# The dilemma of accuracy in bankruptcy prediction: a new approach using explainable AI techniques to predict corporate crises

European Journal of Innovation Management

1

Francesco Fasano, Carlo Adornetto, Iliess Zahid, Maurizio La Rocca, Luigi Montaleone, Gianluigi Greco and Alfio Cariola
*University of Calabria, Rende, Italy*

Received 3 June 2024
Revised 8 August 2024
Accepted 21 September 2024

## Abstract

**Purpose** – Our aim is to develop a highly precise corporate crisis prediction model that surpasses previous versions, rooted in the forefront of technological advancements.

**Design/methodology/approach** – Artificial Intelligence (AI) for corporate default prediction with a novel approach based on a mix of techniques, enabling it to achieve a higher accuracy. We investigated models with sequence lengths that were both fixed and variable, and we chose the best variable sequence length model.

**Findings** – Our findings demonstrate that the artificial techniques implemented lead to very high accuracy in predicting business crises compared to previous research efforts, even those utilising long-time sequences or a high volume of observations.

**Research limitations/implications** – We highlight the key variables with a higher predictive power that need monitoring to prevent business crises. We also aim to open a new avenue of research that, starting from the use of these techniques and our results, can implement models incorporating non-accounting variables to prevent business crises.

**Practical implications** – We provide a model/tool that assesses a possible business crisis in advance through a monitoring and alert system. Policymakers can use our research's output as a tool to combine with current credit-scoring systems and to assess the effectiveness of the new corporate crisis reforms that are upcoming in many European countries. The results of our research can be useful also to banks, public entities, and consulting firms that interact with companies and are interested in the evaluation of a firm's financial health and stability.

**Originality/value** – Our innovative work leverages cutting-edge methodologies such as deep Recurrent Neural Networks and explainable AI. This choice is driven by the rapid evolution of AI techniques in practical application.

**Keywords** Bankruptcy prediction, Corporate failure, Generative Artificial Intelligence, Business crisis management, Digital transformation

**Paper type** Research paper

## 1. Introduction

The topic of predicting corporate crises is very hot nowadays. The statistics revealing the number of businesses that cease to exist every year worldwide, especially startups, as well as the average lifespan of companies, are impressive (Fuertes-Callén *et al.*, 2022). Over the past



We thank the Italian Ministry of University and Research that provided a grant for this research. The article is output of the project titled "Live long and prosper" funded under the National Recovery and Resilience Plan (PNRR)—with the identification code 20229EHBN7, Mission 4, Component 2, Investment 1.1 "Projects of National Relevant Research (PRIN)" Project number: H53D2300229 0006 – Funded by the European Union – NextGenerationEU.

European Journal of Innovation Management
Vol. 28 No. 11, 2025
pp. 1-22
Emerald Publishing Limited
e-ISSN: 1758-7115
p-ISSN: 1460-1060
DOI 10.1108/EJIM-06-2024-0633

decades, millions of companies have filed for bankruptcy [1] with detrimental consequences to society and the economy as a whole (Carruthers, 2015). In general, financial constraints are at the core of many firm difficulties, such as limited investment in innovation (e.g. Acebo *et al.*, 2022). Many papers have investigated the financial and non-financial causes of failure, as it represents a multidimensional phenomenon (Ooghe and De Sofie, 2008), while others have focused attention on the process that brings firms to bankruptcy (Levratto, 2013). Bankruptcy hurts not only firms but also the personal lives of entrepreneurs (Kliestik *et al.*, 2018) and employees (Ellul and Pagano, 2019; Graham *et al.*, 2023), the efficiency of the supply chain (Yang *et al.*, 2015), society (Bower and Gilson, 2003) and the global economy (Tung, 2005). More importantly, bankruptcy has a detrimental impact on innovation (Prusak *et al.*, 2022). Thus, bankruptcy prediction represents a highly significant corporate activity with a growing awareness among businesses [2]. No firm can reduce the risk of bankruptcy to zero, but efforts can be made to minimise it as much as possible. Firms need to manage the risk of crises very well and choose the best model of bankruptcy prediction to discern the nature of the decisions and anticipate any negative consequences of the crises.

