data of 98 firms classified as distressed and non-distressed. The results show that SVM and Logistic regression produced accuracy results such as 83% and 85%, respectively. On the other hand, ANN and DT methods show lower accuracy prediction results at 80% and 78%, respectively.

4.4 Methodological Qualities of Studies included in the Quantitative Meta-Analytics.

We pooled data from eighteen out of the forty-nine articles from the study of Alake et al. (2018)[19]-see appendix 1 for the Summary of reviewed studies aims, variable selection methods, sample characteristics and accuracy values for their study. Table 4.1 below shows a summary of the number of times each tools were used in the reviewed studies.

S/N	Tool	No of authors that used the tool
1	Artificial Neural Network (ANN)	43
2	Support Vector Machine (SVM)	31
3	Decision Tree (DT)	22
4	Rough Set (RS)	4
5	Genetic Algorithm (GA)	10
6	Case Based Reasoning (CBR)	4
7	Multi-discriminant Analysis (MDA)	25
8	Logistic Regression (LR)	43

Table 4.1 Summary of Tools Usage 2010 to 2020 Studies.

Most of the studies reviewed between 2010 to 2020 show ANN to be more accurate on average than any comparing tool and is one of the most popular tools used in developing bankruptcy prediction models (BPMs) alongside the logistic regression. Chen, Yang et al. (2011) reported ANN and SVM as more accurate than GA. Similarly, Kasgari, Divsalar, Javid, and Ebrahimian (2013) proposed ANN for developing bankruptcy prediction models (BPMs) based on the algorithm's accuracy level. As noted in some of the reviewed studies (e.g. Iturriaga & Sanz, 2015; Virág & Nyitrai, 2014), ANN and SVM are the most accurate tools for developing BPMs.

[19] For a detailed narrative and quantitative synthesis of the primary studies, the interested reader can refer to **Alake et al. (2018) Systematic review of bankruptcy prediction models: Towards a framework for tool selection**. *Expert Systems with Applications 94 (2018) 164–184.*

Given the popularity of the ANN as a bankruptcy prediction tool, we explore sources of variations in some of these studies and the potential effects of some moderator variables on the algorithm's predictive accuracy.

In statistical test theory, the notion of statistical error is an integral part of hypothesis testing. The statistical test requires an unambiguous statement of a **null hypothesis** H_0-in this instance, whether a firm will go bankrupt or not. The result of the null hypothesis test may be **positive** (healthy firm) or maybe **negative** (failing firm). Error cost is an essential concept in bankruptcy prediction; hence the tools must be appraised with regards to the errors. We consider the two types of errors in the next paragraphs.

A **type I error** or false positive occurs when the null hypothesis is actually **true** but was rejected as **false** by the testing. Type I error occurs when a tool misclassifies a potentially bankrupt firm as healthy. Type 1 error has severe consequences for the lender or firm. It could cause the lender to lend money to a failing firm and eventually lose it. Also, this type of error could make a firm relax when it is supposed to take active steps against insolvency.

On the other hand, a **Type II error** is when a tool misclassifies a non-bankrupt firm as potentially bankrupt/failing. This error is less costly. Consequently, a tool with relatively lesser type I error is more accurate. Concerning type 1 error rates, the systematic literature review by Alake et al. (2018) shows that ANN has the least average type I error followed by SVM. Since these two machine learning algorithms have the highest performance accuracy, it is plausible to conclude that they are the most accurate tools for bankruptcy prediction.

The GA. DT, and LR errors are close to their accuracy; hence, their total accuracy can be regarded as the same rank. However, MDA appears to be very poor with type I error; therefore, its accuracy is low. ANN, DT, GA and LR have better type I errors than type II errors.

Methodological Quality: The purpose of this appraisal is to assess the methodological quality of the primary studies and to determine the extent to which the studies addressed the possibility of bias in their design, conduct and analysis. We adapted the *Joanna Briggs Institute* (JBI) Critical appraisal tool for assessing the methodological quality of analytical studies that has been successfully employed in prior health research. The JBI Critical appraisal tools were developed by the JBI and collaborators and approved by the JBI Scientific Committee following extensive peer review (https://jbi.global/about-jbi.).

We retained the main methodological quality criteria, but the underlying factors related to each study quality criterion were adapted for this specific context. A copy of this adapted measure is presented in table 4.2 below. We presented quality assessments descriptively to guide our interpretation of findings. As noted earlier, specific aspects of the methodology were tested as moderators of effect sizes. The primary (the student) and secondary (supervisor) reviewers discussed each item in the appraisal instrument for each study included in this review. In particular, we focused our discussions on what is considered acceptable to our review's aims discussed in section 4.1 of this chapter.

Two authors (student and supervisor) independently extracted the data from primary studies that reported the ANN as the tool with the best predictive accuracy. Study characteristics such as sample size, percentage of failed firms, percentage predictive accuracy rate, and type of input dataset (financial ratios, macro-economic variables) were included in the analysis. None of the final sixteen studies published between 2016 and 2021 reported these criteria.

S/N	**Questions**	**Yes**	**No**	**Unclear**	**(N/A)**
1	Were the criteria for inclusion in the sample clearly defined? i.e. corporate Bankruptcy.				
2	Were the type of firms included and the sources of data described in detail?				
3	Were the sample size and input datasets reported?				
4	Were data partitioning method, and standard validation method used for measurement of the model's predictive accuracy described?				
5	Were the percentage of bankrupt firms in the sample reported?				
6	Were attributes selection methods described?				
7	Were the outcomes measured in a valid and reliable way?				
8	Was Artificial Neural Networks (ANN) the machine learning tool with the best predictive accuracy?				

Table 4.2 JBI Critical Appraisal Checklist for Analytical Studies
Overall appraisal: Include □; Exclude □; Seek further info □. N/A denotes Not Applicable. Comments (Including reason for exclusion).

Study	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Overall appraisal
Tseng and Hu (2010)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Kim and Kang (2010)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Yoon and Kwon (2010)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Du Jardin (2010)	Y	Y	Y	Y	Y	Y	Y	Y	Include
De Andres et al. (2011)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Chen, Ribeiro et.al (2011)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Jeong et al. (2012)	Y	Y	Y	Y	Y	Y	Y	Y	Include
De Andres et al. (2012)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Lee and Choi (2013)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Callejon, et al (2013)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Arieshanti et al (2013)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Kasgari et al (2013)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Zhou et al (2014)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Tsai (2014)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Wang, Ma and Yang (2014)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Heo and Yang (2014)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Iturriaga and Sanz (2015)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Du Jardin (2015)	Y	Y	Y	Y	Y	Y	Y	Y	Include
Khademolqurani et al (2015)	Y	Y	Y	Y	Y	Y	Y	Y	Include

Table 4.3 Quality Assessment of the Included Studies in the Quantitative Meta-Analytics

Note: Answers: N=No; U=Unclear or N/A= Not applicable; Y=Yes. Q1. Were the criteria for inclusion in the sample clearly defined? i.e. corporate Bankruptcy. Q2. Were the types of firms included and the sources of data described in detail?? Q3. Was the sample size and input datasets reported? Q4. Were data partitioning method, and standard validation method used for measurement of the model predictive accuracy described? Q5. Were the proportion of bankrupt firms in the sample reported? Q6. Were attributes selection methods described? Q7. Were the outcomes measured in a valid and reliable way? Q8. Was Artificial neural networks the machine learning tool with the best predictive accuracy?

In what follows is a discussion of the eight methodological quality questions. **Question one**: *Were the criteria for inclusion in the sample clearly defined? i.e. corporate Bankruptcy*. We included studies in which the authors provide explicit inclusion and exclusion criteria of the firms included in the study. The inclusion/exclusion criteria (e.g., corporate bankrupt and non-bankrupt firms) should be specified with sufficient detail and all the necessary information relevant to the study. **Question two**: Were the type of firms included and the sources of data described in detail? Studies in which the authors discussed the type of firms and the data sources were included in the meta-analysis. The type of firms could be financial or non-financial firms.

Question three: Were the sample size and input datasets reported? The study sample should be described in sufficient detail. The authors should clearly describe the input datasets (financial and non-financial ratios) used in the study. Where a study has used both financial and non-financial ratios, we included the study if they reported the ANN as the tool with the best prediction accuracy. **Question four**: Were data partitioning and standard validation methods used to measure the model predictive accuracy described? The study should clearly describe the method of data partitioning and validation methods used to assess the model's predictive accuracy.

Question five: Were the percentage of bankrupt firms in the sample reported? The proportion of failed firms, otherwise known as class imbalance, is common in most classification datasets. **Question six**: Were attributes selection methods described? The type of attributes included as inputs to the model has important implications for the model's predictive ability. An essential step in developing bankruptcy prediction models using the ANN technique is determining the importance of variables or attributes to eliminate redundancies. Studies included in the meta-analysis should discuss this explicitly.

Question seven: Were the outcomes measured in a valid and reliable way? The outcome or target variable in a bankruptcy prediction model should be whether a firm is declared bankrupt or not. To qualify for inclusion in the meta-analysis and regression, authors must clearly discuss their Bankruptcy definition. **Question eight**: Was Artificial neural networks the machine learning tool with the best predictive accuracy?

4.4.1 Data extraction.

We extract the following data systematically from all included studies: authors and year of publication, the aim of the study, variable selection method, sample size, percentage of the bankrupt and non-bankrupt firm and input dataset into an excel spreadsheet from *RefWorks* for ease of inputting and coding, then later transferred to a word document. Specific steps that we adopted in carrying out the meta-analysis is depicted in figure 4.3.

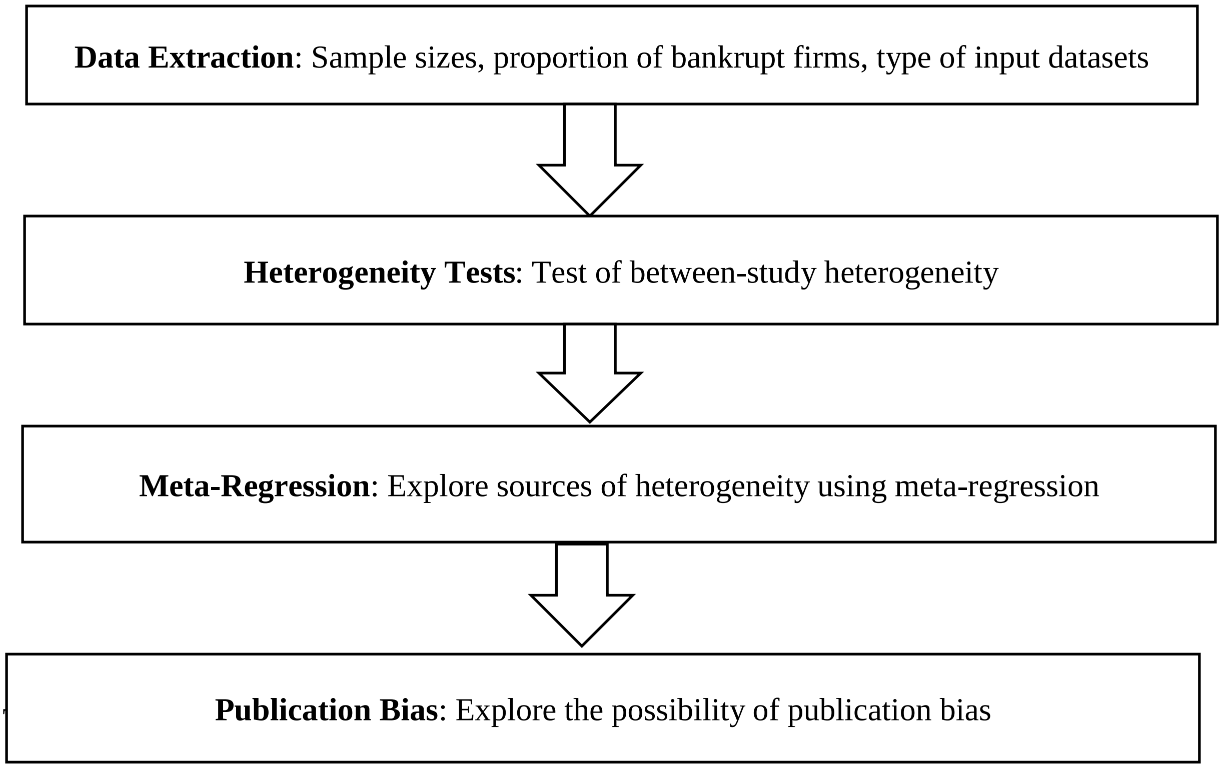


Figure 4.3 Steps in Analytic Meta-Analysis.

Table 4.4 below comprises study attributes such as author and year of publication, type of input datasets, the proportion of failed firms in the sample, the sample size and the predictive accuracy.

Authors and year of publication	Sample size	% non-bankrupt firm	% bankrupt firm	Input data sets	ANN Accuracy rate %
Tseng and Hu (2010)	77	58.4	42	Financial and non-financial ratios	93.75
Kim and Kang (2010)	1458	50	50	Financial ratios	71.02
Yoon and Kwon (2010)	10000	50	50	Non-financial ratios	73.1
Du Jardin (2010)	1020	50	50	Financial ratios	94.03
De Andres et al. (2011)	59474	99	0.23	Financial ratios	92.38
Chen, Ribeiro et.al (2011)	1200	50	50	Financial ratios	91
Jeong et al. (2012)	2542	50	50	Financial ratios	81
De Andres et al. (2012)	122	50	50	Financial ratios	76.03
Lee and Choi (2013)	1775	66	33	Financial ratios	92
Callejon, et al (2013)	1000	50	50	Financial and non-Financial ratios	92.1
Arieshanti et al (2013)	240	53.3	46	Financial ratios	71
Kasgari et al (2013)	135	52.5	48	Financial ratios	94.1
Zhou et al (2014)	2010	50	50	Financial ratios	75.6
Tsai (2014)	690	44.5	56	Financial and non-financial ratios	91.6
Wang, Ma and Yang (2014)	132	50	50	Financial ratios	79.9
Heo and Yang (2014)	2762	50	50	Financial ratios	77.1
Iturriaga and Sanz (2015)	772	50	50	Financial ratios	93.27
Du Jardin (2015)	16880	50	50	Financial ratios	80.8
Khademolqurani et al (2015)	180	42	58	Financial ratios	94

Table 4.4 Characteristics of Included Studies. Source: Author's calculations.

