Corporate Bankruptcy Prediction: Bridging the Gap Between SME and Large Firm Models

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ABSTRACT

Research on corporate bankruptcy prediction has garnered renewed interest due to economic crises and regulatory changes. Most studies focus on large enterprises, leaving a gap in understanding bankruptcy prediction in small and medium-sized enterprises (SMEs). This study carries out a systematic literature review to examine the evolution of this topic, focusing on SMEs. Using a structured methodology based on PRISMA, we analysed 541 academic papers, categorising them into two groups: (i) SMEs and (ii) non-SMEs. Our findings reveal key distinctions between the two groups, particularly regarding the definition of bankruptcy, financial and non-financial predictive factors, and the types of models applied. While statistical models, such as logistic regression and discriminant analysis, remain dominant in SME-focused research, artificial intelligence-based techniques are gaining traction. The study also identifies a lack of comparative studies assessing model effectiveness for SMEs across different economic contexts. Based on these insights, we propose a framework to enhance future research in corporate bankruptcy prediction, emphasising the need for models that integrate macroeconomic variables, governance factors, and alternative risk assessment techniques tailored to SMEs. Our findings contribute to bridging the gap between theory and empirical research, offering practical implications for financial institutions, auditors, policymakers, and SME managers in mitigating bankruptcy risks.

Keywords: Bankruptcy prediction, Predictive models, SMEs, Systematic literature review.

JEL Codes: G33; L25; C83.

I. Introduction

THE FIELD OF BANKRUPTCY forecasting has been the subject of research since the 1930s (Bellovary et al., 2007). In recent years, it has garnered increasing interest from researchers worldwide, primarily due to three significant events: the global financial crisis of 2007-2009, the 2006 reform of the Basel Accord, and the outbreak of the COVID-19 pandemic. These incidents have brought profound changes to the global economy and credit policy, which could threaten the financial system's stability, bank

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viability, and investor protection. Therefore, developing bankruptcy prediction models is crucial in preventing such incidents. Despite several methods being used to predict corporate bankruptcy, there is no definitive and comprehensive model to determine it, particularly one designed for small and medium-sized companies (SMEs).

A vast body of literature has a shared objective of assessing companies' predictive capabilities concerning bankruptcy. However, the pursuit of the best bankruptcy model has led to significant diversity in the literature. As a result, comparative studies (Alaka et al., 2019; Mselmi et al., 2017) and literature reviews have emerged to account for the various perspectives on this topic. More recent literature review studies of corporate bankruptcy focus exclusively on statistical models (Balcaen & Ooghe, 2006), while others focus on artificial intelligence models (Clement, 2020; Kim et al., 2020; Shi & Li, 2019). There have been studies that look for an overview of the models and compare them (Bellovary et al., 2007; Ravi Kumar & Ravi, 2007; Veganzones & Severin, 2021) and more specific ones, such as multiplicity of perspectives on firm exit, bank failure and bankruptcy as a multidimensional event (Cefis et al., 2022; Citterio, 2024; Levratto, 2013).

Concerning the literature on SMEs, the search for more accurate models is accompanied by the diversity of bankruptcy risk between SMEs and large companies. Due to the specific financial characteristics of SMEs, typical bankruptcy prediction models (designed for large companies) are insufficient to predict the bankruptcy probability of SMEs (Abdullah et al., 2016; Srhoj et al., 2024; Yang & You, 2020). It is widely accepted among researchers that smaller companies are at greater risk of bankruptcy (Levratto, 2013). Predicting potential bankruptcy due to low life expectancy is a recommendation from the European Union, particularly because SMEs play a crucial role in job creation, value addition, and overcoming the impacts of economic crises (Navarro-Galera et al., 2024).

As the development of bankruptcy prediction models for SMEs evolved, a distinct and independent section of financial literature was formed (Gallucci et al., 2023). However, the review of key elements in the field of business failure prediction, such as the definition of bankruptcy, theoretical approach, sample data, and company profile (size, industry, and country), focused on a framework for SMEs is limited, despite their enormous importance for the economy and the financing and management restrictions they face, which determine their market survival.

This article addresses the multifaceted nature of predictive bankruptcy models. Furthermore, it aims to provide an up-to-date overview (Berryman, 1993; Ciampi et al., 2021) and complements a previous systematic review focused on methodologies (Cheraghali & Molnár, 2023). The main difference between this study and the previous review studies is the comparative analysis between the research lines (i) SMEs and (ii) non-SMEs.

The bankruptcy prediction literature treats bankruptcy as a binary event - bankruptcy or no bankruptcy - without distinguishing the different levels, such as economic distress, financial distress, insolvency, or liquidation (Aguiar-Díaz & Ruiz-Mallorquí, 2015). Economic distress refers to operational issues that result in low profits, while financial distress pertains to financial issues characterised by high debt

(Kahl, 2002). Nonetheless, having low profits or high debt levels alone does not equate to bankruptcy. Insolvency occurs when there is an imbalance between a company's cash flow and its equity position (Liu & Wu, 2019). On the one hand, liquidation can be reported as a strategic exit process - voluntary liquidation (Kang et al., 2020). On the other hand, liquidation can occur after a default, when creditors are not in control and can liquidate the company (Kahl, 2002). In this study, the events before bankruptcy are considered according to three levels: economic distress, financial distress (default), and insolvency, which are not necessarily in that order.

Despite the extensive literature on bankruptcy prediction and the advancement of artificial intelligence models (Barboza et al., 2017; du Jardin, 2017; Dasilas & Rigani, 2024; Park et al., 2021), few studies distinguish these aforementioned concepts. This distinction is essential, especially for SMEs, whose financial and operational structure amplifies the importance of understanding different levels of business difficulty. Thus, this study aims to answer the following question: How can theoretical/conceptual nuances of bankruptcy be integrated into the analysis of predictive models for SMEs compared to predictive models for large enterprises?

