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# Too Small to Fail?

# Leveraging AI for Early Insolvency Detection in Italian SMEs

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**Abstract**

**Purpose:** This paper investigates the application of Machine Learning (ML) models to predict insolvency in Italian SMEs. The study identifies key factors leading to financial distress, aiming to equip managers and policymakers with tools for timely intervention to prevent insolvency and ensure business continuity.

**Methodology:** The study employs ML models, including Logistic Regression, XGBoost, Gradient Boosting, and Random Forest, to analyze extensive financial and non-financial data from 10,000 Italian SMEs.

**Findings:** ML models, particularly XGBoost with an accuracy rate of 0.87, significantly outperform traditional methods in predicting SMEs insolvency. The study emphasizes the importance of model interpretability, ensuring data-driven insights are actionable and comprehensible for managers. Key predictive features include "*Number of current representatives & managers*," "*CIAA Number,"* and "*Structural Margin*."

**Research Limitations/Implications:** The reliance on historical data from 10,000 Italian SMEs may not capture all relevant variables or industry-specific nuances. Also, models may require adjustments for different regions or industries. Ethical concerns such as data biases and model transparency also pose challenges. Managerial implications are profound. ML models provide tools for continuous financial health monitoring and early distress detection, enhancing resilience, business continuity, and stakeholder protection. Academically, this study advances predictive analytics by demonstrating the efficacy of ML in insolvency prediction and encourages an interdisciplinary approach.

**Originality/Value:** This study underscores the practical benefits of ML for insolvency and crisis prediction, offering Italian SMEs managers robust tools to enhance decision-making, mitigate risks, and promote sustainable growth. By leveraging AI-driven insights, managers can, in fact, better monitor performance, make informed decisions, and ensure business resilience.

**Keywords:** *Insolvency prediction; Italian SMEs; crisis management; Machine Learning; strategic management.*

**Paper Type:** Research Paper.

## 1. Introduction

In the complex and ever-evolving landscape of the Italian context, Small and Medium-sized Enterprises (SMEs) are the backbone of the national economy, representing over 80% of the country's businesses and playing a crucial role in driving economic growth and employment (Altman et al., 1994). However, their limited resources, vulnerability to market fluctuations, and often inefficient management practices make them particularly susceptible to financial distress and insolvency (Barboza et al., 2017). In this dynamic and unpredictable business environment, the ability to predict and manage insolvency and crisis risks is vital for sustaining economic stability and pursuing long-term growth. Insolvency and corporate crisis prediction have been subjects of extensive research during the years, particularly since the pioneering works of Beaver (1966) and Altman (1968). Beaver's (1966) univariate analysis focused on financial ratios as predictors of corporate failure, while Altman's (1968) multivariate approach, famously known as the "*Z-Score model*", provided a more sophisticated method by incorporating multiple financial indicators. These traditional statistical methods laid the groundwork for today's insolvency prediction techniques, yet they have inherent limitations. For instance, they often fail to capture the complex and dynamic relationships within financial data, leading to suboptimal predictions in real-world scenarios (Ferri, 2022; Altman, 1968). The traditional methods, while foundational, are, in fact, often limited by their reliance on static historical data and financial ratios (Aydin et al., 2022; Begley et al., 1996). Altman's Z-Score, which has been widely used to predict bankruptcy, relies on a set of financial ratios and a linear combination of these ratios to calculate a score that indicates the likelihood of insolvency. Despite its historical significance and widespread application, the model can struggle to adapt to the nonlinear and complex nature of modern financial markets, thus reducing its predictive accuracy (Danovi & Quagli, 2012; Altman, 1993).

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) offer promising tools for enhancing the accuracy of these predictions (Jiang et al., 2020). Unlike traditional methods, AI-driven models can analyze vast amounts of data, identify intricate patterns, and continuously improve their predictive capabilities (Joshi et al., 2018). Machine Learning techniques such as Random Forest, XGBoost, and Gradient Boosting provide more sophisticated approaches that can handle high-dimensional data and capture complex interactions among variables (Zhang & Susheng, 2021; Vinuesa et al., 2020). These models significantly outperform traditional statistical methods in terms of accuracy and reliability, offering a dynamic and adaptable framework for predicting financial distress. That said, we can affirm that the importance of early insolvency and crisis detection cannot be overstated. For SMEs, in particular, early detection means the difference between timely intervention and irreparable damage (Kuiziniene et al., 2022; Floridi et al., 2018). By identifying potential risks early, managers can take proactive measures to restructure operations, secure necessary financing, and implement strategic changes to avoid insolvency. This proactive approach not only safeguards the business but also preserves jobs and protects the interests of various stakeholders, including employees, creditors, and suppliers (Davenport & Ronanki, 2018; Mitroff, 2005). Moreover, the integration of AI in insolvency and crisis prediction aligns with broader trends towards digital transformation and sustainable business practices (Lin et al., 2020). AI, in fact, can enhance business ethics and sustainability by optimizing resource use, reducing waste, and improving overall operational efficiency (Russell & Norvig, 2021; Ribeiro et al., 2016). These improvements are crucial for aligning business operations with national and global sustainability goals, such as those outlined in the United Nations Sustainable Development Goals (SDGs) and the Corporate Sustainability Reporting Directive (CSRD). In this context, AI not only serves as a predictive tool but also as a catalyst for promoting ethical and sustainable business practices (Vinuesa et al., 2020). Ethical considerations are then paramount: AI should support, rather than replace, human decision-making, ensuring that data-driven insights are actionable and comprehensible for managers.

Based on these considerations, this study emphasizes the need, for Italian SMES, for transparent and interpretable AI models, which can foster trust among stakeholders and mitigate risks such as moral hazard and opportunism. By maintaining a balanced relationship between AI technologies and human expertise, in fact, businesses can enhance their decision-making processes while adhering to ethical standards and governance frameworks (Floridi et al., 2018; Ribeiro et al., 2016). This paper investigates the application of different Machine Learning models for predicting insolvency and crisis among SMEs in Italy: by understanding the key factors influencing insolvency in the years leading up to financial distress, this study aims to provide managers and policymakers with essential tools for timely intervention, ultimately preventing negative situations and ensuring business continuity (Ferri, 2022). The methodology employed includes a comprehensive review of four advanced AI-based algorithms: Logistic Regression, Random Forest, Gradient Boosting, and XGBoost. By leveraging these ML techniques, the study aims to provide a deep understanding of the advantages and limitations of these approaches, and its interdisciplinary and holistic view ensures that it is both scientifically rigorous and critically reflective, bringing added value to the existing body of research. Economic, financial, and non-economic and financial data for 10,000 Italian SMEs are used, encompassing both firms in crisis and those that are active and offering small business owners tailored tools for ongoing performance monitoring, thus improving crisis management and ensuring business continuity. These tools are designed to enhance the alignment of business practices with the interests and priorities of stakeholders, supporting sustainable and ethical business operations (Ferri, 2022). However, the reliance on available historical data may not capture all relevant variables or the nuances of specific industries. Additionally, while the ML models have achieved high levels of accuracy and precision in terms of predictive power, their implementation can be constrained by the technological infrastructure and expertise available within certain organizations.