Ten out of the nineteen studies used in the meta-analysis and regression reported a bankruptcy predictive accuracy rate of over 90%; two studies reported accuracy rates of 80%, while the remaining studies reported over 70%. Samples sizes range from 77 to 59,474 observations. Most of the studies used financial ratios as input datasets in the analysis.

4.5. Results.

In this section we will discuss the results from the meta-analysis and test for statistical heterogeneity.

4.5.1 Data Synthesis and Meta-Analysis.

Investors, banks and many other institutions and shareholders are interested in predicting how viable a company is. The business objective is to predict whether a given company will be insolvent in the next five years. We extracted data from primary studies included in the systematic review that reported the ANN as the tool with the best corporate bankruptcy predictive accuracy for the meta-analysis and meta-regression.

In the context of dichotomous outcomes, bankruptcy prediction models are intended to reduce the risk of an adverse outcome or increase the chance of a good outcome. In this context, the adverse event is bankruptcy, and the good outcome is no bankruptcy. The Artificial Neural Network (ANN) is the most common model used in corporate bankruptcy prediction studies based on the systematic literature review.

The effectiveness of a bankruptcy prediction tool depends on the purpose for which the tool was developed. For example, a lender may be interested in the accuracy of a model. In this case, the bankruptcy prediction model needs to be able to predict if a firm is financially healthy (unhealthy) to be granted (refused) credit; hence a highly accurate tool/technique is needed.

On the other hand, a business owner may be interested in the transparency of the model as much as accuracy because s/he needs to know what the firm is doing wrong to know where rescue effort should be focused on. In such a case, a model with high accuracy and result transparency will be required. We adopt the mindset of a lender in this thesis and focus on the accuracy of the model as opposed to model transparency. Our reason for doing so is that a firm can use financial ratio analysis and other qualitative methods to evaluate areas where the business is not performing optimally. For example, a company can use a DuPont analysis to assess the financial activities contributing the most changes in its' return on equity (ROE). Using the accuracy value as the performance evaluation criterion, we separated studies that reported high accuracy values for ANN and included them in the meta-analysis. The idea is first to understand if there are variations in these studies and if these variations result from chance.

According to Kane et al. (2016), studies included in a meta-analysis must have common outcome statistics that allow their results to be combined. We used the sample sizes and the percentage of bankrupt firms in the samples for this meta-analysis. We computed event rates for the primary studies. Given that all the studies in our meta-analysis measure a dichotomous outcome (bankrupt or non-bankrupt firms), we used the event rate as our measure of effect sizes.

Our focus/aim is to test for the presence or otherwise of statistical heterogeneity[20] in the studies. Heterogeneity refers to systematic differences between the results of the included studies that cannot be attributed simply to chance. Two statistical methods to analyze statistical heterogeneity are the chi-square test for heterogeneity or the chi-square test for homogeneity and the I^2(also known as Higgins I^2). These tests estimate the probability that the observed

[20] Statistical heterogeneity occurs when the results of a set of studies vary among one another. Because some variation in outcomes among primary studies could be by chance, statistical heterogeneity refers to the level of variation in the predictive abilities of the models reported by primary studies that are not a result of chance.

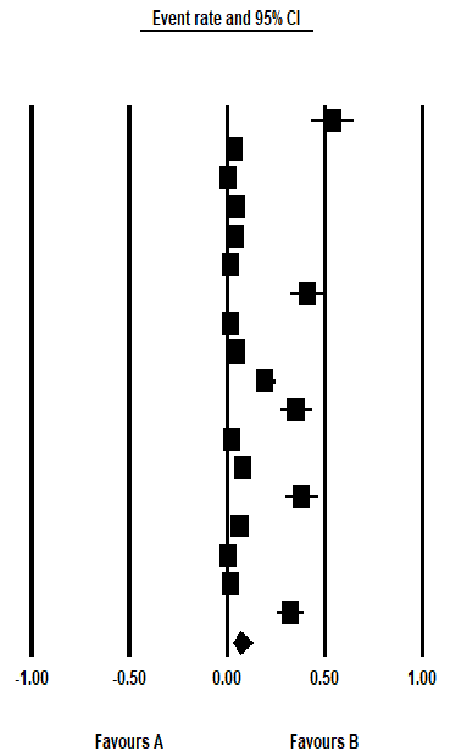
pattern of results from the included studies may have occurred simply as a result of chance. If the $chi - square$ test is significant, statistical heterogeneity is present.

It is important to note that this test has low power when few studies are used in the meta-analysis; therefore, a non-significant test may lead to the wrong conclusion regarding heterogeneity. A compensation for the low power of the $chi - square$ test is to test for heterogeneity at an $alpha$ level of 10%, rather than at 5%, thereby increasing the chance of finding heterogeneity. The presence of statistical heterogeneity is assessed in this thesis via the Q-test of statistical heterogeneity and quantified via the I^2 (Huedo-Medina, 2006).

A summary of the reviewed studies reveals that the authors used different input datasets, sample sizes, and data validation methods. These differences could mean that the studies are not homogenous. Consequently, we use the random-effects model that accounts for the heterogeneity among studies, both in the point estimate of their results and the confidence intervals' width. Essentially, the random-effects model describes the differences between study effects through broader confidence intervals.

The forest plot (figures 4.4) graphically represents estimates of the effect size and corresponding confidence intervals for each study, along with an estimate of the overall effect size of all included studies and the corresponding overall confidence interval. Specifically, the plot shows the event rate and 95% confidence intervals for 18 studies that reported the Artificial Neural Network algorithm as the best bankruptcy prediction tool in terms of accuracy rate. The results show that effect sizes vary among the studies. In addition, the confidence intervals of estimates of the logit event rates were quite wide, especially for studies with small sample sizes.

Study name	Event rate	Lower limit	Upper limit	Z-Value	p-Value
	Statistics for each study				
Tseng and Hu (2010)	0.540	0.429	0.648	0.706	0.480
Kim and Kang (2010)	0.034	0.026	0.045	-23.194	0.000
Yoon and Kwon (2010)	0.005	0.004	0.007	-37.336	0.000
Du Jardin (2010)	0.049	0.037	0.064	-20.447	0.000
Chen, Ribeiro et al (2011)	0.042	0.032	0.055	-21.704	0.000
Jeong et al (2012)	0.020	0.015	0.026	-27.366	0.000
De Andres et al (2012)	0.410	0.326	0.499	-1.981	0.048
Lee and Choi (2013)	0.019	0.014	0.027	-22.698	0.000
Callejon, Casado, Fernandez, and Pelaez (2013)	0.050	0.038	0.065	-20.293	0.000
Arieshanti, Purwananto, Ramadhani, Nuha and Ulinnuha (2013)	0.195	0.149	0.250	-8.712	0.000
Kasgari et al (2013)	0.352	0.276	0.436	-3.390	0.001
Zhou et al (2014)	0.025	0.019	0.033	-25.617	0.000
Tsai (2014)	0.080	0.062	0.103	-17.406	0.000
Wang, Ma and Yang (2014)	0.379	0.300	0.464	-2.757	0.006
Iturriaga and Sanz (2015)	0.065	0.049	0.084	-18.258	0.000
Du Jardin (2015)	0.003	0.002	0.004	-41.085	0.000
Heo and Yang (2014)	0.018	0.014	0.024	-27.981	0.000
Khademo;qorani, Zeinal, Hamadani, and Mpkhatab Rafiei (2015)	0.322	0.258	0.394	-4.662	0.000
	0.066	0.032	0.131	-6.905	0.000



Meta Analysis

Figure 4.4 Forest Plot for the included studies (Random Effect Model).

A qualitative visual analysis of the studies' results via the forest plot suggests between-study variability. The individual study point estimates of the event rate (black squares) are all statistically significant with the exception of the study of Tseng and Hu (2010). These studies do not line up on a vertical axis, indicating a difference in the event rate magnitude among studies. The confidence intervals (CI) for each study's event rate (horizontal lines) overlap, but the upper and lower limits of the CI do not consistently line up on a vertical axis, indicating differences in the rate of bankrupt firms among studies. These qualitative results suggest the presence of heterogeneity.

Model	Number of studies	Point Estimate	Lower Limit	Upper Limit	Z-value	P-value
Fixed	18	0.05	0.047	0.054	-80.61	0.00
Random	18	0.07	0.032	0.131	-6.91	0.00
			Heterogeneity			
Q-value		*Df (Q)*			*P-value*	I^2
1883.05		17			0.00	99.09
			Tau-Squared			
Tau Squared		*Standard Error*		*Variance*		*Tau*
2.62		0.93		0.86		1.62

Table 4.5 Point Estimates and Test for Heterogeneity.

The quantitative tests of heterogeneity statistics - the $chi-square$ test for heterogeneity reported in table 4.5 above is significant at a level of less than 10%, and the I^2 value for the ANN studies is 99%. These quantitative results suggest there is study variability (i.e., heterogeneity). This result is expected because several factors such as sample size, type of input data sets, percentage of bankrupt firms in the sample and the type of validation methods used in the primary studies can influence the magnitude and direction of the effect size. Given the substantial differences in study effects observed from the meta-analysis, we empirically explored the potential sources of these variations using meta-regression.

4.5.2 Description of the Moderator Variables in the Meta-Regression.

As noted in the review aims, some moderators of effect size were explored using meta-regression as part of the review's secondary outcomes. We present a brief discussion of the moderator variables in turn below.

Sample size: Artificial neural networks and their variants have gained immense popularity in the bankruptcy prediction literature. However, the data sample size may affect the model's predictive accuracy, mainly if a deep neural network is used (D'souza et al. 2020). According to the authors, a very deep network with a smaller training data size may not generalize well since it may over fit the small training data requiring the need to apply a different learning scheme (e.g. adding regularization) or another strategy specialized for small datasets. We created dummy variables for the sample sizes as follows- between 1 to 999 observations small, between 1000 to 2000 observations moderate above 2000 observations large.

Percentage of failed firms: The percentage of failed firms is another essential characteristic that should be considered when using neural nets. The percentage of failed firms, otherwise known as class imbalance, is a common feature in most classification datasets. This is where bankrupt and non-bankrupt firms are not represented equally in the dataset. Although, a slight difference in the two classes does not matter. However, when a majority of the datasets belong to one class, developers should give adequate considerations to the so-called accuracy paradox, where the accuracy metric provides misleading classification accuracy reflecting the underlying class distribution. We created a dummy variable for the percentage of failed firms in the samples. If a sample has 50% of failed firms, we classify it as 0; if it contains less than 50%, we classify it as 1.

Type of input datasets. The limited use of non-financial datasets in most bankruptcy prediction models has been a subject of great debate. Although there appears to be some consensus that that annual accounts information in the form of financial ratios provides the best predictions of corporate failure (Aziz and Dar,2006), because of the notion that financial ratios are objective measures based on the publicly available information (Laitinen, 1992), still, there are disagreements regarding the appropriate ratios to be used from the standpoint of accrual-based financial ratios (Casey and Bartczak, 1984), cash-based ratios (Gentry et al., 1987; Aziz et al., 1988) or both (Gentry et al., 1985).

In addition, some authors have highlighted some of the disadvantages of using only financial ratios. For instance, Appiah et al. (2014) argue that small and medium enterprises that are not required to publish their financial accounts publicly imply that prior studies are limited to listed firms. Bankruptcy prediction studies focusing on SMEs' where the incidence of failure may be potentially higher are distinctively lacking in the literature. Except for Luoma and Laitinen's (1991) that focused on unincorporated firms, we are not aware of any other study that used SME datasets.

Secondly, Accounting policies that are chosen regarding depreciation, inventory, revenue, expenditure items, and consolidation of accounts may expose accounting information to manipulation (Rosner 2003). Finally, bankruptcy prediction models based only on financial ratios implicitly assume that all relevant failure indicators are reflected in these ratios. Consequently, we empirically test the response of event-type on the type of input datasets used in the primary studies. We created a dummy variable to measure this variable. Specifically, if a study reported using financial ratios only, we capture it as 1 and non-financial ratios or a combination of both we capture as 0.

Data validation method.

One of the critical issues when fitting a bankruptcy prediction model is to assess how well the fitted model behaves when applied to a new dataset. To address this issue, previous authors split the dataset into multiple partitions: a training sample used to fit the model's parameters and a validation sample used to choose the parameters of the model and track the errors during the training. The validation dataset is used to estimate how the model would perform with unseen data. A good performance in the validation sample indicates that the model can generalize the data. Literature suggests the following different validation procedures; first, validation sample: This method involves randomly splitting the dataset into training and validation sets. The training sample is used in the model estimation phase, while the validation sample is used to evaluate the model (Louzada et al., 2016).

The second method is the $K - fold$ cross validation approach. This approach involves randomly dividing the dataset into k groups, or folds of approximately equal size. The first fold is treated as a validation set, and model is fit on the $K - 1$ folds. For example, suppose that 10 groups are used (10-fold cross validation). The original dataset is split into 10 equal random subsets. The first 9-subsets are used to develop (training sample) the model. The resulting model is assessed for accuracy on the remaining $1/10th$ of the sample (test sample).

Each observation in the dataset is assigned to an individual group and stays in that group for the duration of the procedure. This means that each sample is given the opportunity to be used in the test sample once and used to train the model $K - 1$ times. This process is repeated at least 10-times to get an average of 10 indexes such as standard deviation or standard error. We included a validation dummy to measure the potential effect of validation on the outcome variable.

Covariate	Coefficient	Standard Error	95% Lower	95% Upper	**Z-value**	**P-value**
$\boldsymbol{Intercept}$	-5.17	0.96	-7.06	-3.28	-5.38	0.00
$\boldsymbol{Sample\_Small}$	2.66	0.76	1.17	4.15	3.50	0.00
$\boldsymbol{Sample\_Large}$	-0.72	0.67	-2.03	0.59	-1.08	0.28
$\boldsymbol{Sample\_Moderate}$	0.15	0.76	-1.34	1.64	0.19	0.85
$\boldsymbol{Input\ Data\ Type}$	0.84	0.51	-0.17	1.85	1.64	0.10
$\boldsymbol{Failed\ Firms}$	0.54	0.49	-0.43	1.51	1.09	0.28
$\boldsymbol{Validation}$	1.02	0.42	0.20	1.83	2.43	0.01

Table 4.6 Random Effects Model, Z-Distribution, Logit Event Rate.