This literature review aims to fill this gap by analysing a series of published research papers that address the topic in various ways. It contributes to understanding the differences and characteristics of SMEs concerning studies designed for large companies and developing a structure of key elements that can guide future research. The study is organised into (i) SMEs and (ii) non-SMEs. The second category includes large unnamed companies because the articles hardly make this classification, although they were designed for large companies.

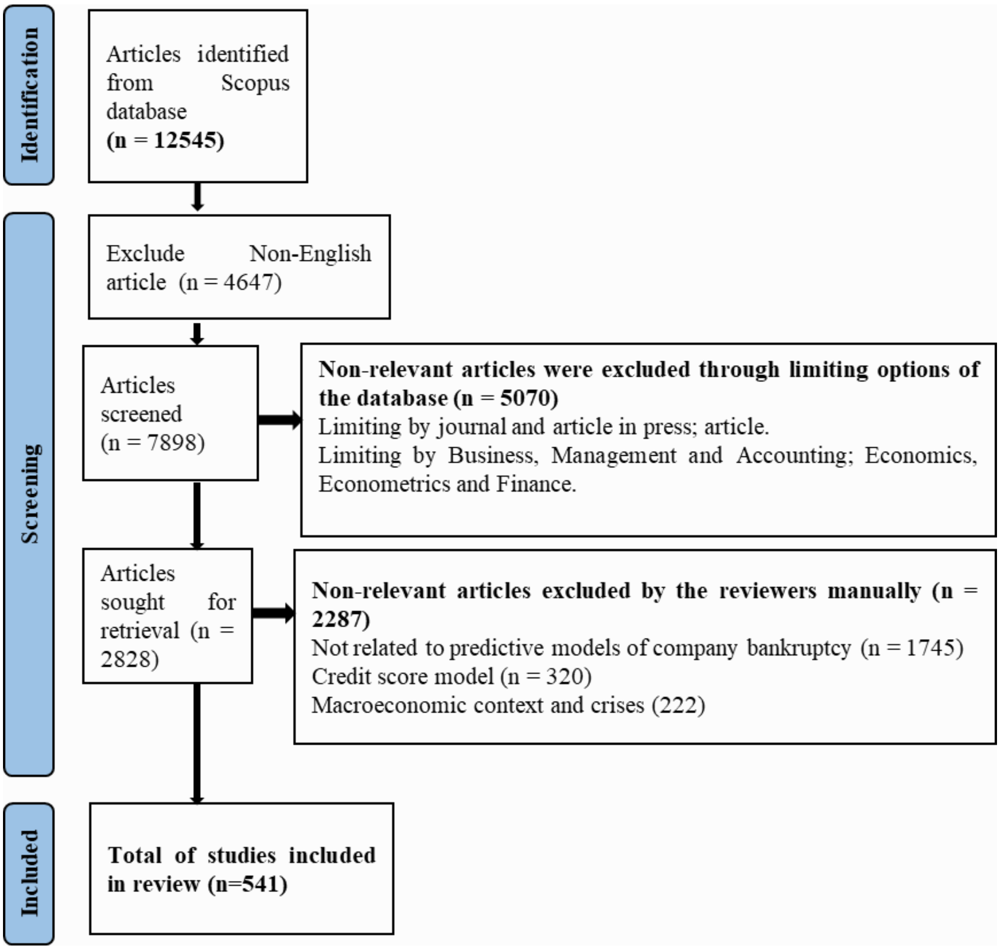
The remainder of this paper is organised as follows: First, we present the methodology. Section 3 classifies the results into four categories: the importance of SMEs, the definition of bankrupt companies, model factors, and types of models. Each category is discussed separately. In Section 4, based on the results, we propose four steps for future studies on company bankruptcy. Finally, the conclusion of the review study is presented.

II. Methods

This study is a literature review that followed a Systematic Literature Review methodology. A protocol was developed based on PRISMA 2020 (see Figure 1). The study used the Scopus databases to identify relevant papers on corporate bankruptcy. The reason for obtaining the articles from a single database is that Scopus provides researchers with extensive guidelines and access to diverse literature covering various subject areas, making it a more comprehensive database than the Web of Science, according to previous research (Harzing, 2019). The Scopus research covered the period up to December 2024.

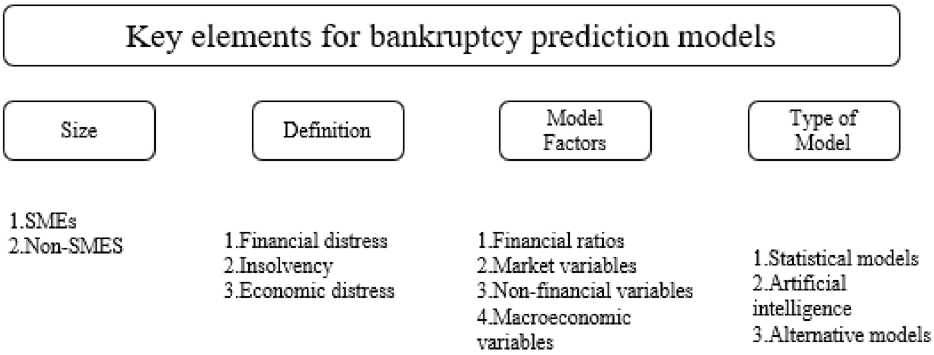
The initial search included papers containing the keywords "bankruptcy", "distress", "insolvent", "default", "failure", "predict*", "forecast*", "compan*", "firm*" and “business*” resulting in a total of 12,545 articles. Subsequently, the filtering process evolved, selecting only articles written in English, yielding a set of 7,898 articles. In addition, filters were selected in the subject area (Business, Management, and Accounting; Economics, Econometrics, and Finance), Publication stage (final; article in press), and source type (journal), totalling 2,828 articles. The titles, keywords, and abstracts of all 2,828 papers were thoroughly reviewed. Following the application of these selection criteria, the final set of selected works comprised 541 articles.