The structure of the paper is designed to comprehensively explore the multifaceted aspects of corporate crisis and insolvency prediction. It begins with an overview of the current literature on the theme, followed by a review of modern prediction methodologies focusing on AI and Machine Learning. The paper then clearly articulates the Research Questions (RQ), detailing the methodology used for data collection, model selection, and evaluation. The results section summarizes the findings from various machine learning models, while the discussion interprets these results, explores managerial implications, and highlights academic contributions. The paper concludes with a recap of key findings, acknowledges limitations, and outlines directions for future research.

## 2. Related Research & Theoretical Background

### 2.1. AI vs ML: differences and similarities

To clarify the study's perspective, it's crucial to distinguish between Generative AI and Machine Learning (ML). Generative AI, like GPT-3 and GPT-4, creates new content based on patterns in existing data, widely used for creative outputs but limited in financial prediction and often misunderstood (Russell & Norvig, 2021). In contrast, ML has been pivotal in predictive analytics since the 1980s (Sun et al., 2014). It analyzes historical data to forecast future events, essential for predicting corporate insolvency (Altman, 1983; Breiman, 2001). This study employs ML techniques like XGBoost and Gradient Boosting, which are validated for their predictive accuracy (Zhang et al., 2021; Sun et al., 2014). Unlike Generative AI, ML learns from historical data to make future predictions, analyzing financial data to identify patterns preceding financial distress (Ferri, 2022; Breiman, 2001). These models then improve their accuracy by learning from new data, making them vital for early insolvency detection (Davenport & Ronanki, 2018; Vinuesa et al., 2020). For SMEs, ML provides significant benefits, offering continuous financial health monitoring and proactive crisis prevention, enhancing resilience, business continuity, and stakeholder protection (Ferri, 2022; Mitroff, 2005). ML models also offer enhanced explainability and transparency, essential for decision-making. Techniques like SHapley Additive exPlanations (SHAP) make insights actionable and more comprehensible (Ribeiro et al., 2016). Ethically, ML minimizes risks associated with AI-generated content, such as biases and misinformation (Floridi et al., 2018). Thus, while Generative AI has its uses, this study's focus on ML ensures precise and actionable insights, enhancing SMEs' crisis risk management and business continuity.

### 2.2. Pioneering Methods in Corporate Insolvency & Crisis Prediction

Corporate insolvency and bankruptcy have been focal points in academic research for decades, with a plethora of studies dedicated to understanding and predicting these phenomena (Beaver, 1966; Altman, 1968, 1983, 2002; Altman et al., 1995; Alberici, 1975; Taffler, 1976, 1982; Wilcox, 1976; Argenti, 1976; Lawrence & Bear, 1986; Flagg et al., 1991; Kern & Rudolf, 2001). In the Italian context, scholars have investigated the underlying causes of corporate crises (Piciocchi, 2003; Lo Conte & Sancetta, 2022), as well as the tools available for managing such crises (Ohlson, 1980; Guatri, 1986; Caprio, 1997; Danovi et al., 2000; Falini, 2008). Among these studies, Altman's work on the Z-Score model is particularly notable. Initially developed for US publicly traded manufacturing firms (Altman, 1968), this model was subsequently refined for non-listed companies (Scott, 1981; Altman, 1993; Danovi & Quagli, 2012). Yet, the origins of insolvency prediction methodologies can be traced back to 1932 with Paul Joseph FitzPatrick's pioneering study on financial ratios as predictors of corporate failure, analyzing a dataset of 19 company pairs (FitzPatrick, 1932).

The shift from univariate to multivariate approaches in insolvency prediction began with Beaver (1966), who introduced statistical methods to the field by examining 13 balance sheet ratios from a sample of 38 companies, half of which had failed. Beaver also compared 30 financial ratios across various economic sectors, including 79 failed and 79 non-failed companies, setting the stage for Altman's (1968) introduction of the discriminant function. This advancement marked a significant leap in predictive accuracy, although Altman later stressed the importance of updating the discriminant function to reflect industry-specific variables and company sizes. The academic landscape surrounding insolvency prediction has expanded considerably over the decades. The 1970s saw 28 related publications, a number that grew to 53 in the 1980s and 70 by the 1990s (Shi & Li, 2019; Sun et al., 2014). The early 2000s added another 11 studies to the corpus, indicating a sustained and growing interest in the field (Shi & Li, 2019).

### 2.3. Breakthroughs in Predictive Analytics

In contemporary times, a novel methodological paradigm has emerged, characterized by the analysis of extensive datasets, commonly referred to as "*big data*" (Shi & Li, 2019). This approach stems from the confluence of several factors, including the widespread availability of substantial volumes of data, enhanced computational capabilities for large-scale processing, and the application of innovative analytical techniques. Today, neural networks are a prominent technique in predictive modeling, alongside other machine learning methodologies such as Support Vector Machines, Logistic Regression, Random Forest, Gradient Boosting, and XGBoost (Sun et al., 2014). Although the conceptual framework of Artificial Neural Networks (ANNs) dates back to the 1950s, only recent advancements in computational power and specialized software have unlocked their significant analytical prowess (Zhang et al., 1999; Breiman et al., 1984). In Italy, significant strides in using neural networks for corporate default prediction began in 2007, marking a notable milestone in applying machine learning techniques to corporate insolvency prediction (Sarangi et al., 2013; Angelini et al., 2007).

Jackson and Wood (2013) made a significant contribution by comparing traditional statistical models and neural networks. Similarly, Zhang et al. (2013) studied a sample of 1,000 companies, half of which were insolvent. Using a combination of Genetic Algorithm (GA) and the Ant Colony Algorithm (ACA), they selected 25 financial ratios for each company, revealing classification errors ranging from 8.9% with GA to 7.9% with GACA on validation data. Le & Viviani (2018) demonstrated the superior performance of machine learning (ML) tools over traditional statistical methodologies, analyzing a sample of 3,000 US banks, with 1,438 insolvent and 1,562 operational. Their study contrasted the outcomes of Discriminant Analysis and Logistic Regression with ML approaches like Artificial Neural Networks, Support Vector Machines, and K-Nearest Neighbours, offering insights into the predictive capabilities of these modern techniques. That said, we can affirm that Artificial Intelligence (AI) and Machine Learning have revolutionized the field of predictive analytics for corporate financial distress. These technologies, in fact, enable the processing of vast datasets and the identification of complex patterns that traditional statistical methods cannot capture. AI models, particularly those utilizing advanced algorithms like XGBoost, have shown remarkable accuracy in predicting crisis and insolvency, offering a powerful tool for stakeholders to anticipate and mitigate financial risks (Vinuesa et al., 2020). The application of AI in this field is not only about achieving high predictive performance but also about providing actionable insights that can guide strategic decision-making. For instance, AI-driven models can continuously learn from new data, improving their predictions over time and adapting to changing market conditions (Zhang et al., 2021).