Sample Size	Sample_Small: 1	2.6614	0.7601	1.1717	4.1511	3.50	0.0005	Q=54.55, df=3, p=0.0000
	Sample_Large: 1	-0.7193	0.6686	-2.0298	0.5912	-1.08	0.2820	
	Sample_Moderate: 1	0.1469	0.7594	-1.3416	1.6354	0.19	0.8467	

Test of the model: Simultaneous test that all coefficients (excluding intercept) are zero

Q = 69.19, df = 6, p = 0.0000

Goodness of fit: Test that unexplained variance is zero

$Tau^2 = 0.6007$, Tau = 0.7751, $I^2 = 96.12\%$, Q = 283.41, df = 11, p = 0.0000

Comparison of Model 1 with the null model

Total between-study variance (intercept only)

$Tau^2 = 2.6207$, Tau = 1.6189, $I^2 = 99.10\%$, Q = 1883.05, df = 17, p = 0.0000

Proportion of total between-study variance explained by Model 1

R^2 analog = 0.77

Number of studies in the analysis 18

We linked the three sample size dummies together (link covariates) in the meta-regression. The results from the meta-regression- see table 4.6 above suggest that sample size and the data validation methods have a statistically significant effect on the performance of the ANN model. Although we did not find a statistically significant relationship between the other moderator variables (type of input datasets, the proportion of bankrupt firms and the event rate); however, our finding reveals that these variables taken together can explain approximately 77% of the variance in the bankruptcy event rate-see figure 4.5 below.

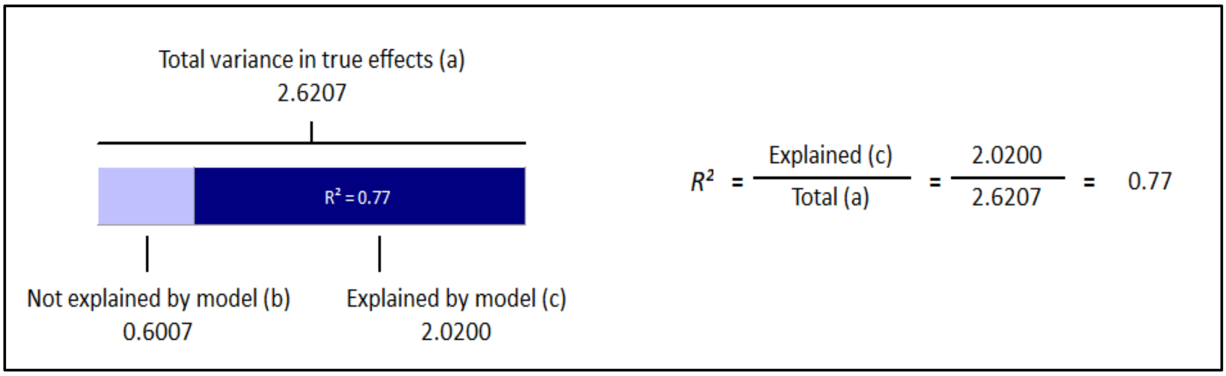


Figure 4.5: Total variance in true effects.

The correlation matrix of the regression coefficients allows us to quickly find the strongest linear relationship among all the pairs of variables. As expected, the sample size dummies are positively correlated, and the magnitude of these correlations are high.

Correlation matrix of regression coefficient estimates for Model 1, Random effects (MM), Logit event rate

	Intercept	Sample_Small	Sample_Large	Sample_Moderate	Input Data Type	Failed Firm	Validation Dummy
Intercept	1.0000	-0.7980	-0.7728	-0.5890	-0.6369	-0.2220	-0.1860
Sample_Small (1)	-0.7980	1.0000	0.7502	0.7853	0.2486	-0.0283	-0.1614
Sample_Large (1)	-0.7728	0.7502	1.0000	0.6522	0.2794	0.2351	-0.1563
Sample_Moderate (1)	-0.5890	0.7853	0.6522	1.0000	-0.0168	0.0046	-0.3219
Input Data Type (1)	-0.6369	0.2486	0.2794	-0.0168	1.0000	0.0923	0.1944
Failed Firm (1)	-0.2220	-0.0283	0.2351	0.0046	0.0923	1.0000	0.1001
Validation Dummy (1)	-0.1860	-0.1614	-0.1563	-0.3219	0.1944	0.1001	1.0000

Table 4.7 Correlation Matrix of Regression Coefficient Estimates

We address the issues of publication bias in the literature using the funnel plot of precision by logit event rate. The notion of publication bias in quantitative meta-analytic is premised on the fact that not all completed studies are published, and the selection process is not random. Given that the result estimated from a biased collection of studies would tend to overestimate the actual effect, it is important to assess the likely extent of the bias and its potential impact on the conclusions.

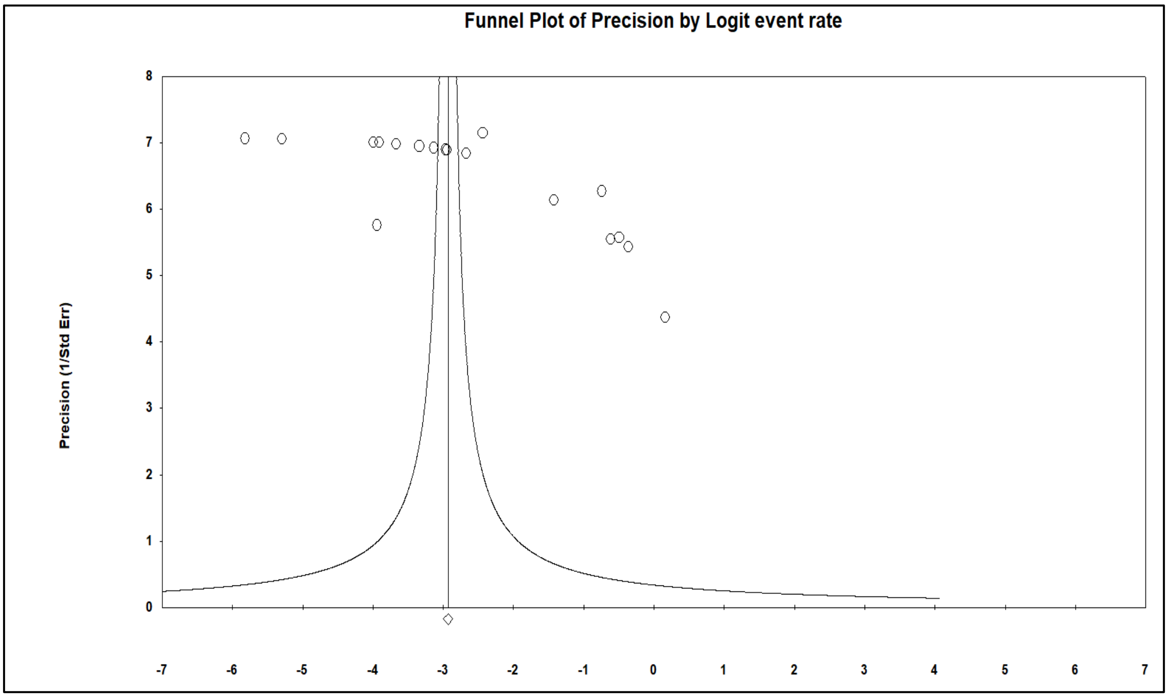


Figure 4.6 Funnel Plot of Precision by Logit Event Rate

The funnel plot in figure 4.6 is a plot of a measure of study size (precision the inverse of standard error) on the vertical axis as a function of effect size on the horizontal axis. Studies with a larger sample size appear toward the top of the graph and tend to cluster near the mean effect size, while smaller studies appear toward the bottom of the chart. If the studies are distributed symmetrically around the combined effect size, we can conclude the absence of publication bias. By contrast, we would see a higher concentration of studies on the bottom of the plot on one side of the mean than the other in the presence of bias.

A visual inspection of the funnel plot suggests the presence of publication bias since the funnel plot is asymmetric. Although effect size is not the focus of our analysis, the result from the publication bias is not surprising given that we have included only published studies in the analysis in line with previous reviews. Future systematic literature reviews and meta-analyses should consider including non-published articles in the analysis.

4.6 Conclusions

This chapter discusses the systematic literature review and the quantitative synthesis of studies that met our inclusion criteria. A plethora of tools has been used to predict the future bankruptcy of corporate firms by companies in the business of lending and business owners alike. Our systematic literature review reported the Artificial Neural Network (ANN) as the tool with the best bankruptcy predictive accuracy. But, the between-study heterogeneity and the sources of these heterogeneities are yet to be explored empirically by researchers.

This systematic review and meta-analysis extended the review of Alake et al. (2018) by including studies published between 2016 to 2020 on the topic. In addition, we tested the presence or otherwise of heterogeneity in the studies that met our inclusion criteria and used meta-regression to explore the sources of these variations.

A systematic search of Engineering Village (EV), Web of Science UK (WoS) and Business Source Complete (BSC) was performed independently by two reviewers using predefined criteria. In addition, abstracts from selected conference proceedings and other sources were screened, and reference scanning of the search results was performed. Sixteen studies met the selection criteria and were reviewed. None of the studies between 2016 to 2020 met our inclusion criteria for the quantitative meta-analytics. We pooled data from eighteen out of the forty-nine articles from the study of Alake et al. (2018) for the quantitative analysis. The results from the meta-analysis suggest the presence of systematic between-study heterogeneity, and the meta-regression shows that a study's sample size and the validation methods used could affect the performance accuracy of the ANN model.

Therefore, the recommendations for practice are to pay attention to the sample size and the methods of validation used in developing a bankruptcy prediction model. The Artificial Neural Network (ANN) model seems to be very sensitive to the number of data points used in the model. A small sample size may negatively impact the performance ability of the model. Although we did not find a statistically significant relationship between the type of input datasets, the proportion of bankrupt firms and the event rate; however, our result shows that these variables taken together can explain approximately 77% of the variance in the event rate.

Consequently, potential developers seeking to use the ANN model in developing bankruptcy prediction models should give adequate consideration to these variables. For instance, class imbalance is a common feature in most classification datasets. This is where the classes (bankrupt and non-bankrupt firms) are not represented equally. A slight difference in the two classes does not matter. The challenge is when a majority of the datasets belong to one class. Developers should give adequate considerations to the so-called accuracy paradox, where the accuracy metric provides misleading classification accuracy reflecting the underlying class distribution. To overcome this challenge, developers could use Cohen's Kappa that normalizes the classification accuracy by the imbalance of the classes in the data and ROC curves.

4.6.1 Recommendations for future studies.

Systematic reviews aim to be as comprehensive and representative of the literature they describe as possible. One key aspect of the methodology of systematic reviews is a concerted effort to search for and include relevant unpublished work (that meets the inclusion and exclusion criteria) to reduce the effects of publication bias. Previous authors maintain that unpublished research may be of lesser quality than published research, hence excluding unpublished studies.

Time constraints, paucity of resources and the review objective meant that we did not conduct a thorough search of grey literature and contacted researchers with one or more publications in this area. Future research in this area could think of including an unpublished body of work in this area to reduce the risk of publication bias. Future studies should also consider conducting a quasi-experiment of firms that use the ANN as part of their credit assessment tools to ascertain how the algorithm performs in practice.

Appendix 1.

Table 4.8: Summary of reviewed studies aims, variable selection methods, sample characteristics and accuracy values.

S/N	Author year	Aim of study	Variable selectin method	Sample size	% of exist firms	% of fail firms	% for val.	Accuracy values (%)							
								SVM	ANN	DT	RS	GA	CBR	MDA	LR
1	Tseng and Hu (2010)	Comparing models	Literature review (stepwise)	77	58.4	41.6	20		93.75						86.25
2	Cho et al.(2010)	Propose new CBR approach	t-test&decision tree	1000	50	50	20		71.8	65.7			73.7		72.2
3	Kim & Kim (2010)	Check enhanced ANN against ord. ANN	Cumulative accuracy profiles	1458	50	50	10		71.02						
4	Yoon & Kwon (2010)	Use credit card data for small bus. And compare techniques	t-test & chi-square	10000	50	50	30	74.2	73.1					70.1	70.1
5	Du Jardin(2010)	To check variable selection methods effect	Error backward-order (stepwise)	1020	50	50	49		94.03					87.20	92.01
6	Lin, Liang & Chu (2010)	Use SVM with ratios & non-fin. variables	Stepwise regression	108	50	50		94.4						90.74	
7	Gepp, Kumar & Bhattacharya (2010)	Compare DT & MDA	Lit.review (stepwise)	200	71	29	20			87.6				84.5	
8	De Andres, Lorca, de Cos Juez & Sanchez-Lasheras (2011)	Propose hybrid model (C-means & MARS)	Altman's ratios (stepwise)	5974	99.77	0.23	20			92.38				91.44	86.56
9	Kim (2011)	Compare techniques	Stepwise	66	50	50		95.95	91.6					72.6	80
10	Yang et al. (2011)	Propose hybrid model (PLS & SVM)	Pearson cor. & PLS	120	53.3	46.7	100	79	78.33						