Figure 1
Prisma flow diagram (Source: Author, based on PRISMA, 2020)



As previously mentioned, the review is divided into two basic categories based on the company size: (i) SMEs and (ii) non-SMEs. Among SMEs, 129 papers predominantly address the logit model. Regarding the second group, 412 papers address different types of models, cover the analysis for other continents, and aim to compare the models to understand which is the best predictive model of bankruptcy. In the systematic literature review studies, the main topics discussed regarding corporate bankruptcy are definition, theory, model factors (variables), types of models applied, model validation, accuracy and predictive power of models (evaluation metric), data source, and time horizon. This study analyses the definition, model factors, model types, and company size. These key elements are presented in the research framework, as shown in Figure 2. The subcategories of each key element were based on previous reviews (Kuizinienė et al., 2022; Veganzones & Severin, 2021) and search results.

Figure 2
Research framework (Source: Author)



Most studies are conducted in the United States, China, India, and the United Kingdom, representing approximately 40 percent of selected studies. When only articles selected for SMEs are considered, European countries publish the most research (Gallucci et al., 2023; Lisboa et al., 2021). Countries like the United States, China, India, and the United Kingdom are likely to conduct more research on this topic because those countries occupy the leading positions in producing research worldwide. Few studies have predicted company bankruptcy models for more than one country (Carvalho et al., 2022; Durica et al., 2019), so this comparison can be useful in understanding the differences between countries.

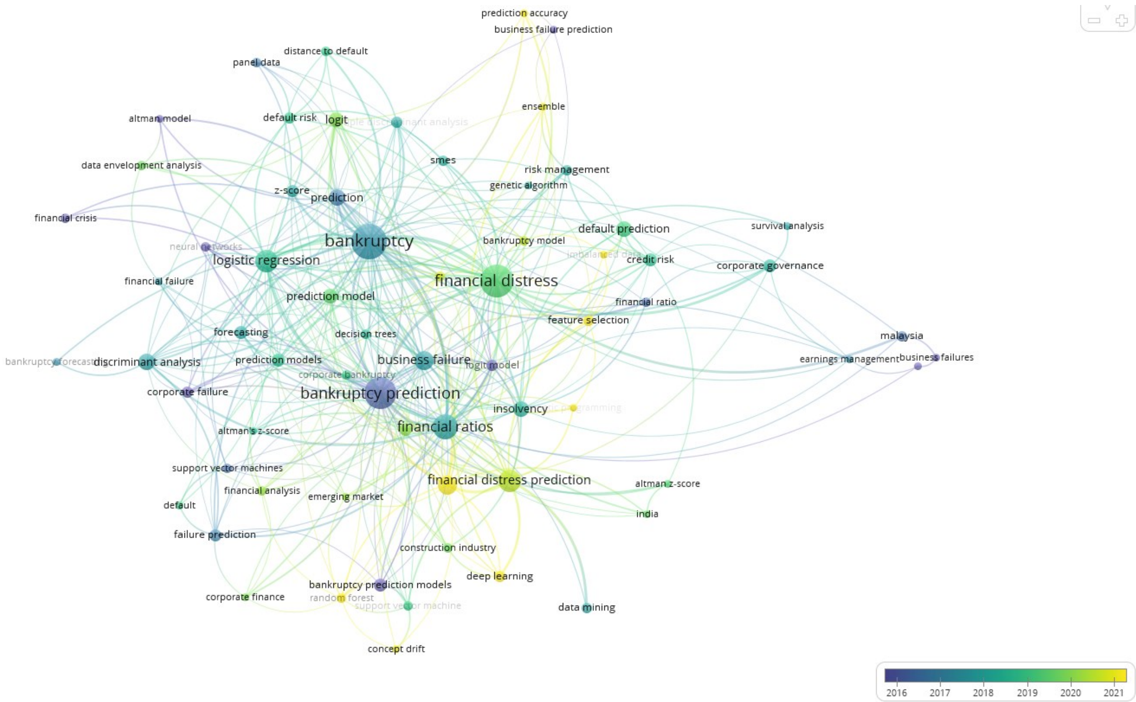
III. Results and Discussion

A. Thematic Analysis

We used VOSviewer to construct a network visualisation map of keywords using terms that appeared at least four times in the articles. Figure 3 shows the breadth of studies for bankruptcy prediction models and several links to this topic that cover 541 articles. There is strong evidence of the approximation of theoretical concepts with applied approaches and different methodologies through the main keywords - bankruptcy, financial distress, financial ratios, and survival analysis (Hammond et al., 2023; Altman et al., 2019; Senbet & Wang, 2010; Hotchkiss et al., 2008). The term "SMEs" appears once in Figure 3, and it only has a few connections. The figure does not clearly show the relationship between viability and failure, making it difficult to understand the factors and indicators for SMEs.

The following discussion provides a comprehensive review of the literature examined based on its topics. Our examination confirmed that there were numerous carefully researched themes. We classified these into four categories based on the clustering patterns: Importance of small and medium enterprises, definition of bankrupt company, model factors, and type of models.

Figure 3
Keyword distribution in bankruptcy prediction models (Source: VOSViewer software)



B. Importance of SMEs

In this context, we would like to emphasise three key factors that highlight the relevance of SMEs. Firstly, due to their small size, SMEs benefit from agility and reactivity to changing situations (Halabí & Lussier, 2014). Secondly, they are important in boosting entrepreneurship using local talent and technology (Abdullah et al., 2019). Thirdly, SMEs also benefit local communities through the supply of goods, services, job opportunities, and assistance to other local enterprises (Halabí & Lussier, 2014; Lisboa et al., 2021; Wang et al., 2021).