### 2.4. The Italian Context

In recent years, the application of ML techniques for predicting insolvency and crisis has gained increasing attention in Italy, especially concerning small and medium-sized enterprises (SMEs) (Ferrari & Ricci, 2022; Angelini et al., 2007). SMEs are, in fact, the backbone of the Italian economy but often face financial instability due to limited resources and market fluctuations. Studies by Rossi et al. (2020) and Biancone et al. (2019) explored the feasibility and performance of ML-based approaches in predicting corporate insolvencies among various types of Italian firms. These investigations typically involve the analysis of extensive datasets comprising financial and non-financial indicators, employing methodologies such as Support Vector Machines, Artificial Neural Networks, Random Forest, Gradient Boosting, and XGBoost (Barile et al., 2021; Le & Viviani, 2018). The pioneering work of Galli et al. (2018) introduced a novel ensemble learning framework for insolvency prediction in Italy, demonstrating promising results in terms of predictive accuracy and robustness. By integrating multiple Machine Learning models and leveraging ensemble techniques, their approach showcased improved predictive capabilities compared to traditional statistical methods. Despite these advancements, limitations remain. The quality and availability of data pose significant challenges. Incomplete or inaccurate data can adversely impact Machine Learning model performance, leading to suboptimal predictions. Additionally, accessing relevant data sources, especially for non-financial indicators, can be limited, constraining the comprehensiveness of insolvency prediction models (Ferrari & Ricci, 2022).

Interpretability of ML models is often cited as another limitation. While algorithms like Artificial Neural Networks, Random Forest, Gradient Boosting, and XGBoost can offer high predictive accuracy, their inner workings are often opaque, making it difficult to understand the factors driving specific predictions. This lack of transparency may hinder the acceptance and trustworthiness of these models, particularly in regulatory or compliance-sensitive contexts (Ribeiro et al., 2016). Ethical considerations also play a crucial role in the development and deployment of ML-based insolvency prediction models (Lo Conte & Sancetta, 2023). Biases inherent in training data or model design can result in discriminatory outcomes, disproportionately affecting certain groups or individuals. However, there remains a noticeable paucity of research specifically focusing on the application of ML algorithms in Italy on a national scale.

## 3. Purpose of the Paper

The primary objective of this paper is to investigate the application of Machine Learning models to predict insolvency and crisis in Italian small and medium-sized enterprises

(SMEs). SMEs are the backbone of Italy's economy, representing a substantial portion of the business landscape and significantly contributing to employment and economic growth. However, these enterprises often face financial instability due to limited resources, market fluctuations, and managerial inefficiencies. That said, the study aims to identify key factors leading to financial distress, leveraging Machine Learning and Artificial Intelligence to develop predictive models that can aid in early detection and proactive management of insolvency risks. By equipping managers and policymakers with these advanced tools, the study seeks to enable timely interventions, thereby preventing insolvency and ensuring business continuity. To achieve this, the study addresses two primary Research Questions (RQs):

- RQ1: *How do the implementation of AI-based algorithms and Machine Learning techniques improve the accuracy of insolvency prediction models for Italian SMEs, and what refinements can be made to enhance the interpretability and explainability of these predictions?*
- RQ2: *What are the potential managerial and ethical challenges associated with deploying AI-based models in the Italian context, and what strategies can be proposed to address these challenges effectively?*

The application of AI and Machine Learning to predict insolvency and crisis in Italian SMEs marks a revolutionary step forward. This study explores the transformative potential of these technologies, offering tools that surpass traditional methods in accuracy and insight. By focusing on early detection and proactive management, this research equips managers and policymakers with the means to safeguard business continuity and enhance decision-making. Emphasizing ethical considerations and model interpretability, it bridges the gap between innovation and practical application, inviting readers to explore the cutting edge of predictive analytics in business management.

## 4. Methodology

### 4.1 Data Collection

The foundation of this study is built on an extensive and meticulously curated dataset, encompassing financial and non-financial information from 10,000 Italian SMEs. This robust dataset provides a comprehensive view of the various factors influencing financial health and distress, making it a critical asset for developing accurate predictive models. A balanced representation of 5,000 insolvent or crisis-stricken companies and 5,000 active and solvent ones ensures the robustness and reliability of our predictive models. Data was sourced from the AIDA database[1], and spans a seven-year period leading up to 2022, providing a rich temporal context for analysis. Data includes metrics such as balance sheet items, income statements, and cash flow statements. Key financial indicators like liquidity ratios, profitability ratios, and leverage ratios are extracted to capture the financial health of each SME. Non-financial data encompasses variables such as the number of current and previous managers, company age,

[1] AIDA is the database, created and distributed by Bureau van Dijk S.p.A., containing the balance sheets, personal and product data of all active and failed Italian joint-stock companies (excluding banks, insurance companies and public bodies).

industry classification. This holistic approach allows us to capture a wide array of factors influencing financial stability and distress. To establish a robust dataset, we utilized propensity score matching with a 1:2 ratio, identifying comparable companies to enhance the reliability of our analysis. Specifically, we selected SMEs based on the European Union's criteria, which define SMEs as firms with up to 249 employees and annual sales not exceeding €50,000,000 (European Commission, 2020). We then included a diverse set of 348 variables per company. In this study, both categorical and numerical features, as well as missing values, were systematically preprocessed to ensure uniformity and compatibility with machine learning models. Features with more than 50% missing values were removed from the dataset to avoid introducing excessive noise and potential biases. Categorical features were transformed using frequency encoding, which replaces each category with the frequency of its occurrence in the dataset. This approach retains the informative value of the categorical features while converting them into a numerical format suitable for model input. Missing values (NaNs) in categorical features were treated as a separate category and similarly encoded.

For numerical features, missing values (NaNs) were handled by replacing them with the median of the respective variable. To prevent data leakage and ensure robust model evaluation, the dataset was split into training and testing sets before any preprocessing was applied. The training and testing sets were processed independently, maintaining the integrity of the model training process and avoiding the introduction of bias from test data into the training data. This meticulous preprocessing strategy preserves data integrity and ensures that the models are trained and evaluated on unbiased and representative datasets.

For a detailed list of all features used in this study, please refer to *Appendix 1*.

### 4.2. Model Selection

Machine Learning encompasses a diverse array of techniques that are widely utilized across different fields. In this research, we address the critical task of predicting corporate insolvency, which involves developing a supervised binary classification model to identify companies at risk of failure within the next few years. To achieve this, we employ four advanced machine learning methods:

- Logistic Regression, models the probability that a given input $X$ belongs to a particular category (usually denoted as 1) using the logistic function. The model is defined as:

  $$P(Y = 1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_k X_k)}},$$

  where $P(Y = 1|X)$ represent the probability of the dependant variable $Y$ being 1, given the independent variables $X_1, X_2, \ldots, X_k$. The parameters $\beta_0, \beta_1, \ldots, \beta_k$ are estimated from the data using maximum likelihood estimation. The logistic function ensures that the output is bounded between 0 and 1, making it suitable for probability prediction (Kleinbaum et al., 2002).

- Random Forest, is an ensemble learning method that is used for both classification and regression tasks. It constructs a multitude of decision trees during training and outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees. This technique mitigates the overfitting typically associated with single decision trees and improves predictive performance. A random forest operates by creating multiple subsets of the training data through bootstrap sampling. Each decision tree in the forest is trained on a different subset, and during the construction of each tree, a random subset of features is considered for splitting at each node. This process ensures that the trees are decorrelated, thereby enhancing the robustness and generalizability of the model. The final prediction of a random forest classifier is determined by a majority vote among the trees. For a classification problem, the formula can be expressed as:

$\hat{y} = \ mode(\{h_t(X)\}_{t=1}^{T}),$

where $\hat{y}$ is the predicted class, $h_t(X)$ is the prediction of the $t$-th decision tree, and $T$ is the total number of trees (Breiman, 2001).