11	Chen (2011)	Use PSO with SVO	Lit.rev. (stepwise), GA	80	50	50	20								
12	Divasalar et al. (2011)	Use GA & NN	SFS	150	51.4	48.6			82.5			95			80
13	Du Jardin & Severin (2011)	Ue self-organizing map	Error backward-order (stepwise)	2360	50	50	37.3		82.61					81.93	81.14
14	Chen, Ribeiro et al. (2011)	Integrate error cost into model		1200	50	50	20	90	90.6			86.7			
15	Chen, Yang et al. (2011)	Propose FKNN		240	53.5	46.7	10	76.67	79.58			83.33			
16	Li et al. (2011)	Propose Random subspace LR (RSBL)	Stepwise & t-test	370	50	50	30				88.46			88.26	87.50
17	Divasalar et al. (2012)	Use new type of GA called GEP	SFS	136	52.5	47.5	33..3		79.41			91.18			76.47
18	Huang et al. (2012)	Propose hybrid KLFDA & MR-SVM					10	86.61	83.67	83.24					77.9
19	Tsai & Cheng (2012)	Check effect pf outlier on BPMs		653	45.3	54.7	10		86.37	86.06	84.69				86.37
20	Shie et al. (2012)	Proposed enhanced PSO-SVM	Factor analysis & PCA	54	55	44.4		81.82	75.76	77.77					72.73
21	Kristof & Virag (2012)			504	86.7	13.3	25		88.7	88.8					88.5
22	Jeong et al. (2012)	To fine-tune ANN factors	GAM	2542	50	50	20	79	81	76			73	73.5	76.48
23	Du Jardin & Severin (2012)	To use Kohonen map to stabilize temporal accuracy)							81.3					81.2	81.6
24	De Andres et al. (2012)	To improve performance of classifiers		122	50	50	19.6		76.03					74.87	
25	Zhou, lai & Yen (2012)	To find the best variables for accuracy	Spearman correlation		50	50	10.8	71.1	67.8	75.6				64.4	54.4

26	Xiong, Wang, Mayers, & Monga (2013)	Use sequence on credit card data						70.94							
27	Lee & Choi (2013)	To do multi industry investigation	t-test & cor. analysis	1775	66.2	33.8	4.2		92					82.01	
28	Tsai & Hsu (2013)	Present met-learning framework (hybrid)	MC	Avg. many			20		78.82	77.29					79.11
29	Callejon et al. (2013)	To increase predictive power of ANN		1000	50	50	20		92.11						
30	Chuang (2013)	To hybridize CBR	Multiple	321	86.9	13.1							90.1		
31	Ho et al. (2013)	Develop BPM for US paper companies	Li. Rev. (stepwise)	366	66.7	33.3	20								93
32	Arieshanti et al. (2013)	To compare techniques	Lit. re. (stepwise)	240	53.3	46.7	20	70.42	71						
33	Kasgari et al. (2013)	Compare ANN to other techniques	Garson's algorithm	135	52.5	47.5	25		94.11			88.57			91.43
34	Zhou et al. (2014)	Propose new feature selection method	GA	2010	50	50			75.6	50.67				71.72	73.99
35	Tsai (2014)	To compare hybrids	SOM	690	44.5	55.5	20		91.61	86.83					87.28
36	Yeh et al. (2014)	To increase accuracy using RF&RS	RF	220	75	25	33	94.58	92.95	91.55	96.99				
37	Wang, Ma. & Yang (2014)	Inject feature selection into boosting		132	50	50	10	79.99	75.69	75.99					73.90
38	Abellan & Mantas (2014)	To correctly use4 bagging scheme	Lit.rev. (Stepwise)	690			30				93.64				
39	Tsern et al. (2014)	To use LR to predict contractors default		87	66.7	33.3									79.18
40	Yu et al. (2014)	Produce BPM using ELM		500	50	50	33.3	93.2						86.5	

41	Gordini (2014)	Test GA accuracy & compare to other techniques	VIF & Stepwise	3100	51.6	48.4	30	69.5				71.5			66.8
42	Heo & Yang (2014)	To prove AdaBoost is right for Korean construction firms		2762	50	50	20	73.3	77.1	73.1				51.3	
43	Tsai, Hsu, & Yen (2014)	To compare classifier ensembles		690	44.5	55.5	10	86.37	84.38	86.37					
44	Virag & Nyitrai (2014)	Toi Show RS accuracy is competitive with SVM & ANN		156	50	50	25	89.32	88.03		89.32				
45	Liang et al. (2015)	To compare feature selections	GA	688	50	50	10	91.77	91.63	92.98					
46	Iturriaga & Sanz (2015)	To develop ANN BMP for US banks	Mann-Whitney test & Gini index	772	50	50	13.5	89.42	93.27					77.88	81.73
47	Du Jardin (2015)	To improve BPM accuracy beyond one year		16880	50	50	50		80.8					80.1	80.6
48	Bems et al. (2015)	Introduce new scoring method called Ginin index	Gini index	459	67	33	579		0.291				0.199	0.207	0.301
49	Khademolqorani et al; (2015)	To develop a novel hybrid	Factor analysis	180		58			94	94				77	80
50	Horak,J. et al. (2020)	create a model for bankruptcy prediction	22 input cont. var. and 1 categor. Output var.	1708	75	25		99.39	82.79						
51	Khoja,L. et al. (2016)	find predictive value of ratios with LR	28 financial rations from 112 firms	112											74.4
52	Ashraf,S. et al.(2019)	Compare prediction	Model scores construction	422	64	36								66.7	

		accuracy of models									
53	Zizi,Y. et al.(2020)	Identify determinants for fin.failure	Financial variables	90	50	50					84.4
54	Shrivastav,S. et al.(2020)	analyse the survival probability of banks	5-folod cross validation, 75% training & 25% testing data	59	71	29	SVMLK 92.86 & SVMRK 71.43				
55	Charalamakis,E. & Garrett,I.(2019)	Examine determinants of the probability of default	Financial ratios used	31000	13	87					80
56	Singh,B. & Mishra,A.(2016)	Predict bankruptcy by examining 3 models	Comparison of original & reestimated models to test sensitivity of models	208	50	50				67.692	
57	Halteh,K. et al.(2018)	Partitioning models chosen to predict credit risk	Training and testing models used	750	84	16			71.72		91.41
58	Munoz-Izquierdo,N. et.al(2019)	Predict bankruptcy	Independent var. – audit report var-s	808	50	50	68.2,76.5,80.8				
59	Voda,A.D. et al.(2021)	Improve predictive power of bankruptcy prediction	37 fin. Indicators from balance sheet	80	50	50				88.75	
60	Zulkifli,H. et al.(2021)	Investigate deep learning models	Fin.data classified as distressed & non-distressed firms	98			83	80	78		85
61	DuJardin(2016)	NN,MDA,LR,DT used together with a proposed new method to improve bankruptcy	Financial ratios used	1.4 million (11 learning samples and 11 test samples)				84.65		85.73	86.65

		prediction forecast								
62	Barboza et. Al.(2017)	Predict bankruptcy one year prior the event	5 years chosen (Altman, 1968); other indicators included influencing fin. performance	449			67	91.09	87.06	
63	Fallahpour,A. et al.(2017)	Develop important criteria for sustainable supplier selection through questionnaire based survey	SVM (hybrid with sequential floating forward selection algorithm)				94.99			
64	Sariev,E. & Germano G.(2018)	Estimate probability of default	33 independent var-s and 1 binary target var. (financial ratios)	7996			Ranges from 64 to 84			Ranges from 67 to 78
65	Korol,T.(2019)	Develop dynamic bankruptcy prediction models	20 financial ratios	Learning sample-100, testing sample-500	50	50		From 91.2 to 95.2		

Table 4.9 Summary of Error Types as Reported for the Tools by some of the Authors

S/N	Author year	SVM		ANN		DT		RS		GA		MDA		LR	
		Type I error	Type II error	Type I error	Type II error	Type I error	Type II error	Type I error	Type II error	Type I error	Type II error	Type I error	Type II error	Type I error	Type II error
1	Kim & Kang (2010)			17.23	30.83										
2	Yoon & Kwon (2010)	11.34	25.14												
3	Du Jardin (2010)			4.72	7.22							16.8	8.8	9.58	6.4
4	Lin et.al. (2010)	5.56	5.56												
5	Kim (2011)			4.8	12.1							47.6	27.4	22	18.4
6	Yang et al. (2011)	8.93	17.2	16.07	26.56										
7	Du Jardin & Severin (2011)			17.95	16.82							18.41	17.73	18.18	19.55
8	Chen, Ribeiro et al. (2011)	15.7	4.3	12.2	6.7					17.1	9.7				
9	Chen, yang et al. (2011)	26.55	18.96	18.52	21.71					14.94	17.02				
10	Divsalar et al. (2012)			15.79						9.52	7.69			20	
11	Tsai & Cheng (2012)	19.9	6.1	12.1	16.2	13.5	17.6							17.4	9.1
12	Shie et al. (2012)		16.7		17.65		22.23								25
13	Du jardin & Severin (2012)			20.1	17.4							22.1	15.5	20.1	16.6
14	De Andres et al. (2012)			26.52	21.71							28.7	22.08	25.67	21.35
15	Lee & Choi (2013)			12.0	6.0							24	14		
16	Tsai & Hsu (2013)			20.19	28.63	21.57	33.02							17.87	30.67
17	Kasgari et al. (2013)			5.0	7.14										
18	Tsai (2015)			6.87	10.09	9.21	17.82							13.79	11.36
19	Yeh et al. (2014)	11.02	3.74	18.02	4.32	26	1.9	10.6	3.5						
20	Wang et al. (2014)	21.55	18.19	20.62	27.69	23.10	24.74							26.38	25.38
21	Gordini (2014)	22.9	38.1							21.1	35.8			23.3	43.1
22	Iturriaga & Sanz (2015)	11.54	9.62	5.77	7.69							23.08	21.15	19.23	17.31
23	Horak,J. et al. (2020)														
24	Khoja,L. et al. (2016)													95.6	73.9

25	Ashraf,S. et al.(2019)				
26	Zizi,Y. et al.(2020)			20	11.1
27	Shrivastav,S. et al.(2020)				
28	Charalamakis,E. & Garrett,I.(2019)				
29	Singh,B. & Mishra,A.(2016)	75	50		
30	Halteh,K. et al.(2018)				
31	Munoz-Izquierdo,N. et.al(2019)				
32	Voda,A.D. et al.(2021)	4	16		
33	Zulkifli,H. et al.(2021)				
34	DuJardin(2016)				
35	Barboza et. Al.(2017)	19.6	50.78	7.8	26.73
36	Fallahpour,A. et al.(2017)				
37	Sariev,E. & Guido,G.(2018)				
38	Korol,T.(2019)				

Chapter 5

A Comparison of Corporate Bankruptcy Prediction Models Neural Network and Logistic Regression

5.1 Introduction.

The systematic review in the previous chapter suggests that authors have used different machine learning and statistical methods in bankruptcy prediction. Algorithms such as rough set (Beynon & Peel, 2001; Mckee, 2003; Xiao et al., 2012; Wang & Wu, 2017), case-based reasoning (Li & Sun, 2009; Li & Sun, 2011), support vector machine (Lin, Yeh & Lee, 2011; Li & Sun, 2012; Kim, 2011; Chandra, Ravi & Ravisankar, 2010) and artificial neural network (Kasgari et al. 2013; Iturriaga & Sanz, 2015; Virág & Nyitrai, 2014) are commonly used in the bankruptcy prediction studies.

Statistical bankruptcy prediction models such as Z-score, logit and probit models have certain advantages-they are simple and easy to use. One of the limitations of the traditional models is that they assume restrictive statistical distributions and are not always accurate when compared with machine learning models with high classification accuracies. Despite the limitations of statistical models in bankruptcy prediction models, some machine learning models can underperform them. For instance, a neural network model for binary classification can be worse than a logistic regression model because neural networks are more challenging to train and are more prone to overfitting than logistic regression, Dreisitl and Machado (2002). Overfitting is less of an issue in the case of logistic regression.

In addition, the literature review shows that many researchers have compared the performance of different machine learning algorithms. Boguslauskas and Mileris (2009) apply various machine learning models to analyze the credit risk of 50 cases of successful and 50 insolvent firms in Lithuanian. Their results show the neural network to be an efficient method of credit risk estimation. Khashman (2010) applied the neural network algorithm on 1000 German credit datasets; their results show 99.25% and 73.17% accuracy rates for the training and test data. Gante et al. (2015), using the same German credit dataset, reveals that the network topology affects the predictive accuracy of the ANN models. Kim (2011) compared the support vector machine and ANN and demonstrated that SVM is superior to the performance of the artificial neural network. (Kim, 2011).

Despite the plethora of comparative and single study analyses in this area, very little empirical work addresses the problem of class imbalance. This is where the classes (bankrupt and non-bankrupt firms) are not represented equally, (Kotsiantis 2007). A slight difference in the two categories does not matter. The challenge is when a majority of the datasets belong to one class. Effective classification with imbalanced data is an important area of research, as high-class imbalance is naturally inherent in bankruptcy predictions.

The current study differs from previous studies in that it uses three data-level methods for addressing class imbalance, including Synthetic Minority Over-Sampling Technique (SMOTE), Random Under-Sampling (RUS), and Random Over-Sampling (ROS) techniques in comparing the predictive ability of the two of the most commonly used algorithms in corporate bankruptcy prediction, namely the logistic regression (LR), and the artificial neural network (ANN).

When a class imbalance exists within training data, learners will over-classify the majority group due to its increased prior probability. As a result, the instances belonging to the minority group are misclassified more often than those belonging to the majority group. Class imbalance in the training dataset makes it very difficult to accomplish the typical objective of accurately predicting the positive class of interest (bankrupt firms). In addition, some evaluation metrics, such as accuracy, may mislead the analyst with high scores that incorrectly indicate good performance.

This is an important line of enquiry as it sheds light on this less explored area in predicting corporate bankruptcy and the performance accuracy of the models. The rest of the chapter is organized as follows; section 5.2 discusses the definition of terms used in this thesis and section 5.3 describes challenges of class imbalance. In section 5.4 we present a brief discussion of the dataset used in the analysis. Section 5.5 presents the results from the two-bankruptcy prediction models and evaluates their forecast accuracy, while section 5.6 concludes the chapter.

5.2. Definition of Terms- Insolvency, Default and Bankruptcy.

Predicting corporate business failure or bankruptcy is one of the most critical problems facing businesses, lenders, government, and other stakeholders. Indeed, the bankruptcy prediction problem has application to a broad base of decision-makers. For instance, lending institutions considering lending money are interested in determining if the business to which the loan is given will be able to repay their obligations as they fall due. Financial institution regulators could use a bankruptcy prediction model to decide whether a particular institution should be closed or receive increased attention and guidance. Consequently, the prediction of bankruptcy is one of the essential decision-making problems facing lenders. Yet the literature is ambiguous in its definition of business failure.