In South Korea, for example, SMEs have a significant influence, accounting for the vast majority (99%) of all businesses and employing a sizable proportion (83%) of the workforce (Yang & You, 2020). In China, this group comprises the vast majority of enterprises (94%) and contributes considerably (65%) to GDP (Wang et al., 2021).

Small firms are crucial in the Japanese construction sector because they protect competition and prevent a few large contractors from monopolising contracts for public works (Konno, 2014). Their participation ensures the presence of numerous companies, which promotes a competitive and balanced marketplace. In the European Union in 2018, SMEs accounted for 99.8% of all non-financial businesses, accounting for 56.4% of their value-added and 66.6% of their employment (Crosato et al., 2021).

While recognising the value of SMEs, it is also necessary to acknowledge the problems they confront. Financial information in small enterprises may be volatile, untrustworthy, and easily manipulated (Kärkinen & Laitinen, 2015). Furthermore, the shortage of data and the possible absence of an annual report make evaluating and understanding studies on SMEs problematic.

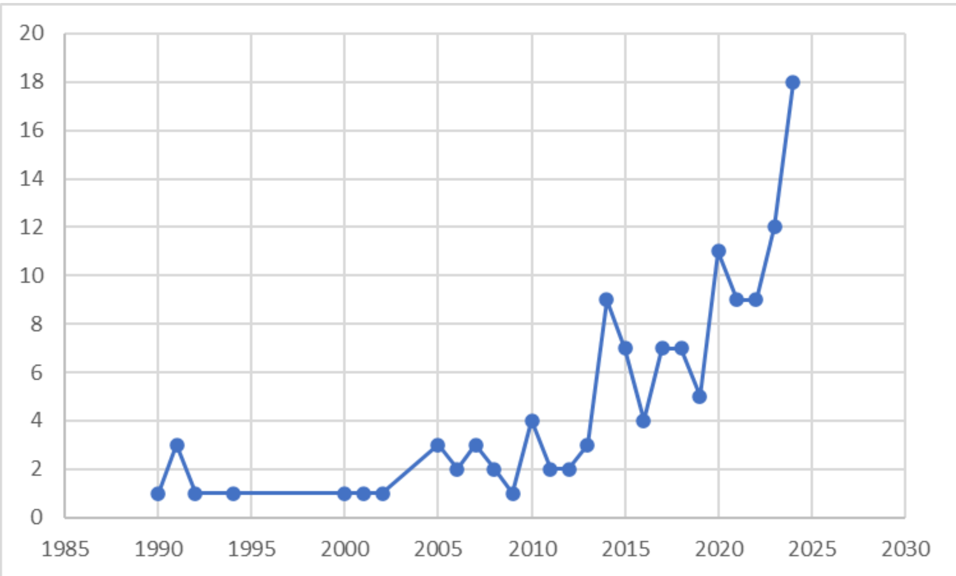
Although some bankruptcy prediction problems may be overcome through a data analytics approach (Son et al., 2019), the literature on bankruptcy prediction has been evolving for several years, particularly with the application of financial indices. This field is still developing, especially concerning micro, small, and medium-sized enterprises (SMEs) (Andresson & Lukason, 2024). However, despite the widespread use of financial indicators, models based solely on information collected from financial statements do not provide a complete picture of companies (Navarro-Galera et al., 2024; Ragab & Saleh, 2022), particularly in the case of SMEs, where qualitative factors and non-financial dimensions may be equally relevant.

Incorporating non-financial information substantially improves the models, which are especially useful for enhancing SME bankruptcy models (Altman et al., 2023), and machine learning techniques often contribute to this enhancement (Iparraguirre-Villanueva & Cabanillas-Carbonell, 2024). Machine learning algorithms are also helpful in selecting different subsets of features as a dimensionality reduction method (Wang & Wu, 2017). The accuracy of bankruptcy predictive models is primarily affected not by the limitations of the study or the technique but by the lack of data availability (Shetty et al., 2022). This data scarcity hinders our ability to better understand the importance of SMEs.

Recent studies have sought to overcome this data problem, especially when the data is imbalanced. Some techniques deal with class classification (bankrupt and non-bankrupt) and aim to understand the number of bankruptcies, in relation to the non-bankruptcies for that period (Zoričák et al., 2020).

Figure 4 shows a considerable increase in studies on small business failure from 2012 onwards. This increased relevance of studies for SMEs is even more relevant when we note the different ways of classifying what constitutes "bankruptcy".

Figure 4
Trends from studies on SMEs in predicting bankruptcy (Source: Author)



There are at least two ways in the literature that show how “bankruptcy” can occur: economic distress - when a company fails to meet its business success goals, such as profit maximisation or enhancing company value or financial distress - when the definitive legal dissolution of a company occurs (Beade et al., 2024).

The next section will discuss a wide range of meanings. This covers issues such as the fulfilment of debt obligations and the various legal terms associated with insolvency and liquidation.

C. Definition of a bankrupt company

To discuss the topic of predicting bankruptcy, one must first grasp the notion of business bankruptcy (Alfaro et al., 2008; Cheng & Wang, 2015), which refers to the process through which a company declares the cessation of operations and can be described using various terms found in the literature review, including “exit”, "failure," "insolvency," "default," "distress," and "bankruptcy." However, depending on the study being examined, this concept may also encompass a merger/acquisition or voluntary liquidation (Cheng & Wang, 2015).