- Gradient Boosting, is an ensemble learning technique used for both classification and regression tasks. It builds models in a sequential manner, where each new model corrects the errors made by the previous ones. This method leverages decision trees as base learners and optimizes them by minimizing a specified loss function through gradient descent. In gradient boosting, the prediction model is composed of an ensemble of weak learners $h_t(X)$,typically shallow decision trees. The overall prediction $\hat{y}$ is a weighted sum of these weak learners:

$$\hat{y} = \sum_{t=1}^{T} \beta_t h_t(X),$$

where $\beta_t$ are the weights determined during training, and $T$ is the total number of trees. Each new tree is fitted to the residual errors of the combined ensemble of previous trees, effectively reducing the overall error in a stepwise manner (Natekin et al., 2013).

- XGBoost, (Extreme Gradient Boosting) is an advanced implementation of gradient boosting designed for speed and performance. It builds an ensemble of decision trees sequentially, where each tree aims to correct the errors of the preceding ones by optimizing a specified loss function using gradient descent. XGBoost introduces several enhancements over traditional gradient boosting, such as regularization techniques to prevent overfitting, handling missing values, and parallel processing capabilities. The model prediction is formulated as:

$\hat{y} = \ \sum_{t=1}^{T} \beta_t h_t(X),$

where $\beta_t$ are the weights assigned to each tree $h_t(X)$, and $T$ is the total number of trees (Chen et al., 2016).

These methodologies enable us to rigorously assess and compare their predictive capabilities in the context of insolvency forecasting.

### 4.2.1 Model Evaluation

The evaluation of the models' performance was conducted using several key metrics (Hossin et al., 2015) in the context of supervised classification:

- Accuracy measures the proportion of correct predictions among the total predictions made and is defined as:

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

  where $TP$ are the true positives, $TN$ the true negatives, $FP$ the false positives, and $FN$ the false negatives.

- F1 Score is the harmonic mean of precision and recall, offering a balance between precision (positive predictive value) and recall (true positive rate), and is defined as:

  $F1 = 2 \times \frac{precision \times recall}{precision + recall}$,

  with precision and recall given by:

  $precision = \frac{TP}{TP+FP}$, and $recall = \frac{TP}{TP+FN}$.

- The Area Under the Curve (AUC) is a performance metric derived from the Receiver Operating Characteristic (ROC) curve, which plots the True Positive Rate ($TPR = \frac{TP}{TP+FN}$) against the False Positive Rate ($FPR = \frac{FP}{FP+TN}$) at various threshold settings (Fawcett, 2006). The ROC curve illustrates how well a classifier distinguishes between classes by showing the trade-off between recall and the false positive rate. The AUC is the integral of the ROC curve and can be formulated as:

  $$AUC = \int_0^1 TPR(FPR)d(FPR)$$

  This represents the probability that a randomly chosen positive instance is ranked higher than a randomly chosen negative instance, providing a single scalar value to evaluate the model's discriminatory power. An AUC of 1 indicates perfect classification, while an AUC of 0.5 suggests no discriminative ability, equivalent to random guessing.

These metrics collectively provide a comprehensive assessment of the models' predictive capabilities, allowing for an understanding of their performance in classifying the data accurately.

### 4.3. Feature Importance with XGBoost

Computing feature importance in XGBoost can be done using several methods, with the most common being the Gain, Cover, and Frequency metrics. Gain measures the improvement in accuracy brought by a feature to the branches it is on; Cover calculates the relative quantity of observations affected by a feature; and Frequency simply counts the number of times a feature is used in all trees. The Gain metric, used in this work, is often preferred as it directly relates to the model's performance. In the context of XGBoost and decision trees, a "split" refers to a decision point within a tree where the data is divided based on the value of a feature. Each node in a decision tree represents such a split. To compute the Gain for a feature $f$ at a particular split $i$, the formula is (Chen et al., 2016):

$$Gain_i(f) = \frac{1}{2}\left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}\right] - \gamma$$

Here, $G_L$ and $G_R$ are the sums of the gradients for the left and right child nodes, respectively, and $H_L$ and $H_R$ are the sums of the Hessians (second-order gradients) for the left and right child nodes, respectively. $\lambda$ lambda is the regularization parameter to avoid overfitting, and $\gamma$ is the regularization term for the number of leaves in the tree. The Gain value represents the improvement in the loss function achieved by splitting the data at this node based on feature $f$. Summing the Gain values for all splits involving feature $f$ across all trees in the model provides an overall measure of the feature's importance. This metric helps in understanding which features contribute the most to the predictions.

### 4.4. SHapley Additive exPlanations (SHAP)

Shapley values, derived from cooperative game theory, provide a robust method for computing feature importance in machine learning models, including XGBoost. They attribute the contribution of each feature to the model's predictions by considering all possible combinations of features. The Shapley value for a feature $i$ is the average marginal contribution of that feature across all possible coalitions of features.

The formula for calculating the Shapley value $\phi_i$ of a feature $i$ is:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [v(S \cup \{i\}) - v(S)],$$

where $N$ is the set of all features, $S$ is a subset of features that does not include feature $i$, $v(S)$is the value function, representing the prediction with the features in the subset $S$, and $v(S \cup \{i\}) - v(S)$ is the marginal contribution of feature $i$ when added to the subset $S$ (Lundberg et al., 2017). Shapley values account for the interaction between features by averaging the contribution of each feature across all possible subsets, ensuring a fair distribution of the total contribution among all features.

## 5. Results

In this section, we unveil the findings of our study, showcasing the results of our Machine Learning model training and evaluation process. Our analysis emphasizes the significant academic advancements and the critical managerial implications derived from applying these models to predict insolvency and crisis in Italian SMEs. By thoroughly examining dataset preprocessing, model selection, and evaluation metrics, we demonstrate how our approach not only advances the existing literature but also provides indispensable tools for managers. This dual focus underscores the transformative potential of ML in enhancing decision-making processes and ensuring business continuity. Academically, our study contributes to the evolving field of predictive analytics by employing advanced ML techniques and SHapley Additive exPlanations (SHAP). The inclusion of SHAP values in our analysis is particularly noteworthy, as it enhances the interpretability of the models. This interpretability is crucial for understanding the contribution of each feature to the model's predictions, thus bridging the gap between complex algorithms and practical insights that managers can utilize.

Moreover, our findings underscore the importance of AI as a complementary tool to human decision-making rather than a replacement. AI and Machine Learning can handle large volumes of data and identify patterns that may not be immediately apparent to human analysts. However, the ultimate goal is to support and enhance human judgment. By providing clear, actionable insights, these technologies enable managers to make more informed decisions, foresee potential crises, and implement proactive measures. This approach fosters a collaborative environment where AI augments human expertise, ensuring transparency, accountability, and ethical considerations in decision-making processes. Overall, the results of our study highlight the academic relevance of integrating advanced models with interpretability techniques like SHAP, and the practical significance of using AI as a supportive tool in business management. This synergy between human insight and technological innovation is vital for driving sustainable growth and resilience, particularly in Italian SMEs.