Authors such as Balcaen and Ooghe (2006) posit that failure criterion in the extant literature is chosen arbitrarily. Some authors use the juridical definition of failure, namely bankruptcy (Altman, Marco & Varetto, 1994; Hillegeist, Keating, Cram & Lundstedt, 2004). Others use the financial distress definition (Pan, 2012; Sun & Li, 2008; Xiao, Yang, Pang & Dang, 2012). The latter can also be described as failure-related events such as insolvency (Lepetit & Strobel, 2013; Jackson & Wood, 2013), default (Tserng, Chen, Huang, Lei & Tran, 2014; Peresetsky, Karminsky & Golovan, 2011), etc. The literature uses four genetic terms to describe unsuccessful business enterprises: failure, insolvency, default, and bankruptcy (Altman and Hotchkiss 2006).

In line with Altman and Hotchkiss (2006), we define insolvency as a situation in which the liabilities of a firm are greater than its assets making the firm unable to meet its current obligations and, therefore, sending a signal of a lack of liquidity. On the other hand, default occurs when a firm fail to fulfil its obligation, primarily to repay a loan. The debtor in a default situation violates a condition of an agreement with a creditor and can be the grounds for legal action. Default and bankruptcy are mainly used interchangeably in the literature. While both default and bankruptcy can hurt a firm's credit rating, both are different.

A default event occurs when a borrower falls behind on payments. Bankruptcy is a legal process that a debtor can use to get their debts discharged or negotiate on a more manageable repayment plan. Essentially a default is a failure to meet the legal obligations or conditions of a loan. While bankruptcy is a legal process through which an entity that cannot repay debts to creditors may seek relief from some or all of its obligations. In most jurisdictions, bankruptcy is imposed by order of the court, often initiated by the debtor.

As discussed in chapter three, bankruptcy is not the only legal status an insolvent person may have. In the United Kingdom, corporate organizations enter into differently named legal insolvency procedures, including liquidation and administration. In this thesis, we adopt Ross, Westerfield and Jaffe's (1999) legal bankruptcy definition, which means that the company goes to court for a declaration of bankruptcy. Legal bankruptcy imposes court supervision over the financial affairs of firms that are insolvent or in default.

5.3 Challenges of Class Imbalance

One of the essential techniques to manage credit risk (risk of default and eventual bankruptcy) associated with lending is customer selection- proper credit risk management starts with a good selection of potential borrowers and loan pricing that reflects the risk associated with the loan. Robust risk assessment models and qualified credit officers are critical requirements for a good selection strategy. Financial institutions' fundamental dilemma is how to discriminate between good and bad corporate credit risk in assessing a loan application. Most international lending institutions use bankruptcy prediction models to support this decision making process.

These models require labelling training data, and in classification problems, each data sample belongs to a known class or category, (Witten et al 2016). A significant challenge in most bankruptcy prediction datasets is the problem of class imbalance. A classification dataset with skewed class proportions is said to be imbalanced. Imbalanced data refers to classification problems where the classes are not represented equally. For instance, bankruptcy prediction is a two-class (binary) classification problem involving bankrupt and none-bankrupt firms. In most cases, the datasets do not have an equal number of instances in each class. We find that the number of cases belonging to the bankruptcy case may be significantly lower than those belonging to none-bankrupt cases.

The predictive model developed using machine learning algorithms could be biased and inaccurate in such situations. Since machine learning algorithms are designed to improve accuracy by reducing error, they do not consider the class distribution or balance of classes. Learning from imbalanced datasets can be very difficult, especially when working with big data (Bauder et al. 2018). Surprisingly, we found that studies in bankruptcy prediction models do not address this critical problem or are unclear on handling skewed class proportions in the datasets. This differs from most medical predictive and diagnostic studies that take class imbalance seriously (Bauder et al. 2018; Bauder and Khoshgoftaar, 2018). Understanding the class imbalance problem and the methods for addressing it is indispensable since such skewed data exists in many real-world applications.

Classes/cases that make up a large proportion of the data set are called the majority classes, while those that make up a smaller proportion are the minority classes. Machine Learning algorithms tend to produce unsatisfactory classifiers when faced with imbalanced datasets. For any imbalanced data set, if the event of interest belongs to the minority class and the event rate is less than 5%, it is referred to as a rare event. At this point, it is good to understand what counts as imbalanced. According to research, imbalance could range from mild to extreme. The table below illustrates class imbalance.

Degree of imbalance	**Proportion of minority class**
Mild	20-40% of the dataset
Moderate	1-20% of the dataset
Extreme	<1% of the dataset

Table 5.1 Class Imbalance Classification. Source: Google Analytics.

Johnson and Khoshgoftaar (2019) noted that when a moderate and extreme class imbalance exists within training data, learners will typically over-classify the majority group due to its increased prior probability. As a result, the instances belonging to the minority group are misclassified more often than those belonging to the majority group. Indeed, classifier algorithms like Decision Tree, Logistic Regression, amongst others, have a bias towards the majority classes. Some of these classifiers tend only to predict the majority class, Du Jardin (2015). The features of the minority class are treated as noise and are often ignored. Thus, there is a high probability of misclassification of the minority class compared to the majority class.

In addition, some model performance evaluation metrics, such as accuracy, may mislead the analyst with high scores that incorrectly indicate good performance. The main question faced in developing bankruptcy prediction models is how to get a balanced dataset by getting a decent number of samples for these anomalies, given the rare occurrence for some of them. So how do we deal with class imbalance? Research shows three broad methods of dealing with class imbalance in machine learning models to include- data-level techniques, algorithm-level methods, and hybrid approaches (Krawczyk, 2016).

According to Krawczyk (2016), data-level techniques attempt to reduce the level of imbalance using different data sampling methods. Algorithm-level methods for handling class imbalance are implemented with a weight or cost schema, including modifying the underlying learner or its output to reduce bias towards the majority group. Finally, hybrid systems combine both sampling and algorithmic methods.

5.3.1. Data-Level Methods for Handling Class Imbalance.

Skewed data distributions are inherent in applications where the positive class occurs with reduced frequency. Some examples of knowledge domain where skewed distribution occur include data found in disease diagnosis (Krishnan and Niculescu 2006), fraud detection (Wei et al. 2013; Khoshgoftaar and Bauder 2018), and image recognition (Kubat, Holte and Matwin 1998). In this section we will discuss the data level methods we employed to address the skewed data distribution in our dataset namely- Synthetic Minority Over-Sampling Technique (SMOTE), Random Under-Sampling (RUS), and Random Over-Sampling (ROS) in turn below.

Random Under-Sampling: technique modify the training distributions to decrease the level of imbalance or reduce noise, e.g. mislabelled samples or anomalies. Random under-sampling (RUS) discards random samples from the majority group in their simplest forms. A major disadvantage of this method is that it can discard potentially helpful information, which could be important for building rule classifiers (Hulse, Khoshgoftaar and Napolitano (2007).

Random Over-Sampling: this is another data-level method for handling class imbalance. Random Over-Sampling (ROS) duplicates random samples from the minority group (Van, Khoshgoftaar and Napolitano (2007). Under-sampling discards data, reducing the total information the model has to learn from (Chawla, Japkowicz and Kotcz 2004). Over-sampling may cause an increased training time due to the increased size of the training set and can lead to over-fitting. Zhang and Mani (2003) suggest intelligent under-sampling such as Near-Miss algorithms that use a K-nearest neighbours (K-NN) classifier to select majority samples for removal based on their distance from minority samples. In their contributions, Kubat and

Matwin (2000) proposed a One-Sided Selection as a method for removing noisy and redundant samples from the majority class as they are discovered through a 1-NN rule.

The *Synthetic Minority Over-Sampling Technique* (SMOTE) produces artificial minority samples by interpolating between existing minority samples and their nearest minority neighbours (Chawla et al.2002). Several variants to SMOTE were introduced, including *Borderline-SMOTE* (Han et al. 2005) and *Safe-Level-SMOTE (*Bunkhumpornpat et al. 2009) to improve the original algorithm by considering majority class neighbours. According to Johnson and Khoshgoftaar (2019), the Borderline-SMOTE limits over-sampling to the samples near class borders, while Safe-Level-SMOTE defines safe regions to prevent over-sampling in overlapping or noise regions.

Many studies on image recognition have used ROS and RUS methods to address the class imbalance in Convolutional Neural Network (CNN). For example, Hensman and Masko (2015) show that balancing the training data with ROS can improve the classification of imbalanced image data. Lee et al. (2016) used different variants of RUS to reduce class imbalance for the purpose of pre-training a deep CNN. Their study shows that pre-training DNNs with semi-balanced data generated through RUS or augmentation-based over-sampling improves minority group performance.

5.3.2. Formulation of Study Hypothesis.

Despite the plethora of comparative and single study analyses in bankruptcy prediction, very little empirical work addresses the problem of class imbalance. A situation in which the classes (bankrupt and non-bankrupt firms) are not represented equally in the dataset. As alluded to in the previous sections, a slight difference in the two categories does not matter. The challenge is when a majority of the datasets belong to one class. Effective classification with imbalanced data is an important area of research, as high-class imbalance is inherent in bankruptcy predictions.

Consequently, we empirically compared the predictive abilities of Logistic Regression and Artificial Neural Network commonly used bankruptcy predictive models correcting for class imbalance in the data. We corrected for class imbalance in the training dataset because it makes it very difficult to accomplish the objective of accurately predicting the positive class of interest (bankrupt firms). We employed three data-level methods Namely-Synthetic Minority Over-Sampling Technique (SMOTE), Random Under-Sampling (RUS), and Random Over-Sampling (ROS) techniques to address the less explored area of class imbalance in corporate finance and banking literature.

Some studies suggest that classifier algorithms like Logistic Regression models are biased toward the majority classes because the model tends only to predict the majority class, Du Jardin (2015). The features of the minority class in these algorithms are treated as noise and are often ignored. Consequently, there is a greater probability of misclassification of the minority class than the majority class.

We tested the null hypothesis of the accuracy paradox in highly imbalanced datasets versus the alternative hypothesis of no effect. The following hypothesis was formulated and tested in the logistic regression and artificial neural network models:

$$H_0 = A\ class\ imbalance\ in\ the\ datasets\ affects\ the\ prediction\ accuracy\ of\ the\ logistic\ regression\ and\ artificial\ neural\ network\ models.$$

H_1

$\neq$ $A\ class\ imbalance\ in\ the\ datasets\ does\ not\ affect\ the\ prediction\ accuracy\ of\ the\ logistic\ regression\ and\ artificial\ neural\ network\ models.$

This is an essential line of enquiry as it sheds light on this less explored area in predicting corporate bankruptcy and the performance accuracy of the models. Developers of bankruptcy prediction models should consider the so-called accuracy paradox, where the accuracy metric provides misleading classification accuracy reflecting the underlying class distribution.

5.4. Data Description and Methods.

One of the major problems in machine learning is identifying a representative set of attributes/features from which to construct a classification model for a particular task. Attribute/feature selection is a common challenge in the machine learning technique. This section describes the dataset used in this study and the challenges of irrelevant attributes in the training phase.

5.4.1 Description of Variables.

The data used in this thesis is open-source data of Twainese companies with over 6000 observations and 86 attributes. A major problem in machine learning is the problem of redundant variables. Including redundant/irrelevant features in the training/learning phase would make knowledge discovery during the training complex. Various feature selection methods could be used to reduce the number of input variables to those that are most useful to a model. Feature selection/dimensionality reduction on sample sets will improve the estimators' accuracy scores and boost their performance on high-dimensional datasets.

Indeed, feature selection's main aim is to remove non-informative or redundant predictors from the model (Kuhn and Johnson 2016). Consequently, attribute selection is an important stage of data pre-processing. Previous studies have used statistical-based feature selection methods that target to model the relationship between the input variables and the target variables (D.Lavanya et al. 2011; Suresh, 2016; Abusamra, 2013). We used feature importance scores to select 22 variables relevant to the classification model. The table below shows the list of variables included in the models.

Return on Assets	Cash to Turnover Rate
Net value per-share	Fixed Assets to Total Assets
Quick Ratio	Current Liability to Equity
Debt Ratio	Equity to Long-Term Liability
Net Worth to Assets	Cash Flow to Total Assets
Borrowing Dependency	Cash Flow to Liability
Inventory and Accounts Receivable	Cash Flow to Equity
Total Assets to Turnover	Current Liability to Current Assets
Operating Profit Per Person	Net Income to Total Assets
Working Capital to Assets	Total Assets to GNP Price
Quick Assets to Total Assets	No Credit Interval
Cash to Total Assets	Gross Profit to Sales
Cash to Current Liability	Net Income to Stockholders Equity
Current Liability to Assets	Degree of Financial Leverage
Operating Funds to Liability	Equity to Liability
Working Capital to Equity	Inventory to Current Liability
Retained Earnings to Total Assets	Total Income to Total Expenses
Total Expense to Assets	Working Capital to Turnover Rate

Table 5.2 Attributes Importance.

These ratios measure different aspects of the firms' financial health. These aspects include the ability of the company to generate profit relative to revenue, balance sheet assets, and shareholders' equity (Profitability ratios). The level of debt against other accounts on the balance sheet, income statement, and cash flow statement allows credit analysts to gauge the ability of a business to repay its debts (Leverage ratios). The ability of companies to convert assets into cash. Other aspects of the company's repayment abilities measured include the coverage ratios that measure the coverage that income, cash, or assets provide for debt or interest expenses.