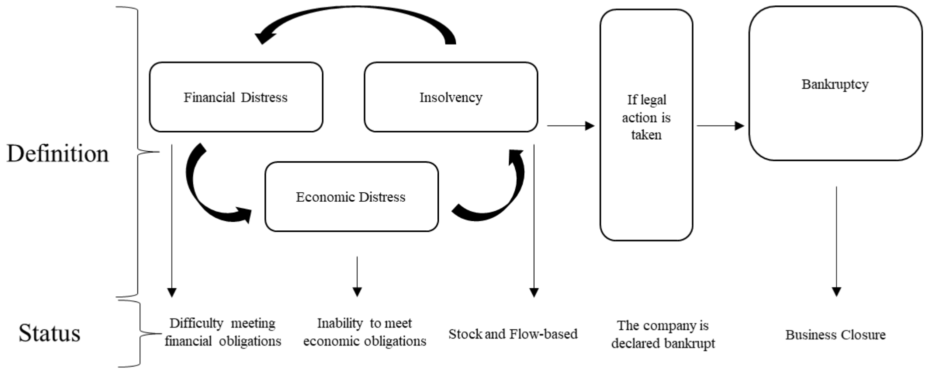
The definition of a bankrupt company depends on the researcher's criteria (Balcaen & Ooghe, 2006). Employing one definition or another as an exit strategy depends on factors such as the firm's age, size, labour productivity, and whether it is involved in research and development (R&D) or advertising activities (Ho et al., 2013). In general, researchers use the concept of legal bankruptcy, as it makes it possible to understand the legal characteristics of the process in each country (Alfaro et al., 2008).

As size is one of the factors that help in choosing the definition of bankruptcy, it is important to understand whether there is a difference in the concept of bankruptcy in scientific literature for SMEs. The size of a corporation, as measured by its assets, has a non-linear connection with the probability of bankruptcy (Altman et al., 2010). Creditors are unlikely to look for companies with smaller assets because when they enter the bankruptcy process, they usually do not leave assets for debt recovery (Altman et al., 2010). SMEs are more financially risky and have weaker asset correlation among themselves than large corporations (Gupta et al., 2015).

The perspective in the scientific literature that defines financial distress as equal to bankruptcy is not valid for SMEs (Kuizinienė et al., 2022). SMEs face difficulties in solving financial distress that must be thoroughly clarified and analysed (Tong & Serrasqueiro, 2021). Accurate estimates of the SME risk of failure can assist policymakers in implementing restructuring policies, rating agencies and credit analytics firms in assessing bankrupt, public, and private investors in allocating funds, entrepreneurs in accessing financing, and managers in developing effective strategies (Altman et al., 2023). Therefore, distinguishing financial distress from bankruptcy and developing a typology for small enterprises is legitimate (Figure 5).

Financial distress differs from bankruptcy in that it represents a situation in which a company is in distress (Andrade & Kaplan, 1997), which can result in one of two outcomes: 1) a recovery state in which the company can regain its financial health, or 2) a bankruptcy state in which the organisation must be reorganised or liquidated (Tong & Serrasqueiro, 2021). As a result, the probability of default, reorganisation failure, and financial distress can be considered as being from the same group, as they all refer to financial problems and the difficulty of complying with financial obligations. Even though bankruptcy often arises from liquidity issues, many models for predicting business bankruptcy overlook the role of operating cash flow (Piatti, 2014).

Figure 5
Stages of bankruptcy (Source: Author)



Insolvency is the group that represents the operating cash flow broadly defined as the inability to repay debts when they become due, distinguishing healthy companies from bankrupt ones (Levratto, 2013). The meaning of insolvency is when a company's operating cash flow is insufficient to meet its regular obligations (Liu & Wu, 2019).

This type of bankruptcy shows that cash flow indicators are less susceptible to earnings management, given that cash ratios are theoretically better suited to predict bankruptcy (Karas & Reznakova, 2020). Auditors use their experience and access to internal data to identify internal factors or reasons to identify information that is not available in publicly available financial statements (Young & Wang, 2010). Using bankruptcy prediction models may be instrumental in auditors conducting going concern assessments (Koh, 1991). The premise of going concern is that the entity will not go bankrupt in the defined future and that the financial statements are prepared using earnings other than the liquidation value (Achyarsyah, 2016). Going-concern opinions are helpful not only for predicting bankruptcy but also for understanding how the bankruptcy process unfolds (Xie et al., 2014). Hybrid models demonstrate the predictive power of intellectual capital (IC) and provide superior accuracy with lower error rates in going-concern prediction. In addition to predictive models being useful for assessing a company's going concern assumption, they are also important for assessing its financial fraud risk (Javaid & Javid, 2018). These challenges are worth highlighting, especially for the concession of loans for SMEs (Gupta et al., 2014).

Insolvency can also be considered a stock-based insolvency when a company's total liabilities exceed its assets (Liu & Wu, 2019). Shareholders are most interested in this definition since the estimate of the company's future activity or inactivity is determined by the value of the shares (Salehi & Davoudi Pour, 2016). Stock-based difficulties are generally more severe than flow-based ones (Liu & Wu, 2019).

Economic distress occurs when a firm fails to generate sufficient economic returns, often due to poor operational performance or unfavourable market conditions (Levratto, 2013). It typically arises during challenging times, such as crises or events like the COVID-19 pandemic (Nurhayati et al., 2022). Although financial and economic distress are different, they are related. Financial distress can result in economic distress if a firm is unable to restructure effectively, while economic distress can lead to financial distress if it results in unmanageable debt. In this study, most papers concentrate on the concept of financial distress, even though few studies focus on the definition of economic distress (Costa & Lisboa, 2023). Differentiating between bankrupt and non-bankrupt enterprises is difficult but necessary for developing a typology of companies based on their robustness (Levratto, 2013). Furthermore, when the company finally declares bankruptcy, it is a business closure (Tobback et al., 2017). Therefore, there are three classes of bankruptcy: 1) financial distress, 2) insolvency, and 3) economic distress.