### 5.1 Model Performance

Five diverse classifiers (Logistic Regression, Random Forest, Gradient Boosting, and XGBoost) were selected and individually trained on the training data. Each classifier's performance was evaluated using key metrics such as Accuracy, Area Under the Curve (AUC), and F1 Score on the testing set. The evaluation of the Machine Learning models for predicting company insolvency revealed significant differences in their performance. XGBoost demonstrated the highest efficacy, achieving an accuracy of 0.87, an AUC of 0.87, and an F1 score of 0.88 (Table 1). Random Forest followed in performance with an accuracy of 0.81, an AUC of 0.80, and an F1 score of 0.83. While slightly less accurate than XGBoost, Random Forest still provides substantial predictive power, correctly classifying the majority of companies. Logistic Regression showed moderate performance with an accuracy of 0.64, an AUC of 0.63, and an F1 score of 0.68, indicating its limited capacity to effectively differentiate between solvent and insolvent companies compared to the more advanced ensemble methods. Gradient Boosting exhibited the least effectiveness in this context, achieving an accuracy of 0.55, an AUC of 0.54, and an F1 score of 0.67.

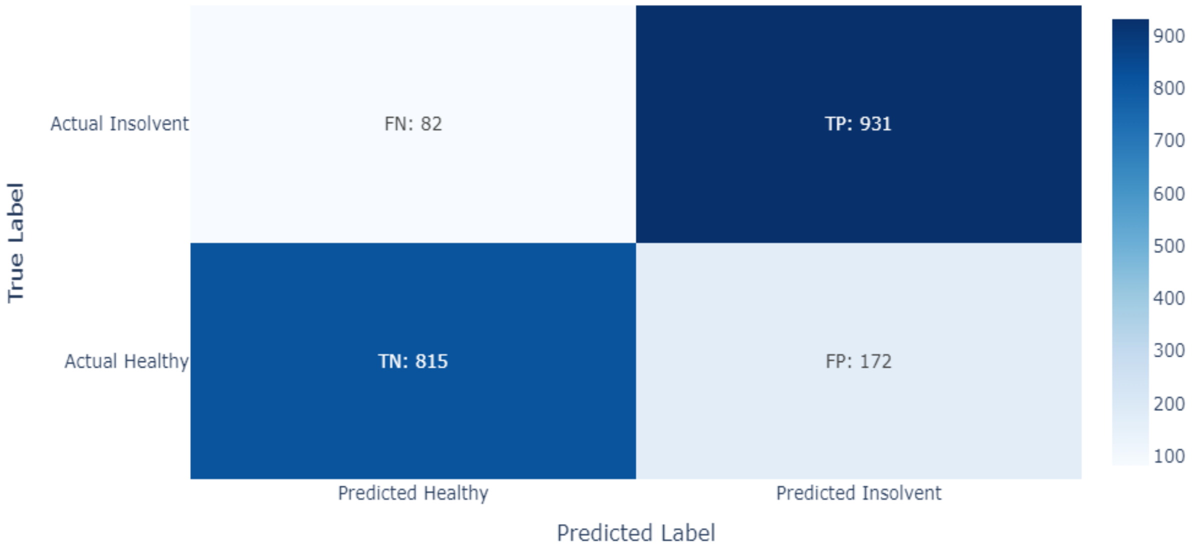
**Table 1. Performance assessment using classification metrics of Machine Learning models in identifying insolvent companies (bold values indicate the model with the best overall performance)**

| Model | Accuracy | F1 Score | AUC |
|---|---|---|---|
| Logistic Regression | 0.64 | 0.68 | 0.63 |
| Random Forest | 0.81 | 0.83 | 0.80 |
| Gradient Boosting | 0.55 | 0.67 | 0.54 |
| XGBoost | **0.87** | **0.88** | **0.87** |

**Source: our processing**

Figure 1 displays the confusion matrix for XGBoost on the testing set. The model correctly classified 931 instances of true positives (insolvent companies correctly identified) and 815 instances of true negatives (healthy companies correctly identified). It also identified 82 false negatives and 172 false positives. This suggests that XGBoost is highly reliable in distinguishing between insolvent and healthy companies, making it a powerful tool for stakeholders in business management.

**Figure 1. Confusion matrix for the model XGBoost on the test set**




**Source: our processing**

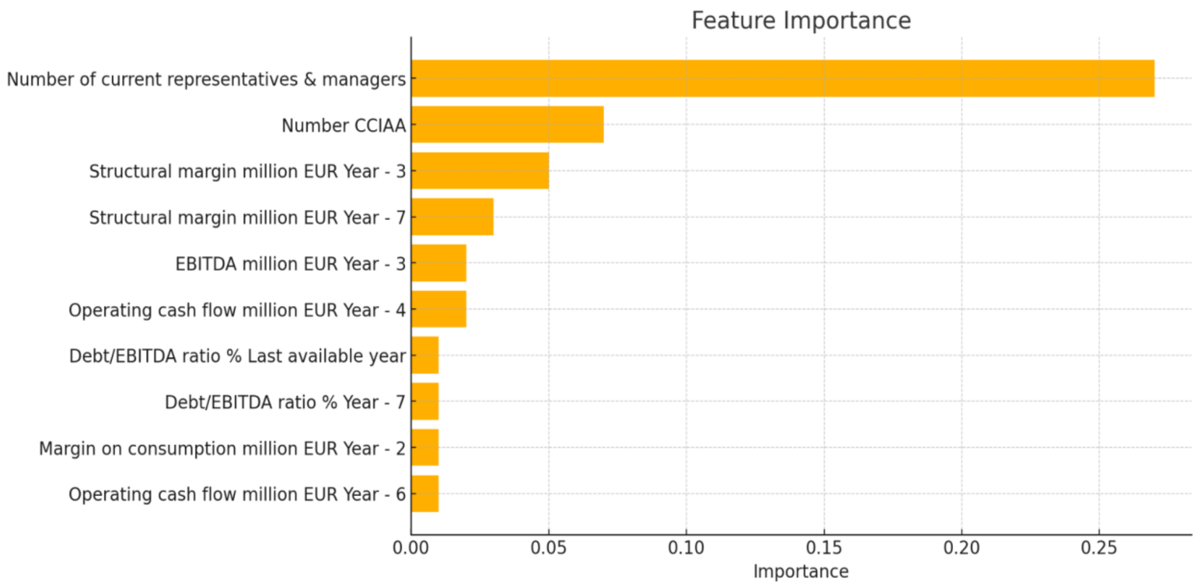
In summary, XGBoost emerged as the most proficient model, delivering high accuracy and robust classification capabilities, which are crucial for stakeholders requiring precise insolvency predictions to inform financial decision-making and risk management strategies. The superior performance of XGBoost underscores the potential of advanced techniques in revolutionizing business management practices through improved predictive analytics. This enhanced predictive capability allows managers to proactively address financial distress, thus avoiding the severe repercussions of insolvency. The XGBoost model's superior performance can be attributed to its ability to handle complex datasets with high-dimensional features, which is particularly relevant given the diverse and intricate financial environments of Italian SMEs. Unlike traditional models and even some other ML techniques like Logistic Regression and Gradient Boosting, XGBoost effectively manages the heterogeneity in the data. This includes variations in financial health indicators, operational metrics, and market conditions that are typical of SMEs. Its robustness against overfitting ensures that the model remains reliable and accurate even with the diverse characteristics of SMEs.