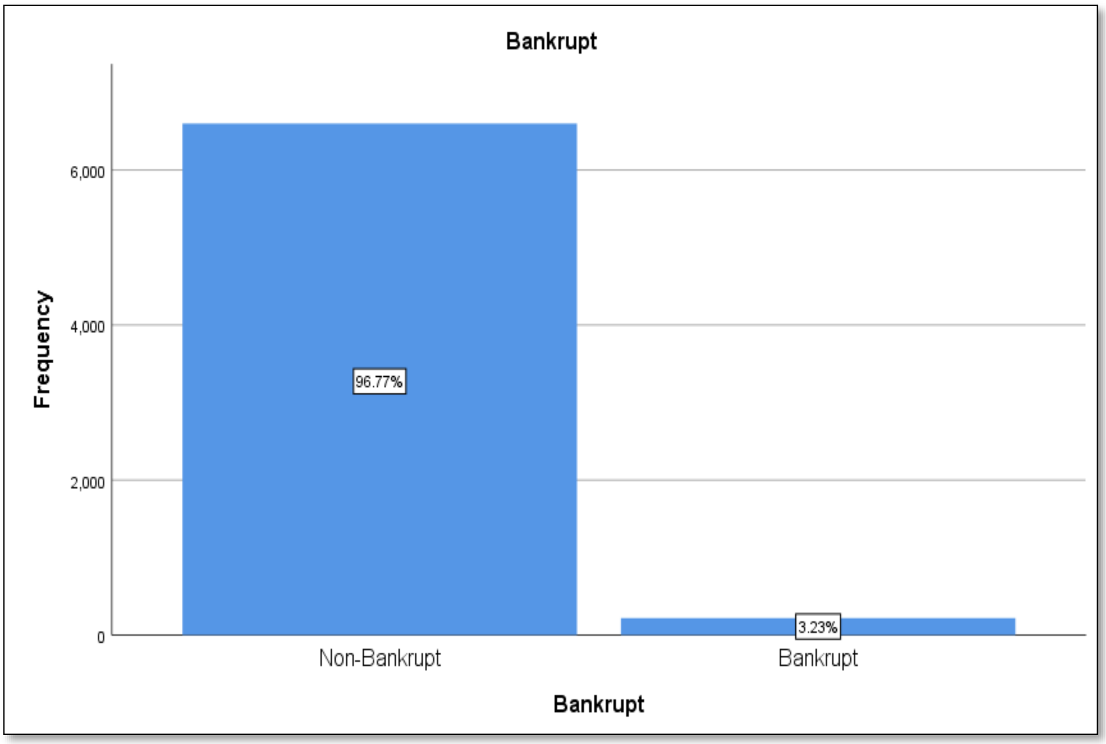


Figure 5.1. Distributions of the Output Variable.

The variable of interest (Bankrupt firms) shows a high skewness level, as shown in figure 5.1 above. There are approximately 97% non-bankrupt firms and 3% bankrupt firms. Given this high level of distribution skewness, there is a high probability of misclassification of the minority class compared to the majority class. As alluded to in the previous sections, the accuracy paradox may arise in the presence of class imbalance. We present the analysis results before accounting for class imbalance in the dataset.

5.5. Comparison of ANN and LR Algorithms.

This section presents the results from machine learning and statistical model. Two primary goals in corporate bankruptcy analysis are inference and prediction. Inference creates a mathematical model of the data-generation process to formalize understanding or test a hypothesis about how a system behaves, (Nwafor 2023). According to Nwafor (2022), prediction aims at forecasting unobserved outcomes or future behavior, such as whether a firm with given financial characteristics will default. Prediction makes it possible to identify the best courses of action (e.g., to lend or not to lend) without requiring an understanding of the underlying mechanisms.

Machine learning (ML) is a field that focuses on drawing conclusions from large amounts of data by letting a model find structures and relationships in the data, (Nwafor 2022; Witten et al. 2016). By presenting a machine learning model with samples from a dataset, the model learns to represent hidden relationships and patterns in the data via a process referred to as training. After the training phase, the algorithm generalizes what it has learned to new, unseen samples. Researchers who use ML algorithms are interested in the ability of these algorithms to generalize to new datasets. On the other hand, a statistical model uses statistics to build a representation of the data and then conduct analysis to infer any relationships between variables or discover insights. A statistical model will include sampling, probability spaces, assumptions, and diagnostics, to make inferences (Nwafor 2022; Bzdok, Altman, & Krzywinski, 2018).

In most cases, models from statistics and machine learning (ML) may be used for prediction and inference. However, statistical models mainly focus on inference achieved by creating and fitting a project-specific probability model. The model allows us to compute a quantitative measure of confidence that a discovered relationship describes a 'true' effect that is unlikely to result from chance (Bzdok, Altman, & Krzywinski, 2018). On the contrary, ML concentrates on prediction by using learning algorithms to find patterns in big datasets (Bzdok 2017). The machine learning models make minimal assumptions about the data-generating process. They can be effective in the presence of complicated nonlinear interactions. Despite the ability of ML tools to generalize in unseen datasets, the best-known disadvantage of ML tools like artificial neural networks (ANN) is their "black box" nature- the inability of model developers in understanding how or why the ANN came up with a specific output.

Artificial Neural Networks: ANN falls within the supervised machine learning algorithms. According to Kuan, C.M and White, (1994), supervised learning involves finding a predictive model that maps inputs to outputs. The learning algorithm is presented with examples of input and output pairs to achieve this goal. The focus of the learning process is to produce a function that gives the desired output for inputs that have not been presented to the algorithm during training. This is achieved by fitting internal parameters referred to as θ to the data it tries to approximate, (Nwafor 2022). The optimal set of parameters found by the algorithm is often denoted by $\hat{\theta}$. A major limitation of ANN is that the values of the fitted parameters cannot easily be analyzed with statistical rigor, and they typically lack causal interpretation.

An artificial neural network is a computational model inspired by biological nervous systems. It is a network structure built up of many interconnected processing units (LeCun et al., 2015). The neurons or nodes of the network can be seen as information-processing units. In neural networks, these processing units are arranged in layers. Signals are passed to the input layers, and they travel through the network to the output layer. Layers between the input and output layers are called hidden layers.

Neural networks can be seen as complex functions that generate an output Y for a given input X. The function parameters are called weights, and the number of layers defines the depth of the network. The number of nodes in a layer is the width of that layer. The activation function maps the weighted input signal to an output activation. Neural networks can approximate non-linear relations that linear models cannot reproduce. The non-linearity is introduced by non-linear activation functions. Given a set of inputs x_1, x_2,…,x_N a weighted sum of the inputs is formed as

$$a_j = \sum_i^N W_{i,j}.x_i + b_j \tag{31}$$

Where $W_{i,j}$ are the network weights, x_i are the inputs and b_j the bias term and a_j is the activation which is the signal that activates the neuron. We used the feed forward neural network (FFNN) that has only forward pointing connections and the nodes are structured in layers as shown in figure 5.2.

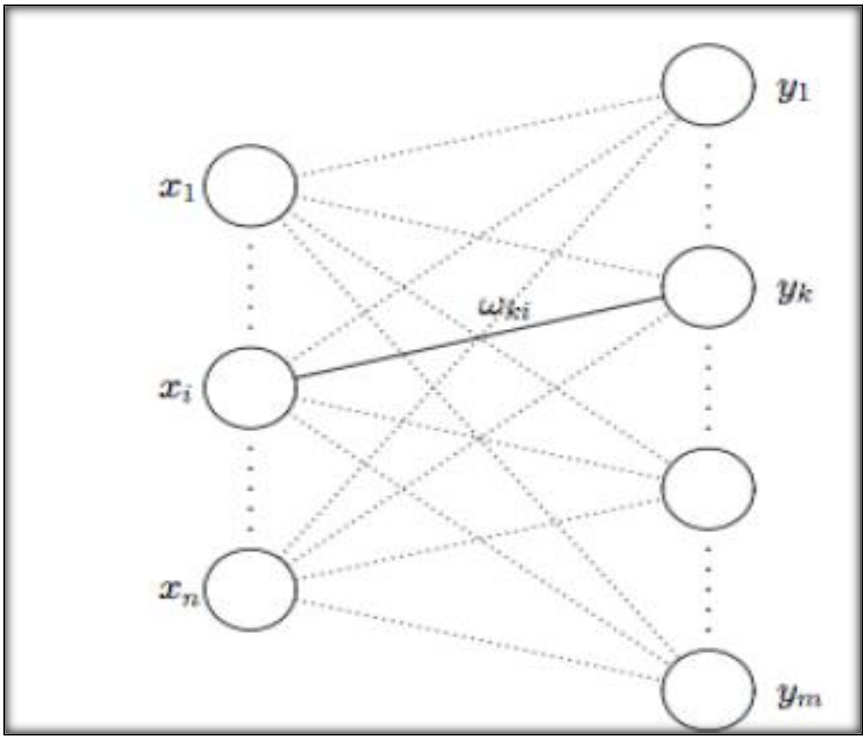


Figure 5.2. Feed Forward Neural Network (FFNN)

Figure 5.2 shows a schematic diagram of a feed forward neural network with two connected layers x and y while w denotes the network weights. We used the hyperbolic tangent function as the activation function. The hyperbolic tangent function is represented as:

$$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1 \qquad (32)$$

As can be seen in Figure 5.2 the hyperbolic tangent function returns a value in the range [-1,1]. We use the normalised method to normalise the covariates. Another important data pre-processing decision concerns data normalization. Normalizing data to use a common scale is a general requirement for many machine learning algorithms. The objective of data normalization is to have the same range of values for each of the inputs to the model. Normalisation of the data is done by replacing each feature x_i by y_i calculated as:

$$y_i = \frac{x_i - \hat{x}}{S} \qquad (33)$$

Where $\hat{x}$ and S are the estimated mean and standard deviation computed on the training data set. The dataset used in this thesis is a complete dataset with no missing values. The error function used is the Cross-entropy. Cross entropy is a type of loss function used in machine learning and classification problems. A loss function, sometimes called a cost function, is used to quantify how well a machine learning model performs its intended task. It can be seen as a quality-of-fit measure. In the context of a classification task, the loss function defines the penalty for an incorrect classification of an observation. By taking the sum over the complete training set, the performance of a model can be represented as an actual number. In this two-class classification problem (Bankrupt and Non-bankrupt firms) the cross entropy is defined as:

$$C = -\frac{1}{N}\sum_{n=1}^{N}[y_n ln\hat{y}_n + (1 - y_n)ln(1 - \hat{y}_n)] \tag{34}$$

Where N is the total number of observations, $\hat{y}$ is the output of the machine learning model and y is the variable of interest (output variable). The function is positive and when $\hat{y}$ is close to y the penalty is close to zero, (LeCun et al., 2015).

5.5.1. Data Partitioning/Splitting.

One of the critical issues when fitting a bankruptcy prediction model is to assess how well the fitted model behaves when applied to a new dataset. To address this issue, previous authors split the dataset into multiple partitions: a *training* sample used to fit the model's parameters and a *validation* sample used to choose the parameters of the model and track the errors during the training. Literature suggests the following different validation procedures; first, *validation sample*: This method involves randomly splitting the dataset into training and validation sets. The training sample is used in the model estimation phase, while the validation sample is used to evaluate the model (Louzada et al., 2016).

Essentially, the training sample is used to fit the model's parameters, and the validation sample is used to choose the parameters of the model (e.g., the number of hidden units in the network) and track the errors during the training. The validation set is used to obtain an estimate of how the model would perform with unseen data. A good performance in the validation sample indicates that the model can generalize the data.

Nevertheless, the challenge with using one independent sample is that the validation dataset may sometimes be used to "fine-tune" the model parameters during the training process. For instance, a researcher might try out neural network models with different architectures and test the accuracy of each on the validation dataset to choose the best model amongst the competing architectures. If the validation data is utilized to compute the accuracy of the final model fit, the result would be an overly optimistic estimate of the model's accuracy. This is because the model fitting process ensures that the model's accuracy for the validation data is as high as possible. The second method is the $K - fold$ cross-validation approach, (Hastie; Tibshirani; and Friedman 2009). This approach involves randomly dividing the dataset into k groups or folds of approximately equal size. The first fold is treated as a validation set, and the model is fit on the $K - 1$ folds.

For example, suppose that 10 groups are used (10-fold cross-validation). The original dataset is split into 10 equal random subsets. The first 9-subsets are used to develop (training sample) the model. The resulting model is assessed for accuracy on the remaining $1/10th$ of the sample (test sample). Each observation in the dataset is assigned to an individual group and stays in that group for the procedure duration. This means that each sample can be used in the test sample once and used to train the model $K - 1$ times.

This process is repeated at least 10-times to get an average of 10 indexes such as standard deviation or standard error. The results of a $K - fold$ cross-validation run are often summarized with the mean of the model skill scores. One of the drawbacks of the $K - fold$ cross-validation method is that the entire dataset is used for training and testing models.

The final method is the *Train/Validation/Test* method. This is the method advocated in this paper. This is an essential departure from most studies in this area that use only a single learning scheme- training and validation samples, (Hastie; Tibshirani; and Friedman 2009). This validation approach involves partitioning the dataset into 3 samples- training, validation, and test samples. The purpose is to avoid some overfitting into the validation set. It is good to set aside another portion of data that is not used in the training or the validation processes- the '*test*' sample.

That is, the model's performance should be confirmed by measuring the performance on a third independent dataset. Evaluating the accuracy of the fitted model on the test data gives a realistic estimate of the model's performance on completely unseen data. The evaluation of the final model performance must be done on an unseen sample (test sample) that is "*locked*" away completely until all model tuning is complete.

The problem with using only a single learning scheme is that the model may suffer from overfitting. The errors in the validation sample may not provide an unbiased estimate of the generalization error which may result in a biased score. In this study, cases were randomly assigned based on a relative number of cases into 3 groups- training sample: 60%; validation sample: 25%; and (test) sample: 15%. Using a holdout test sample ensures that the errors are unbiased estimates of the generalization error.

Logistic Regression: Logistic regression is a statistical method used to build machine learning models where the dependent variable is dichotomous: i.e. binary. Logistic regression is used to describe data and the relationship between one dependent variable and one or more independent variables. The model uses a logistic function to model a binary dependent variable in its basic form, although many more complex extensions exist. A binary logistic model has a dependent variable with two possible values, such as Bankrupt/No-Bankrupt represented by an indicator variable, where the two values are labelled *"0"* and *"1"*. Please, refer to chapter two section 2.2.2 for the reduced functional form of a logit model.

5.5.2 Presentation of Results.

This section discusses the results from the experiment using both the extremely imbalanced dataset and a resampled dataset. The two most important criteria used in assessing the quality of a classification model are discrimination and calibration. Discrimination accesses how well the two classes in the data set are separated while calibration determines how accurate the model probability estimate $f(x, \alpha)$ is to the true probability $P(y|x)$. To provide an unbiased estimate of a model's discriminatory and calibration accuracy, the values must be calculated from a dataset not used in the training process. As stated in section 5.5.1, we used the holdout sample to evaluate the model's performance.