There is a hiatus between the empirical and theoretical literature that needs to be studied further (Cheng & Wang, 2015). Theoretical studies categorise financial suffering at several levels. Mild distress refers to transitory cash flow issues, whereas severe distress refers to corporate collapse or insolvency, with organisations transitioning between both situations dynamically. In empirical research, to overcome sample criteria and data constraints, financial hardship is frequently described using signs such as legal bankruptcy (Cheng & Wang, 2015). Other forms of differentiation were also found in the literature, such as severity and credit treatment (Modina et al., 2023), banking restrictions (Srhoj et al., 2024), and financial solidity (Costa & Lisboa, 2023).

D. Model Factors

The number of factors used in predicting bankruptcy models can vary (Bellovary et al., 2007), as well as the analysed perspective (Kuizinienė et al., 2022). The most frequent perspectives are based on the accounting and market models (Pham Vo Ninh et al., 2018). Several factors were found in the literature, and non-financial variables have become increasingly significant when it comes to strengthening the predictive power of bankruptcy models for SMEs. Macroeconomic variables are not used in the literature surveyed for SMEs and are commonly used as predictors to predict bankruptcy in non-SMEs.

Accounting models based on Altman's Z-score model (Altman, 1974) and Ohlson's conditional logit model use financial ratios to predict the probability of a company’s failure (Succurro et al., 2019). In general, accounting ratios are used to develop forecasting models mainly by measuring five financial aspects of a company: liquidity, solvency, profitability, leverage, and operational efficiency (Cheraghali & Molnár, 2023; Kim & Gu, 2006). However, studies question whether financial indices alone can accurately predict bankruptcy (Ohlson, 1980). As accounting ratios depend on accounting information, market variables allow a broader analysis of the company based on stock prices (Succurro et al., 2019). The market model introduced by Robert C. Merton (1974) presents a relationship between a company's default risk and its capital structure when considering its equity as a call option on its assets (Succurro et al., 2019). The default occurs when the market value of the company's assets falls significantly relative to the value of its debt (Carvalho et al., 2022).

Accounting ratios and market variables are widely used in the literature. While carrying out research in relation to SMEs, it is not easy to identify studies that employ market variables since they are only available for listed firms, which are often huge businesses. For these companies, creditors need to give more weight to market information concerning accounting information (Li & Faff, 2019).

One approach to improve the predictive power of bankruptcy models concerning SMEs has been to consider non-financial variables. Non-financial variables are related to corporate governance, ownership structure, and managerial ownership (Chang et al., 2008; Gupta et al., 2015). This includes the size and composition of the board of directors, the duality of the CEO, the frequency and existence of audit committees, the size and composition of these committees, and the frequency of meetings (Ragab & Saleh, 2022). In addition, other non-financial variables, which may have important information for the probability of bankruptcy for SMEs, are the age of the company (or life cycle stage), the gender of the managing director (Kärkinen & Laitinen, 2015), intangible costs (organisational capital and social capital) (Chang et al., 2008), credit-related variables (Modina et al., 2023), and management- and employee-related variables (Srhoj et al., 2024).

Regarding the prediction of the bankruptcy of companies, macroeconomic variables can be used to supplement accounting variables (Ninh et al., 2018). They give insight into the larger economic situation and can influence a company's financial performance and general health (Carvalho et al., 2022). SMEs are influenced by macroeconomic variables (Halim et al., 2017). Macroeconomic conditions such as interest rates, exchange rates, inflation, economic growth, government policies, and financial stability significantly impact small businesses. More studies need to be carried out on small business failure based on macroeconomic variables, imposed regulations concerning environmental and social issues, and gender quotas.

E. Type of Models

This literature review has organised the types of models into three groups: Statistical Models (SM), Artificial Intelligence (AI), and Alternative Models (AM), following previous works (Ravi Kumar & Ravi, 2007; Singh & Mishra, 2016). SM refers mainly to logit and probit regressions, the Hazard model, univariate discriminant analysis, and multiple discriminant analysis (MDA). AI refers to methods such as Neural networks, Support Vector Machines, Data Mining, Decision Trees, and Genetic algorithms (Liashenko et al., 2023; Sermpinis et al., 2023). Finally, AM includes literature reviews and hybrid models that do not fit the two previous groups. This classification is divided between groups (i) SMEs and (ii) non-SMEs. The objective is to understand what predictive bankruptcy models can be applied to SMEs in corporate bankruptcy. The most recent papers on corporate bankruptcy have compared several techniques in a single study to verify the best predictive bankruptcy model. When an article compares different predictive models, it is classified according to the model that serves as the main reference in the comparative analysis. In other words, the predictive model to which the article belongs is defined by the central approach that supports the study's logic, even if other techniques are also present. For example, concerning a paper on predictive models where

SM, AI, and AM are compared in their standalone mode and the model that motivates the comparative study's proposal is Logistic Regression, the article is classified and reviewed as an article in the group of statistical models because logistic regression was the reference used to compare it (Ravi Kumar & Ravi, 2007).

Proportionally, there are fewer studies on AI for SMEs compared to the number of studies for non-SMEs. More models are still in scope, and this tool can be used to better understand the phenomenon in SMEs (Shetty et al., 2022). There are also fewer studies on SMEs that compare different models to verify the most predictive model. This is a trend for non-SME studies. However, two points are worth mentioning: 1) This trend can be misleading due to disagreement in both the definition of bankruptcy and the measurement of forecast accuracy (Berent et al., 2017); and 2) while AI models can deliver accurate forecasts, their inability to self-explain restricts their value for decision-makers. The logistic regression model, on the other hand, stands out for its capacity to explain model variables and outline management implications to prevent bankruptcy (Zhou et al., 2022).