From a managerial perspective, the ability to anticipate financial trouble with such precision empowers leaders to make informed, strategic decisions well in advance of crises. This could involve reallocating resources, renegotiating terms with creditors, or even restructuring the business to improve financial stability. The proactive stance facilitated by these insights not only safeguards the business's continuity but also protects jobs and maintains the trust of investors and other stakeholders. Moreover, XGBoost's superior performance in this context is indicative of its ability to capture the unique dynamics of Italian SMEs, such as specific financial structures and operational challenges. This specificity makes it an invaluable tool for managers who need tailored insights that reflect the actual conditions of their businesses.

### 5.2 Insights into Feature Importance in XGBoost for Insolvency Analysis

Feature importance was determined using the XGBoost model's built-in feature importance functionality, which calculates the importance of each feature based on the gain, coverage, or frequency. In this context, gain measures the improvement in accuracy brought by a feature to the branches it is on, coverage measures the relative quantity of observations concerned by a feature, and frequency counts the number of times a feature is used in all generated trees. For this analysis, we primarily relied on the gain metric, which provided the most significant insights into the contribution of each feature towards the model's predictive accuracy. Among these, the most significant feature is the "*Number of current representatives & managers*" with an importance score of 0.26, indicating that the number of current executives and managers plays a crucial role in determining a company's solvency status (Figure 2). The second most important feature is the "*CCIAA Number*" with an importance score of 0.02. Other notable features include various financial metrics such as the "*Structural margin - Year 3*", "*Structural margin - Year 7*" and "*EBITDA*," highlighting the relevance of structural margins and debt management in predicting insolvency.

**Figure 2. Feature importance plot generated using the XGBoost model, highlighting the importance scores calculated based on gain**




**Source: our processing**

### 5.3 Understanding Feature Contributions to Insolvency Prediction with SHAP and XGBoost

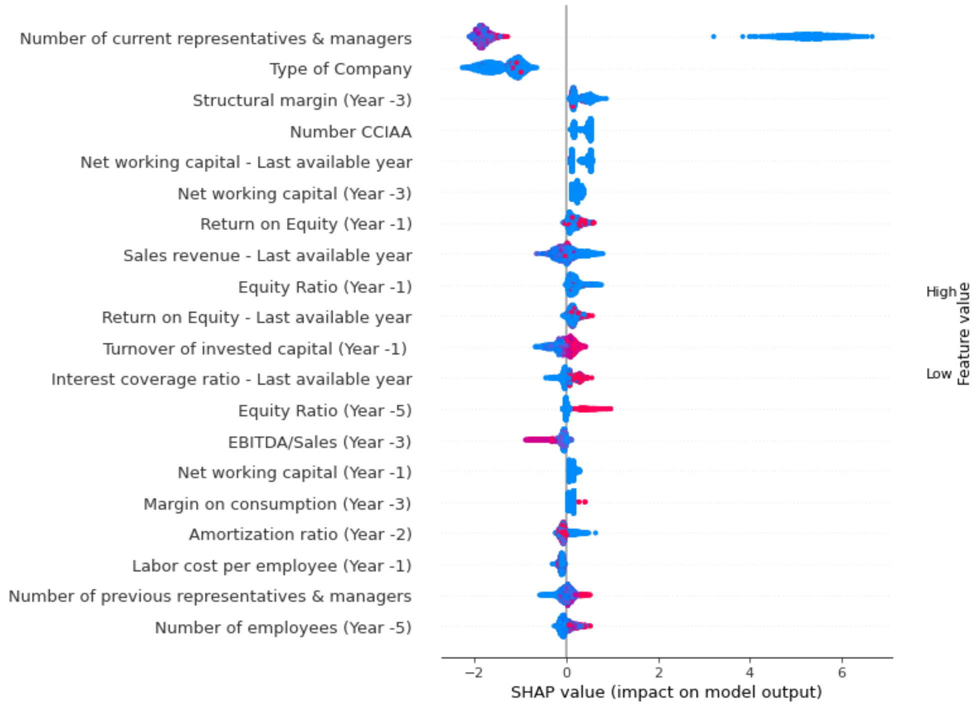
The SHAP summary plot presented in Figure 3 provides an insightful visualization of the impact of various features on the model's output, emphasizing the importance and influence of each feature in predicting whether a company is healthy (active) (0) or insolvent (1). The SHAP values on the x-axis represent the magnitude and direction of the feature's effect, with positive values indicating a higher likelihood of insolvency and negative values indicating a higher likelihood of the company being healthy. The colors represent the feature values:

- ➢ red indicates high feature values;
- ➢ blue indicates low feature values.

Among the features, the "*Number of current representatives & managers*" shows a substantial impact, predominantly positive, suggesting that a higher number of current representatives and managers is strongly associated with an increased likelihood of insolvency. This feature exhibits a high level of importance and variability, as indicated by the widespread of SHAP values, with red (high values) mostly contributing to positive SHAP values, thus indicating insolvency. The "*Type of Company*" and "*Structural margin (Year -3)*" are also significant predictors, with notable positive and negative impacts respectively. The structural margin (three years before the crisis/insolvency) appears to have a diverse effect, implying that past financial stability can either increase or decrease the likelihood of insolvency depending on its context within the company's overall financial health. Here, red (high values) for the "*Type of Company*" contributes positively, suggesting a higher likelihood of insolvency, whereas for "*Structural margin (Year -3)*" it contributes negatively, suggesting a lower likelihood of insolvency. Interestingly, "*CCIAA Number*" and various measures of "*Net working capital*" across different years are influential, showing both positive and negative contributions. These features highlight the complexity of working capital's role in the company's health, reflecting the nuanced nature of liquidity management over time. Red (high values) for "*CCIAA Number*" generally impacts the model output positively, indicating a higher likelihood of insolvency, while for "*Net working capital (Year -3)*" it shows a mix of positive and negative impacts. Other features such as "*Return on Equity*" and "*Equity Ratio*" at different points in time also play crucial roles, with their impacts varying between positive and negative. This variability underscores the dynamic nature of equity measures and their conditional influence based on other financial metrics. For instance, red (high values) for "*Return on Equity (Year -1)*" tends to have a positive impact, indicating a higher likelihood of insolvency, whereas for "*Equity Ratio (Year -5)*" it has a more mixed impact.

The SHAP plot additionally reveals that features like "*Interest coverage ratio*" and "*EBITDA/Sales*" have a more concentrated impact, typically around specific SHAP values, indicating a consistent effect on the model's predictions. Red (high values) for these features consistently contributes to positive impacts on the model's output, indicating a higher likelihood of insolvency. In summary, the SHAP analysis delineates a complex interplay of financial and structural characteristics influencing the model's output in predicting company health. It highlights key areas such as management representation, company type, historical financial margins, and liquidity indicators, which are critical for accurately classifying a company as healthy or insolvent.

**Figure 3. SHAP plot illustrating feature importance for XGBoost**




**Source: our processing**

## 6. Discussion

The results of our study reveal that the XGBoost model stands out as the most effective in predicting insolvency among Italian SMEs, achieving high accuracy and robust classification capabilities. Additionally, we emphasize the importance of SHAP (SHapley Additive exPlanations) for managers, academia, and stakeholders. The XGBoost model identifies several critical features that significantly impact the prediction of insolvency and crisis among Italian SMEs. These features include the number of current representatives and managers, the CCIAA number, structural margins over different years, and EBITDA. Understanding these features and their implications can enhance decision-making and crisis management strategies. Below is a summary table highlighting the key features and their importance scores (Table 2).