First, we start by discussing the results from the original dataset. Table 5.3 below shows that the logistic regression slightly out-performs the neural network in terms of performance accuracy (97% versus 96%), and area under the curve (0.94 versus 0.93). Both algorithms could be sensitive to class imbalance. Although, the use of an unbalanced training data in logistic regression affects only the estimate of the model's intercept, it is necessary to take class imbalance into consideration because the biased intercept could skew all the predicted probabilities, which in turn may compromise the predictions.

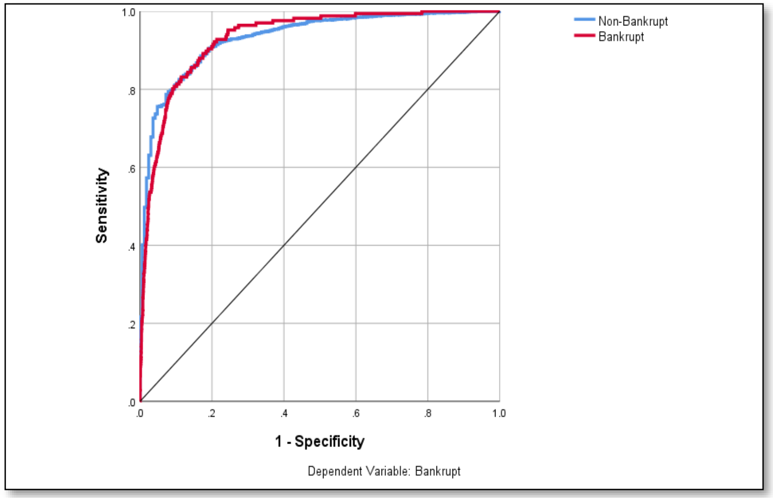
Figure 5.3 presents the ANN model's specificity, ROC, and Lift charts. The ROC curve suggests that the ANN does an inferior job predicting the minority class (bankrupt firms) and a great job in predicting the majority class (non-bankrupt firms). The classifier assumes that the wrong prediction of either category (bankrupt and non-bankrupt firms) has the same cost. But in fact, the incorrect prediction of the minority class (bankrupt firms) is worse than the wrong prediction of the majority class (non-bankrupt firms). A ROC curve lying on the diagonal line, as in figure 5.3, reflects the performance of a classifier that is no better than chance level, i.e. a classifier which yields positive or negative results unrelated to the actual financial distress status.

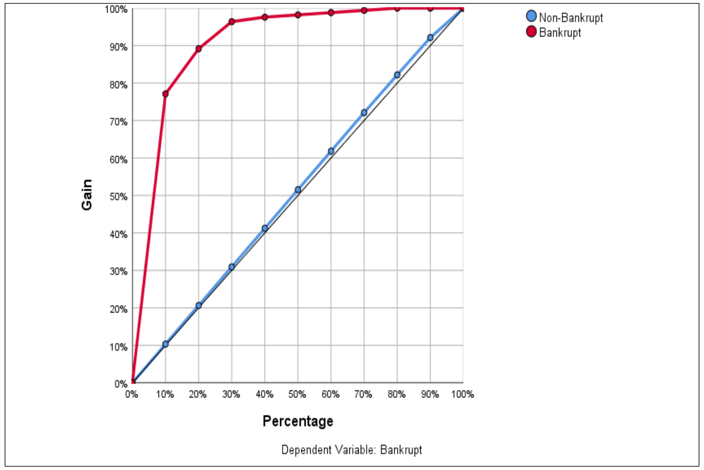
	Overall Accuracy	AUC	Hosmer and Lemeshow Test
Neural Network	96.3%	0.93	
Logistic Regression	97.1%	0.94	0.18

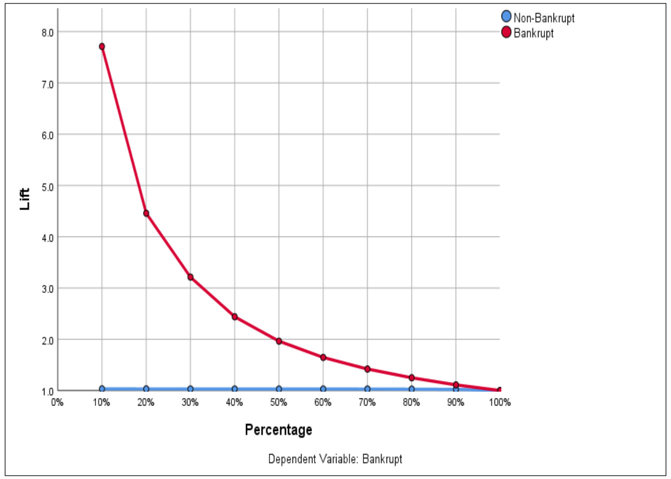
		60% Training Data		
	Non-Bankrupt	Bankrupt	Percentage Correct	Cross Entropy Error
Neural Network	3935	105	97.1%	357.3
		20% Validation/Testing Data		
	Non-Bankrupt	Bankrupt	Percentage Correct	Cross Entropy Error
Neural Network	1300	38	96.7%	119.6
		20% Test Data (Hold-Out Sample)		
	Non-Bankrupt	Bankrupt	Percentage Correct	ROC (AUC)
Neural Network	1339	47	96.3%	0.93

Table 5.3 Artificial Neural Networks and Logistics Regression with Class-Imbalance

Figure 5.3: Specificity, ROC and Lift Charts.







The results provide a baseline for comparing any modifications performed to the original dataset. The Hosmer and Lemeshow (HL) test for the goodness of fit assesses whether or not the observed event rates match expected event rates in subgroups of the model population, (Bilder and Loughin 2014). The $null\ hypothesis$ for the HL tests is that the observed and expected proportions are the same across all groups. The Hosmer and Lemeshow P^2 value rejects this null hypothesis. We can conclude that the model is a good fit for our dataset. We now turn our attention to the resampled dataset.

We used the three discussed data-level methods for handling class imbalance (refer to section 5.3.1), namely- Random under-sampling, Random over-sampling and Synthetic minority over-sampling techniques, to correct the class imbalance in the original dataset. Figure 5.4 shows the new distribution of the output variable. Although the distribution of the output variable shows a level of imbalance, it falls within the mild/acceptable region-(see table 5.1.).

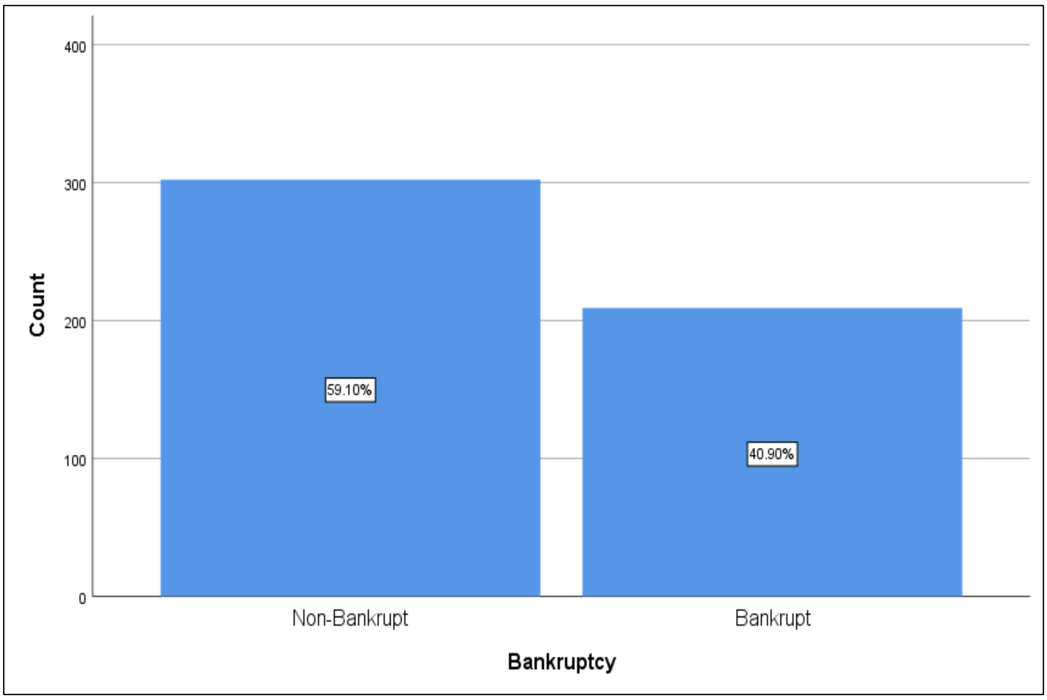


Figure 5.4 Distribution of the Output Variable after correcting for class imbalance.

The results from the resampled datasets shown below suggest slight difference in terms of the overall percentage accuracy rate between the two models, but an improvement in the prediction of the minority class. The ANN slightly outperforms the LR at (89.8% versus 88.9%). The previous results reveals that the model suffered from the so-called 'accuracy' paradox. The choice of the performance evaluation metrics used to evaluate the performances of bankruptcy prediction models should be made carefully, particularly in the presence of high-class imbalance. Literature suggests that using an accuracy score as an evaluation metric for a highly imbalanced dataset may not be a good measure of classifier performance.

	Overall Accuracy	**AUC**	**Hosmer and Lemeshow Test**
Neural Network	89.8%	0.93	
Logistic Regression	88.9%	0.96	0.61

Table 5.4 Artificial Neural Networks and Logistics Regression Resampled Dataset

What is evident from the results is that the AUC for the ANN seems to be invariant to the class imbalance, while that of logit shows a slight improvement in the AUC scores of imbalanced and balanced models (0.94 versus 0.96). There is also an improvement in the logistics regression Hosmer and Lemeshow Test as reported in tables 5.3.and 5.4, respectively. Another thing that is evident from the analysis is that accounting for class imbalance in the dataset affects the performance of the two classification algorithms, particularly in predicting the minority cases. Our experiment shows that addressing class imbalance could improve the goodness of fit for logistics regression models and the area under the curve.

5.5.3 Comparison of the Artificial Neural Network and Logistics Regression.

We conducted a formal Receiver Operating Characteristic (ROC) and its score Area Under the Curve (AUC) analysis to choose between the two classification algorithms. Evaluation metrics like the ROC-AUC curve are a good indicator of classifier performance. The Receiver

Operating Characteristic (ROC) Curve Analysis plays a central role in evaluating the classification ability of models to discriminate the actual state of firms, finding the optimal cut off values, and comparing two alternative models when each task is performed on the same dataset, (Hanley, 1982).

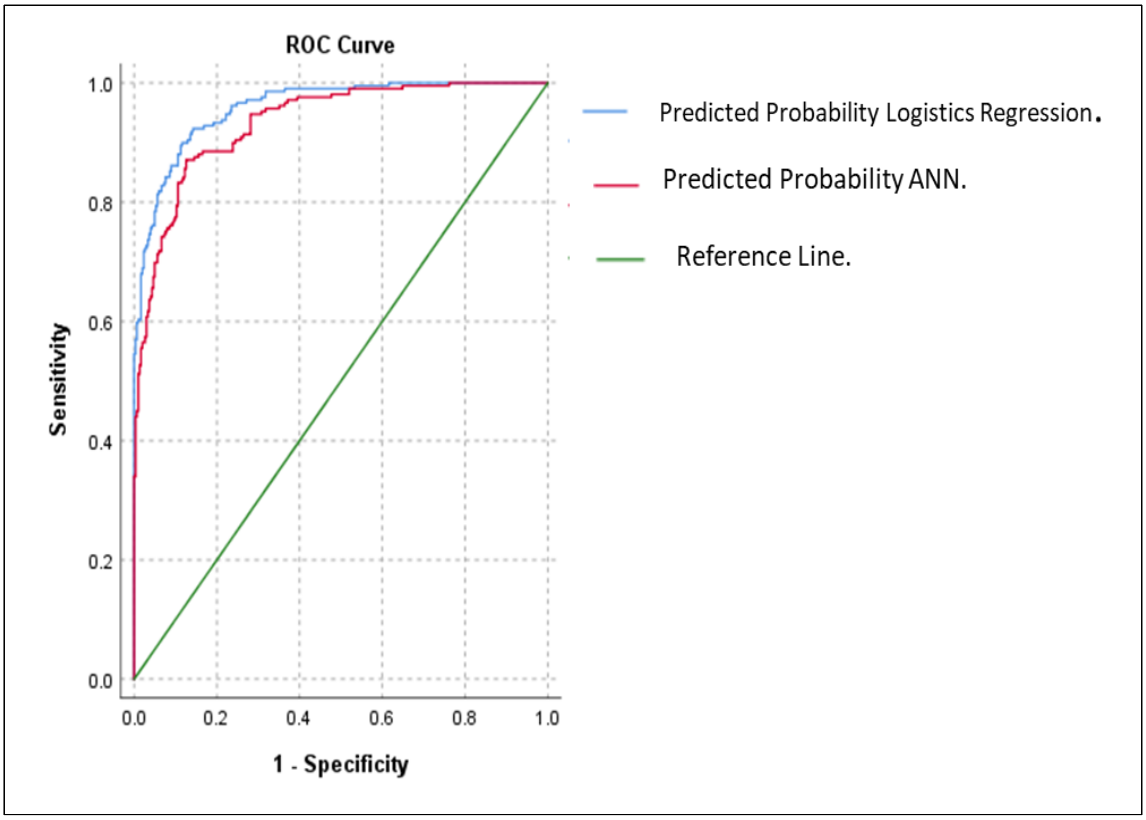


Figure 5.5 ROC Curve Analysis.

A ROC curve is based on the notion of a "separator" scale, on which results for the bankrupt and non-bankrupt firms form a pair of overlapping distributions. ROC curves corresponding to a model's progressively greater discriminant capacity are located closer to the upper left-hand corner in "ROC space. Figure 5.5 shows that the logistic regression model has a slight discrimination ability than the artificial neural network.

Test Result Variable (s)	Area	AUC Difference
Predicted Probability (LR)	0.960	0.026***
Predicted Probability (ANN)	0.934	

Table 5.5 Area Under the ROC Curve.