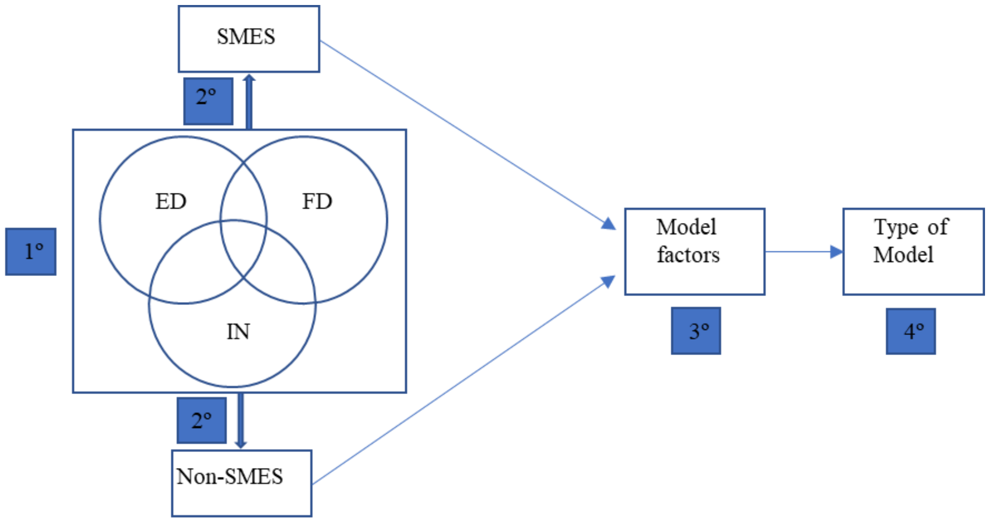
Therefore, the decision of which model to choose to predict the bankruptcy of companies will depend on the researcher's objectives (Youn & Gu, 2010). Artificial intelligence models will be recommended when the objective is accurate classification. Otherwise, if the objective is a practical interpretation of the model or understanding the role of each variable in the prediction, statistical models are more appropriate.

IV. Recommendations for future research

Based on our comprehensive review of bankruptcy prediction modelling, we argue for theoretical and methodological sophistication and the need for further research to bring empirical literature closer to theory. No comprehensive financial theory accurately explains the causes and dynamics of bankruptcy in the field of bankruptcy prediction (Chen et al., 2011). Most of the studies surveyed in this research show that the main objective is to identify more accurate models to predict bankruptcy, making bankruptcy prediction an area of solving classification tasks based on numerous financial and non-financial characteristics.

To provide new directions and insights for small to medium companies, we suggest four steps to study company bankruptcy in Figure 6. In the first step, size and determinants are identified for the company, and finally, the model type. This involves developing a theory and a way to apply models better.

Figure 6
The framework of bankruptcy companies (Source: Author)



ED – Economic distress, FD - Financial distress, and IN – Insolvency

A. *Clear Definition and Theory of Company Bankruptcy*

Most studies assume bankruptcy based on legal criteria, ignoring the different stages of financial difficulty. A broader criterion that considers the company's real situation and legal bankruptcy is of great importance for emerging economies, as they are characterised by weak law enforcement and low protection for creditors (Tomas Žiković, 2018). There are differences in the provision and implementation of law for developing economies that differ from developed economies (Ong et al., 2011). Therefore, more studies should be conducted in developing countries, considering a broader definition. Less than half of the studies (approximately 25 percent) analysed were carried out in emerging economies; the numbers become even smaller when considering the broader definition. Only three studies associate these two aspects as important for bankruptcy studies (Konstantaras & Siriopoulos, 2011; Laitinen, 1992; Tong & Serrasqueiro, 2021).

Furthermore, the definition may make bankruptcy techniques questionable in assessing prediction (Konstantaras & Siriopoulos, 2011), and the interpretability and generalisability of empirical results may be limited (Jones & Wang, 2019).

More consistent definitions would help scholars explore the theoretical mechanisms specific to each stage of the company's bankruptcy: financial distress, insolvency, and economic distress. For instance, limited empirical evidence determines and compares bankruptcy levels (S. M. Lin et al., 2012). Given the different definitions of bankruptcy, future studies could also explore the impacts of the definition on the choice of predictor variables and consider the predictive accuracy of the model, taking it into account for the development of the country. Furthermore, a single federal register of bankruptcy information is still needed to distinguish the stage and identify companies for which legal bankruptcy action has begun (Karminsky & Burekhin, 2019).

B. Size of the Company

The literature suggests that there is a difference between non-SMEs and SMEs. They differ in terms of, e.g., capital structure, firm size, access to external finance, management style, and staff numbers (Gupta et al., 2015). In addition, it reveals that SMEs are an under-explored area within corporate bankruptcy. Therefore, it encourages future studies to explore SME literature.

The development and expansion of SME literature based on the non-SME literature would already contribute to the literature. For example, only one paper predicts the bankruptcy of small and medium French firms using multiple models (Mselmi et al., 2017). Therefore, further investigation into comparing predictive precision among various techniques may serve as a crucial research domain to ascertain the model that serves as the most precise classifier (Dube et al., 2023). Moreover, a comparison of models for the bankruptcy of non-SMEs and SMEs should be made to identify the financial and non-financial factors crucial to a company's survival from a size perspective.

For SME literature, subjective data is a significant supplemental tool for model prediction (Fantazzini & Figini, 2009). In this way, we should develop future research based on companies focused on innovation and agility in business, and companies in which management and ownership are intrinsically linked are essential to identify the subjective factors. These corporations often encounter specific market challenges and must expeditiously adapt to evolving trends and consumer demands.