**Table 2. Key Features Summary**

| Feature | Importance Score | Description | Implications |
|---|---|---|---|
| **Number of Current Representatives & Managers** | 0.26 | Indicates the number of current executives and managers. | Suggests robust governance structures, diversified expertise, and better crisis management. |
| **CCIAA Number** | 0.02 | Unique identifier assigned to companies by the Italian Chambers of Commerce. | Reflects firm's registration status, age, and compliance history, indicating credibility and stability. |
| **Structural Margin - Year 3** | 0.015 | Difference between revenue and the sum of variable and fixed costs, three years ago. | Sustained positive margins indicate strong operational efficiency and cost management. |
| **Structural Margin - Year 7** | 0.015 | Difference between revenue and the sum of variable and fixed costs, seven years ago. | Long-term financial health indicator, reflecting operational stability over time. |
| **EBITDA** | 0.015 | Measure of a company's operating performance, excluding financing, accounting decisions, and taxes. | High EBITDA values indicate robust core business operations and financial health. |

**Source: our processing**

The above table highlights key features identified by the XGBoost model in predicting insolvency among Italian SMEs. The "*Number of Current Representatives & Managers*" emerged as the most significant feature, underscoring the importance of robust governance structures in ensuring effective crisis management and operational stability. A higher number of managers typically indicates more diversified expertise, which is crucial for managing financial challenges effectively. The "*CCIAA Number*" provides valuable insights into a firm's formal registration status, age, and compliance history. Maintaining a clean and consistent

CCIAA registration is indicative of good standing with regulatory bodies and adherence to local business laws, contributing to overall financial health. Companies with a stable and long-standing registration are generally perceived as more credible and financially stable. Structural margins for years three and seven are critical indicators of financial health and operational efficiency. Sustained positive structural margins over these periods suggest that the company has managed its operational costs effectively and can generate surplus revenue, making it less likely to face insolvency. Lastly, EBITDA is a core profitability metric that excludes the effects of financing, accounting decisions, and tax environments, providing a clear picture of a company's operational performance. High EBITDA values are essential for Italian SMEs as they directly impact their ability to secure financing, invest in growth opportunities, and withstand economic fluctuations.

The superior performance of XGBoost underscores the potential of advanced machine learning techniques in revolutionizing business management practices through improved predictive analytics. This enhanced predictive capability allows managers to proactively address financial distress, thus avoiding the severe repercussions of insolvency. From a managerial perspective, the ability to anticipate financial trouble with such precision empowers leaders to make informed, strategic decisions well in advance of crises. Academically, the study highlights the value of integrating sophisticated ML algorithms like XGBoost into financial distress prediction models. It pushes the boundaries of current research by demonstrating that advanced ML techniques can significantly outperform traditional models, offering solid actionable insights. This progress in predictive analytics is crucial for developing comprehensive frameworks that can be applied across various sectors, ensuring that the findings are not only theoretically sound but also practically relevant.

## 7. Implications

### 7.1. Academic relevance

The findings of this study provide substantial academic contributions, advancing the existing body of knowledge in multiple ways:

- This research demonstrates the superior predictive capabilities of advanced algorithms, such as XGBoost, over traditional statistical methods. By systematically evaluating and contrasting the performance of various models, this study sets a new benchmark in the academic literature for predicting financial distress and insolvency among Italian SMEs. It also underscores the importance of incorporating sophisticated AI-driven methodologies in financial prediction models, thereby encouraging further exploration and refinement in this domain;
- Comprehensive Feature Analysis: The detailed analysis of feature importance and the use of SHapley Additive exPlanations (SHAP) provide a deeper understanding of the factors influencing insolvency predictions. This methodological innovation not only enhances model interpretability but also paves the way for future research to build more transparent and explainable AI

models. The application of SHAP values, in particular, offers a robust framework for interpreting complex ML models, making a significant contribution to the field of explainable AI;
- Novel Insights into SME Financial Health: By focusing on Italian SMEs, this study fills a critical gap in the literature, which often overlooks the unique challenges faced by smaller enterprises. The identification of key financial and non-financial indicators, such as the number of current representatives and managers, and the CCIAA number, provides novel insights into the governance and operational structures of SMEs. These findings can inform future academic inquiries into SME-specific financial dynamics, promoting a deeper understanding of this crucial sector.

Furthermore, the practical applicability of the study's findings bridges the gap between theoretical research and real-world business practices. By offering actionable insights that can be directly utilized by managers and policymakers, this research exemplifies how academic studies can drive tangible improvements in business management and policy formulation. This practical orientation enhances the relevance and impact of academic work, encouraging scholars to pursue research that addresses real-world challenges. Finally, this study also contributes to the ongoing discourse on the ethical use of AI in financial decision-making. By highlighting the importance of transparency, accountability, and ethical considerations, it sets a precedent for future research to integrate these crucial aspects into the development and deployment of AI models. This emphasis on ethical AI aligns with global trends towards responsible AI use and sustainable business practices, promoting a holistic approach to technology adoption in finance.

### 7.2. Managerial Implications

For managers, particularly those in SMEs, this study offers profound practical implications. The focus on feature selection addresses information overload by identifying the most relevant variables that impact insolvency predictions. This helps managers monitor critical aspects of their operations, enhancing strategic planning and risk management. The study emphasizes the importance of model interpretability, fostering a collaborative environment where AI supports human expertise. This transparency builds managerial trust in the models, encouraging their adoption and integration into strategic planning and crisis management. One of the key strengths of using the XGBoost model, augmented by SHapley Additive exPlanations (SHAP), is the enhanced interpretability and explainability of the predictions. SHAP values provide clear insights into the contribution of each feature to the model's output, making complex AI-driven predictions more understandable for managers. This transparency is crucial in fostering trust in AI systems and ensuring that managers can confidently rely on these tools for decision-making. From a strategic management perspective, integrating advanced predictive analytics into decision-making processes helps businesses anticipate and prepare for potential financial challenges. Understanding key factors contributing to insolvency enables managers to develop targeted strategies to strengthen their company's financial health and competitive position. Effective crisis management is crucial for

SMEs, particularly in volatile economic environments. Furthermore, the interpretability and transparency afforded by SHAP are not just beneficial for internal management but also for external stakeholders. Investors, creditors, and regulatory bodies require clear explanations of a company's financial health and the predictive models used to assess it. Transparent AI models can enhance stakeholder confidence, as they offer a reliable and understandable basis for evaluating a company’s risk profile. By utilizing models with explainable outputs, managers can better communicate financial risks and mitigation strategies to stakeholders. This transparency helps in building stronger relationships based on trust and accountability, essential components for sustaining long-term business partnerships and securing necessary support during financial uncertainties.

The practical implications of this study are particularly significant for crisis management. By identifying key predictive features, managers are better equipped to detect early warning signs of financial distress and take proactive measures. For SMEs, which often operate with limited resources and narrower margins for error, the ability to anticipate and respond to financial challenges swiftly can mean the difference between survival and failure. The insights provided by AI-driven models allow for more efficient allocation of resources, timely interventions, and strategic adjustments, thereby enhancing the overall crisis management framework. Finally, the study also highlights the importance of ethical considerations in deploying AI models. Ensuring that AI is used responsibly, with transparency and accountability, helps in aligning business practices with broader sustainability goals. By providing objective, data-driven insights, AI can reduce biases and promote fairer decision-making processes, which are essential for maintaining ethical standards and fostering sustainable business practices.