Null Hypothesis: True Area Difference =0.

The paired-sample Area Difference Under the ROC Curves tests the null hypothesis of true area difference. Specifically, the Z-test tests the hypothesis that the true area difference between the predicted probabilities from the two models is zero. The p-square from this test reported in table 5.5 rejects the null hypothesis of no difference. We can, therefore, conclude that a difference of 0.026 exists between the logit and ANN models.

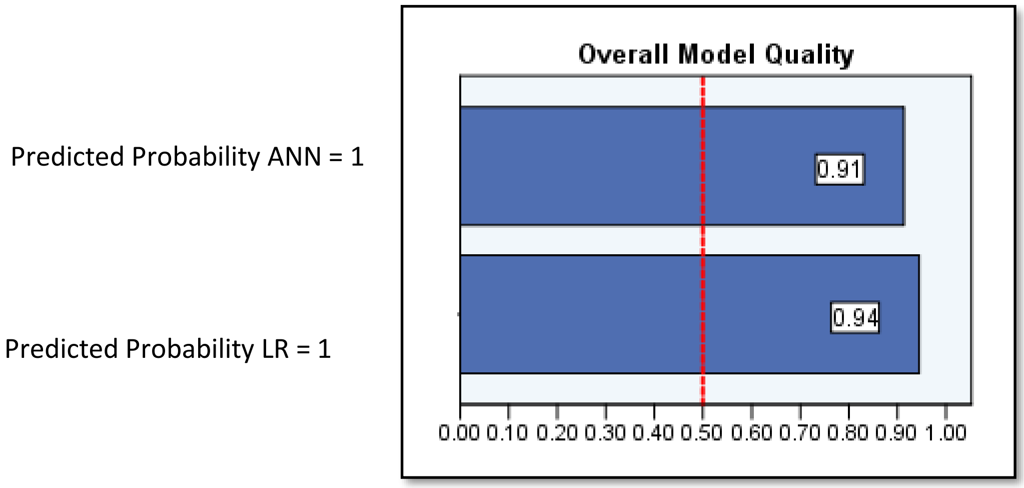


Figure 5.6 Overall Model Quality.

Figure 5.6 shows that both models perform on about the same level, with logistic regression generally outperforming the artificial neural network in terms of overall model quality.

5.6. Conclusion.

This chapter compares the predictive ability of logistics regression and artificial neural networks in the presence of serve class imbalance. Using real-world bankruptcy prediction datasets with over six thousand observations and ninety-six attributes, we compare these two approaches using various performance criteria of sensitivity, specificity, accuracy, and area under receiver operating characteristics (AUC) curves. The results of our empirical analysis indicate that the Logistic regression slightly outperforms the Artificial Neural Network techniques for specificity, accuracy and AUC performance evaluation metrics.

After correcting for class imbalance in our dataset, the Operating Characteristic (ROC) Curve Analysis shows that the logistic regression model has a slight discrimination ability than the artificial neural network. Our findings confirm the 'accuracy paradox' from previous studies. We can conclude that accounting for class imbalance in the dataset can improve the fit of logistic regression and the ability of ANN to predict the minority cases in a dataset.

Chapter Six

Summary, Conclusion and Recommendations.

6.1. Introduction.

The need for reliable and robust corporate bankruptcy prediction models is critical, particularly in today's world of financial and economic uncertainties. Since the development of Beaver (1966) univariate model and Altman's (1968) Multi-Discriminant Z-score model, there has been a constant improvement in methodologies and statistical techniques to forecast corporate bankruptcy accurately. The purpose of these models is to improve the efficiency and stability of both the credit markets and the broader financial and economic system. Bankruptcy prediction models can act as early warning indicators to alert company managers and shareholders of the possible impending danger of financial distress of the corporations in which they are stakeholders.

In the light of the COVID-19 global pandemic that caused significant contractions in global GDP and, therefore, resulted in the defaults of financially weak firms and a constrained global economic recovery, global corporate insolvencies in 2022 and beyond are expected to be higher than the insolvencies recorded during the 2007/09 financial crisis. Hence, the need to understand the financial position of firms is imperative to different stakeholders, including lenders, shareholders and managers. The prediction and classification of corporate firms to determine whether they are potential candidates for financial distress is an area that has been widely explored in the extant literature.

Following the seminal works of Beaver (1966) and Altman (1968), academics and practitioners have developed different bankruptcy prediction models to predict future bankruptcies better.

Bankruptcy prediction tools have evolved from conventional statistical models to sophisticated machine learning algorithms.

Our study reviewed some of the literature's most frequently used bankruptcy prediction tools. Following Alaka et al. (2018), we conducted a systematic literature review of two statistical bankruptcy predictive tools, namely Multi-Discriminant Analysis (MDA) and Logistic regression and the following artificial intelligence tools- artificial neural network (ANN), support vector machines (SVM), rough sets (RS), case-based reasoning (CBR), decision tree (DT) and genetic algorithms (GA). We included the hazard model, a popular tool used in predicting the time-to-default of a firm. Despite the plethora of statistical and machine learning models within this field, the apparent lack of consensus regarding model development's methodological issues led to adopting a systematic literature review (SLR) methodology.

Our review of existing literature suggests that the artificial neural network (ANN) is one of the most widely used algorithms in developing bankruptcy prediction tools. Yet results from the ANN studies differ in accuracy level and other performance evaluation metrics. Our study contributes to knowledge in this field by testing for statistical heterogeneity in studies that reported the ANN as the tool with the best predictive accuracy and the use of meta-regression to explore the potential sources of between-study differences in the pooled ANN studies.

6.2. Summary of the Thesis Chapters.

This thesis contains five main chapters. In chapter one, we discussed the challenges of corporate bankruptcy/insolvency worldwide. The chapter provided a detailed perspective on the study and the motivation for the research. In that chapter, we provided statistics on corporate bankruptcies and how the COVID-19 global pandemic exacerbated the rate of insolvency globally. The research aim, objectives and contributions to literature were also discussed, and a brief summary of the findings. Chapter two of this thesis reviews the literature on the bankruptcy prediction models and the commonly used statistical and machine learning algorithms used in this area. We summarized and analysed the extant literature while highlighting the historical evolution of this knowledge domain and facilitating future research in this area.

Chapter three presents a review of theoretical developments on financial distress and bankruptcy. We discussed three main theories of bankruptcy, namely- trade-off theory, value-based theory and risk-sharing theory and how they relate to the thesis. Given that this thesis focuses on corporate bankruptcy, we discussed the different methods of resolving financially distressed firms and the associated problems. We highlighted the resolution mechanisms in the private and public domains using corporate finance paradigms to interpret some of the far-reaching developments in financial distress of systemic nature.

Chapter four presents the methodology for this thesis-systematic literature review and quantitative meta-analysis. We reviewed eight popular tools that previous studies used to develop Bankruptcy Prediction Models between 2010 and 2015. We used meta-analysis and meta-regression statistical techniques to combine data from Artificial Neural Networks (ANN) studies on bankruptcy prediction models to test the presence of statistical heterogeneity and explore the possible sources of these variations. The meta-regression allowed us to evaluate how sample sizes, types of input datasets, validation methods and percentage of failed firms in the samples affect the performance of the Artificial Neural Networks in predicting corporate bankruptcy.

The problem of class imbalance in bankruptcy prediction models has received limited attention in the literature. Despite the plethora of comparative and single study analyses in this area, very little empirical work addresses the challenges of class imbalance. Effective classification with imbalanced data is an essential area of research, as high-class imbalance is naturally inherent in bankruptcy predictions. Chapter five of this thesis addresses the issues of class imbalance. It shows that reducing class imbalance in the datasets can improve the goodness of fit of LR models and enhance the ability of the ANN to predict the minority class.

The final chapter of this thesis presents the study's summary, conclusion, and recommendations. A summary of the research methods and research approach, and results were discussed in this chapter.

6.3 Summary of Research Methods and Approach.

This study reviews analytical methods used in predicting corporate bankruptcy. Using a systematic literature review, we aimed to distil from a barrage of tools the most commonly used algorithms in developing bankruptcy prediction models. Although, previous studies have employed a systematic review method in this knowledge area-(see Balcaen and Ooghe 2006; Aziz and Dar 2006; Appiah, Chizema, and Arthur 2015; and Alaka et al., 2018). However, none of these studies used a meta-regression to create a model describing the linear relationship between study-level covariates and the effect size (Jakubowski 2015).

Specifically, we used a systematic literature review i) to evaluate the extent to which existing research has progressed in using statistical and machine learning tools to develop models that can predict corporate bankruptcy. Also, we used this methodology to identify study characteristics that could influence model performance and evaluate the performance ability of different bankruptcy prediction models using the percentage accuracy levels and type I and type II errors in their models.

We obtained relevant studies in bankruptcy prediction studies by systematically searching several online databases. In line with Alaka et al. (2018), we limited our search to studies that used logistic regression, artificial neural network (ANN), support vector machines (SVM), rough sets (RS), case-based reasoning (CBR), decision tree (DT) and genetic algorithm (GA). The review adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009).

We used meta-analysis to estimate the magnitude of systematic heterogeneity in existing studies-thus extending the scope of earlier systematic reviews that have attempted to evaluate evidence using a narrative synthesis and summary of findings approach (Kirkos 2015; Appiah, Chizema, and Arthur, 2015; and Alaka et al. 2018). We also developed a novel critical appraisal tool for assessing the methodological quality of analytical studies by adapting the Joanna Briggs Institute (JBI) quality appraisal tools. Our critical appraisal checklist includes eight questions specific to the research aim. This is a significant contribution to the extant literature as new reviews on bankruptcy prediction, and credit scoring studies can use the checklist to assess the methodological quality of the primary studies.

6.4 Summary of Research Findings.

The central focus of this thesis is to explore between-study heterogeneity and the potential sources of these variations in studies that use the ANN in predicting corporate bankruptcy; and to compare the performance of ANN and logistic classifiers after correcting for class imbalance in the dataset. We extracted data from eighteen primary studies included in the systematic review that reported the ANN as the tool with the best corporate bankruptcy predictive accuracy for the meta-analysis and meta-regression.

A summary of the reviewed studies reveals that the authors used different input datasets, sample sizes, and data validation methods. These differences could mean that the studies are not homogenous. Consequently, we use the random-effects model that accounts for the heterogeneity among studies, both in the point estimate of their results and the confidence intervals' width.

A qualitative visual analysis of the studies' results via the forest plot suggests between-study variability. The quantitative tests of heterogeneity statistics confirm the presence of heterogeneity. This result is not surprising because several factors such as sample size, type of input data sets, percentage of bankrupt firms in the sample and the type of validation methods used in the primary studies can influence the magnitude and direction of the effect size. Given the substantial differences in study effects observed from the meta-analysis, we empirically explored the potential sources of these variations using meta-regression.

The results from the meta-regression suggest that sample size and the data validation methods have a statistically significant effect on the performance of the ANN model. Although we did not find a statistically significant relationship between the other moderator variables (type of input datasets, the proportion of bankrupt firms and the event rate); however, our finding reveals that these variables taken together can explain approximately 77% of the variance in the bankruptcy event rate- i.e. the model's performance accuracy. In addition, we found that correct for class imbalance in the dataset can improve the classification of logistic and ANN classifiers.

6.5 Recommendations and Suggestions for Future Reviews.

We conducted a systematic search of Engineering Village (EV), Web of Science UK (WoS) and Business Source Complete (BSC) using predefined criteria. In addition, we scanned abstracts from selected conference proceedings and other sources, and reference scanning of the search results was performed. Sixteen studies met the selection criteria and were reviewed. None of the studies between 2016 to 2020 met our inclusion criteria for the quantitative meta-analytics. The results from the meta-analysis suggest the presence of systematic between-study heterogeneity, and the meta-regression shows that a study's sample size and the validation methods used could affect the performance accuracy of the ANN model.

Our recommendations for practitioners are to pay attention to the sample size and the model validation methods used in developing a bankruptcy prediction model. The Artificial Neural Network (ANN) model seems to be very sensitive to the number of data points used in the model. Small sample size may negatively impact the performance ability of the model. To get the best performance from a bankruptcy prediction model, practitioners should select tools based on the output criteria preferences and available data characteristics.

In addition, other methodological issues such as the percentage of failed and non-failed firms in the sample and the nature of input data sets used in the model should also be given adequate attention. For instance, class imbalance is a common feature in most classification datasets. The challenges of learning from imbalanced data are rampant in numerous real-life applications where we face the problem of uneven data representation. In such instances, the minority class is usually the more important one, and hence we require methods to improve its recognition rates. In cases of severe class imbalance, the minority class is harder to predict because there are limited examples of this class, making it more challenging for a model to learn the characteristics of examples from this class and differentiate examples from this class from the majority class.

When most of the datasets belong to one class, developers should consider the accuracy paradox. The accuracy metric may provide misleading classification accuracy reflecting the underlying class distribution. Some authors suggest that ANN can perform relatively well under a class imbalance of 20:80- i.e. a dispersion at 20% failed firms before the ANN algorithm could recognize the pattern (Boritz et al., 1995; Du Jardin, 2015).

Our recommendation is to use data-level methods that normalizes the classification accuracy by the imbalance of the classes in the data and use the Receiver Operating Characteristics' (ROC) Area Under the curve (AUC) matrix as a measure of the model's performance. Ensemble learning algorithms are also popular approaches for handling class imbalance in real-world applications. Research shows that hybridizing Bagging, Boosting, and Random Forests ensemble methods with sampling or cost-sensitive methods proves highly robust to imbalanced datasets (Blaszczynski and Stefanowski 2015; Galar et al. 2012; Krawczyk, Woźniak, and Schaef; 2014).

The challenge with using ensemble methods is that most of the ensemble approaches used are heuristic-based. Still, there is a lack of proper insight into the performance of classifier committees with skewed classes. Future research should consider methods to empower the minority class and predict or reconstruct a potential class structure. As per sample size, developers faced with a paucity of datasets can consider the use Support Vector Machine that is robust to small samples. Finally, in order to expand the branch of bankruptcy prediction models, future research should use meta-regression to explore the effects of specific study characteristics on the performance accuracy of some promising machine learning tools.

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