C. Model Factors

Our analysis highlights the importance of exploring non-financial and macroeconomic variables for non-SME and SME contexts. There is a tendency for future research to include non-financial variables such as the corporate governance structure (Abdullah et al., 2016; Mselmi et al., 2017; Shen et al., 2020), management skills of the entrepreneur (Kamaluddin et al., 2019; Yang & You, 2020), type of ownership (Kamaluddin et al., 2019), the sentiment information (Kamaluddin et al., 2019), organisational culture (Wu et al., 2008), operational characteristics (Alan & Lapré, 2018), earnings management (H.-W. W. Lin et al., 2016), innovation activities (Abdullah et al., 2016) and macroeconomic variables (Chang et al., 2008; Kamaluddin et al., 2019; Wu et al., 2008).

After analysing the data sources used, it is worth mentioning that researchers choose data sources from companies listed on the stock exchange, the use of quantitative information is predominant, and there is a preference for the banking or manufacturing sectors.

Literature development may be improved by researching newly founded companies in different sectors and markets based on information from annual reports and considering the abovementioned variables. It is important to note that, despite the growing interest in Environmental, Social, and Governance (ESG) factors (Citterio & King, 2023; Habib, 2023; Song et al., 2024), very few studies have empirically examined the relationship between financial distress and the environmental and social components of ESG. There is limited understanding of how these components impact the likelihood of company bankruptcy (Citterio, 2024). The literature on corporate bankruptcy related to environmental and social factors may have developed fragmentedly, partly due to how these factors can be measured. Additionally, the excessive focus on finding the best bankruptcy model has created increasingly complex bankruptcy prediction models. As a result, the predictive capability of these models has become a priority in addressing contemporary issues.

D. Type of Models

Few studies in SME literature compare different models to verify which model is the most predictive (Crosato et al., 2021; Fantazzini & Figini, 2009; Mselmi et al., 2017). Future research could be directed towards combining these three types of models (static, dynamic, and Machine learning) (Yousaf et al., 2022). The advancement of hybrid models was founded on Computational Intelligence to enhance the precision of modelling (Divsalar et al., 2012; do Prado et al., 2019). The opportunity exists to contrast techniques across diverse industries, ascertain the extent of predictability of indications of bankruptcy, and depict the hazards inherent in specific sectors (Karminsky & Burekhin, 2019). One constraint of the extant literature is its incapacity to construct models specific to a particular sector. This constraint impedes the possibility of improving model accuracy and achieving a more profound comprehension of the variables resulting in a firm's bankruptcy (do Prado et al., 2019).

Models with a longer time horizon would be important, as panel data would help determine how companies' financial performance indicators change (Konno, 2014), in addition to capturing changes in corporate governance and bank-company relationships that will probably not be able to save a company on the verge of bankruptcy (Gallucci et al., 2023). The discrete risk model captures changes in time-varying firm characteristics in the model, leading to more robust estimation results (Shumway, 2001). This risk model, superior to the logit model, can benefit future research since a robust model can detect SMEs in financial difficulties, subject to data availability (Abdullah et al., 2019). Comparisons of predictive accuracy may be extended to Merton-type models (S. M. Lin et al., 2012).

Other directions that can be explored in future work are the specific issues of a given model (F. Lin et al., 2013), such as classification problems (Cheng & Wang, 2015), which may be improved by utilising random subsampling to adjust for imbalanced data (Syed Nor et al., 2019). Several studies suggest increasing sample size (Alaka et al., 2019), especially for SMEs. In predicting models for SMEs in financial distress, the number of observations exhibits a significant reduction as the timeframe preceding a state of financial difficulty nears the actual year (Abdullah et al., 2019).

V. Conclusions

This study enhances the existing literature on predicting bankruptcy in SMEs by identifying critical factors that must be considered. In terms of practical implications, the specific SME bankruptcy prediction models may be useful to assist managers, auditors, investors, and financial institutions in evaluating risks, highlighting the challenges in adapting to environmental regulations. Moreover, it can be used to shape public policies and support programmes to maintain the financial stability of SMEs, particularly in economies where they play a critical role. Academically, this study is unique from other literature reviews as it addresses a significant gap in existing research by providing a systematic review that focuses on the specific needs of SMEs, essential to the global economy, and compares them with the literature designed for large enterprises. It identifies key factors and offers a multidimensional analysis covering financial, non-financial, macroeconomic, and market variables. It brings the theoretical and applied approaches closer together based on studies of predictive bankruptcy models.

This analysis highlights the need for the adaptability of bankruptcy models for SMEs because the risks between SMEs and large companies are not homogeneous. Relying solely on accounting ratios to indicate financial distress is insufficient for accurately reflecting a company's past performance. Establishing a connection between accounting ratios and other indicators—non-financial, market, and macroeconomic factors—provides theoretical support for incorporating non-accounting variables into bankruptcy predictions for SMEs. Additionally, the rapid global changes and the need for companies to adapt to new regulations, technologies, and market trends may influence accounting ratios and market, non-financial, and macroeconomic variables. Stakeholders need to be aware of all these developments to identify companies' financial condition more accurately. Predictive models linked to machine learning techniques tend to increase even more, along with the incorporation of variables that are unclear in the financial statements.

However, it is imperative to acknowledge that this study possesses certain limitations. The reliance on articles from Scopus and the concentration of studies in specific regions may limit generalisability. This constrained database may not encompass the entirety of research conducted on the subject, and the narrow focus on geographic context may not accurately depict the circumstances of SMEs within diverse economic and geographic frameworks. Furthermore, the diverse array of models examined presents difficulties in identifying a singular optimal universal model for predicting bankruptcy in SMEs.

Despite its limitations, the study provides valuable insights and a robust foundation for future research. The evident requirement for more adaptable and specific bankruptcy prediction models tailored to SMEs opens avenues for future research to explore this necessity across various contexts and with a broader database. To conclude, this study furthers the understanding of bankruptcy prediction in SMEs and establishes a clear trajectory for future advancement.

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