## 8. Limitations of the Study

Despite the valuable insights provided by our study on insolvency prediction for Italian SMEs using Machine Learning, several specific limitations warrant consideration.

- ➢ Dependence on Historical Data: Our analysis is based on historical financial and non-financial data from 10,000 Italian SMEs. While comprehensive, this reliance on historical data may not fully capture evolving market conditions or emerging trends;
- ➢ Data Quality and Availability: The quality and completeness of the dataset significantly influence the model's performance. Incomplete or inaccurate data can lead to suboptimal predictions. Access to high-quality, updated, and comprehensive data, especially non-financial indicators, is crucial for the robustness of Machine Learning models;
- ➢ Regional and Industry Variability: Our models are tailored to the Italian SME context. The applicability of these models to other regions or industries may be limited due to different economic, regulatory, and market conditions. Adapting and validating these models for diverse contexts is necessary to ensure their broader utility;
- ➢ Model Interpretability and Complexity: While Machine Learning models like XGBoost provide high predictive accuracy, their complexity can make them difficult to interpret

for SME managers. The '*black box*' nature of these models necessitates the use of interpretability tools like SHapley Additive exPlanations (SHAP) to make insights actionable. However, even with SHAP, explaining complex interactions in a simple and understandable manner remains a challenge;

- Ethical Considerations and Bias: AI models can inadvertently perpetuate existing biases present in the training data. Ensuring fairness and mitigating biases is essential to prevent discriminatory outcomes;
- Cost and Resource Intensity: Implementing and maintaining advanced Machine Learning models can be costly and resource-intensive. SMEs often operate with limited budgets and may find it challenging to allocate resources for the deployment and ongoing management of these models. Future research should explore cost-effective solutions and support mechanisms for SMEs;
- Limited Scope of Non-Financial Variables: Although our study includes non-financial variables like the number of current representatives and managers, the scope of such variables is limited. Expanding the range of non-financial indicators, such as market sentiment or industry-specific factors, could provide a more comprehensive understanding of insolvency risks.

## 9. Future Research

Future research should advance the field of corporate crisis and insolvency prediction, particularly for Italian SMEs, by focusing on several key areas. Emphasis should be placed on enhancing feature selection, expanding data sources, developing sector-specific models, integrating emerging technologies, creating tailored approaches for SMEs, and balancing AI with human judgment. A primary focus should be on transitioning from feature importance to feature selection, which refines predictive models by choosing the most relevant variables, thereby improving their predictive power and practical applicability. This shift ensures models are more accurate and easier for managers to interpret and act upon. Future research should also incorporate alternative data streams such as market sentiment, social media analytics, macroeconomic indicators, and qualitative data from industry reports. This comprehensive approach can uncover patterns and insights that traditional data might overlook, ensuring models remain relevant across different contexts and economic conditions. Moreover, developing sector-specific models tailored to various industries will enhance predictive accuracy and provide more actionable insights. Generic models often fail to account for sector-specific nuances, leading to suboptimal predictions. Targeted models that incorporate industry-specific variables and risks will enable SMEs to adopt more precise risk management strategies and make informed decisions aligned with their specific operational contexts. Future research should also prioritize developing user-friendly interfaces and tools that allow managers with limited technical backgrounds to utilize predictive models effectively. Additionally, cost-effective solutions that do not require significant financial or technical investments will make advanced predictive capabilities accessible to a wider range of SMEs. However, predictive models should support and enhance human decision-making rather than replace it. Future research should focus on improving the interpretability and transparency of AI-driven models, ensuring that managers can understand and trust the insights generated. Finally, ensuring effective knowledge transfer from academic research to practical applications is crucial. Future research should facilitate collaboration between academia and industry practitioners, adapting predictive models to comply with varying legal frameworks and promoting their widespread adoption and integration into existing business practices.

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*Appendix 1. Features (Complete list)*

| Features (Years) in A-Z order |
|---|
| Asset Coverage Ratio (Balance Sheet) (%) (7 years before the last available year) |
| ATECO 2007 Code |
| Average Days Payables (7 years before the last available year) |
| Average Days Receivables (7 years before the last available year) |
| Average Inventory Days (7 years before the last available year) |
| Bank Debt to Revenue Ratio (%) (7 years before the last available year) |
| Capital Turnover Ratio (7 years before the last available year) |
| CCIAA Number |
| Commercial Cycle Duration (7 years before the last available year) |
| Company Name |
| Consumption Margin (thousands EUR) (7 years before the last available year) |
| Cost of Borrowing (%) (7 years before the last available year) |
| Current Ratio (7 years before the last available year) |
| Debt Ratio (7 years before the last available year) |
| Debt/EBITDA Ratio (7 years before the last available year) |
| Debt/Equity Ratio (7 years before the last available year) |
| Depreciation Rate (%) (7 years before the last available year) |
| EBITDA (thousands EUR) (7 years before the last available year) |
| EBITDA to Sales (%) (7 years before the last available year) |
| Employee Productivity (7 years before the last available year) |
| Employees |
| Employees - Latest Available Year |
| Extraordinary Income/Expenses Incidence (%) (7 years before the last available year) |
| Financial Asset Coverage Ratio (%) (7 years before the last available year) |
| Financial Charges to Revenue Ratio (%) (7 years before the last available year) |
| Financial Independence Index (%) (7 years before the last available year) |
| Financial Statement Closing Date - Latest Available Year |
| Gross Working Capital Turnover Ratio (7 years before the last available year) |
| Independence from Third Parties Index (%) (7 years before the last available year) |
| Interest Coverage Ratio (%) (7 years before the last available year) |
| Inventory Coverage Days (7 years before the last available year) |
| Labor Cost per Employee (EUR) (7 years before the last available year) |
| Legal Form |
| Liquidity Ratio (7 years before the last available year) |
| Long-term Debt Ratio (%) (7 years before the last available year) |
| Net Financial Position (thousands EUR) (7 years before the last available year) |
| Net Working Capital (thousands EUR) (7 years before the last available year) |
| Number of Advisors |
| Number of Current Executives & Managers |
| Number of Previous Advisors |
| Number of Previous Executives & Managers |
| Operating Cash Flow (thousands EUR) (7 years before the last available year) |
| Operating Working Capital Incidence (%) (7 years before the last available year) |
| Province |
| Return on Assets (ROA) (%) (7 years before the last available year) |
| Return on Equity (ROE) (%) (7 years before the last available year) |
| Return on Investment (ROI) (%) (7 years before the last available year) |
| Return on Sales (ROS) (%) (7 years before the last available year) |
| Revenue per Capita (EUR) (7 years before the last available year) |
| Sales Revenue (thousands EUR) - Latest Available Year |
| Short-term Debt Ratio (%) (7 years before the last available year) |
| Structural Margin (thousands EUR) (7 years before the last available year) |
| Treasury Margin (thousands EUR) (7 years before the last available year) |
| Value Added per Capita (EUR) (7 years before the last available year) |
| Year of Establishment |