In this context, the research community contributed to predicting business crises, and several models and techniques have been developed to support executives of companies in managing potential collapses. Academics have paid attention to this topic since the 1960s, and some models for predicting corporate crises stand as milestones in this field of study (Altman, 1968; Deakin, 1972; Ohlson, 1980; Zmijweski, 1984) that is currently the focus of great attention. In particular, the noteworthy contribution of Altman (1968) laid the groundwork and has been an inspiration for numerous subsequent studies on the topic. Following Altman, over time researchers and practitioners have developed crisis prediction methods and techniques that go beyond the traditional mathematical and statistical models, with the purpose of predicting the bankruptcy of firms quickly and more accurately (Barboza *et al.*, 2017). In addition to traditional methods, since the 1990s machine learning (ML) models have been extensively applied in this field of research as tools to predict the bankruptcy of firms (Lin *et al.*, 2012) and provide managerial support for businesses. Recently, deep learning (DL) has emerged and gradually developed into a powerful technique for a wide range of applications in economics studies (Zhou *et al.*, 2023), and in bankruptcy prediction. Indeed, a neural network can learn from data automatically, so it can be trained to recognise patterns, classify data and forecast future events (Atiya, 2001; Charalambous *et al.*, 2023; du Jardin, 2023; Dube *et al.*, 2023; Jabeur *et al.*, 2020; Kim *et al.*, 2022; Mai *et al.*, 2019; Tsai and Wu, 2008). A particular neural network architecture called Recurrent Neural Network (RNN) can process information with a temporal dimension in the form of time series. Such RNNs can identify data patterns that evolve by considering a set of features measured at subsequent time steps (Kim *et al.*, 2022). Some authors have used the ML algorithm to predict bankruptcy (Barboza *et al.*, 2017; Nanni and Lumini, 2009; Shin *et al.*, 2005), and more in general, there is extensive literature investigating bankruptcy prediction using Artificial Intelligence (AI) techniques (Bell, 1997; Charitou *et al.*, 2004; Heo and Yang, 2014; Hosaka, 2019; Huang *et al.*, 2004; Jackson and Wood, 2013; Jang *et al.*, 2019; Kim *et al.*, 2022; Lin *et al.*, 2012; Mai *et al.*, 2019; Narvekar and Guha, 2021; Perboli and Arabnezhad, 2021; Shin *et al.*, 2005; Tsai and Wu, 2008; Zhao *et al.*, 2015).

All these contributions interestingly demonstrate that bankruptcy prediction models based on AI techniques outperform classic mathematical and statistical models, even considering different industries, and both cross-country and single-country studies. Therefore, AI can be very important for the survival of businesses. The importance of these models based on computational solutions is additionally demonstrated by the fact that since their first use in this area of investigation, researchers have never stopped developing new and more accurate solutions. In a context where many models of bankruptcy forecasting have been developed (Lundberg and Lee, 2017), we questioned what drove researchers in this ongoing pursuit, reaching a point where, to date, it is difficult to find a universally accepted and standard model to prevent corporate crises. Certainly, one of the reasons is linked to the fact that previous models utilising this research approach employ various AI techniques, each of which naturally yields different results. Furthermore, prior works have certain limitations, such as using short-term temporal sequences or a limited number of observations.

Within this strand of research, our innovative work leverages cutting-edge methodologies such as deep RNN and explainable AI. This choice is driven by the rapid evolution of AI techniques in practical applications. Thus, our aim is to develop a highly precise corporate crisis prediction model that surpasses previous versions, rooted in the forefront of technological advancements. Major challenges in bankruptcy prediction concern sample size, quality of input data and the choice of time series length, which is critical in the context of historical data of companies. In contrast with previous state-of-the-art approaches, this work stands out by utilising a large sample (4,172,046 observations) over a broad time span (from 2012 to 2021) for building a prediction model able to process variable length time series of financial indexes. Decisions made by such a model are then interpreted by using an explainable AI methodology. This is very important also to understand the contribution of each variable to the bankruptcy prediction and provide useful managerial implications. Another unique aspect of our work involves the utilisation of data extracted from the Orbis database by Bureau Van Dijk. Orbis, which is Moody's analytics company, represents the most extensive database of financial and business information across Europe, as it contains detailed and well-harmonised accounting, financial and business information for firms. Moreover, it is the world's most powerful comparable data resource on private companies [3].

Our sample also consists of small and medium-sized enterprises (SMEs). This is important because SMEs have a key role in economic growth as they represent 99% of businesses in Europe [4]. Hence, their bankruptcy prediction could be very relevant both for local and global economies. Additionally, SMEs are businesses that are particularly affected by asymmetric information problems within financial markets (Fasano and Deloof, 2021; Fasano and La Rocca, 2023a, b), especially during difficult periods (La Rocca *et al.*, 2022).

Our findings demonstrate that the artificial techniques implemented lead to very high accuracy in predicting business crises compared to previous research efforts, even those utilising long-time sequences or a high volume of observations. Furthermore, our results highlight the key variables that need monitoring to prevent business crises. Finally, with this contribution, we aim to open a new avenue of research that, starting from the use of these techniques, can implement models incorporating non-accounting variables such as governance, Environmental, Social and Governance (ESG) and information from companies' social media to prevent business crises.

The paper is structured as follows: the second section presents the theoretical framework and research gap, while the third section outlines the materials and methods used. The fourth section provides results with a focus on exploitability in the fifth section. The sixth section offers conclusions, discussions and the managerial contribution of the work.

## 2. Theoretical framework and research gap

Bankruptcy prediction in the business community is a field of growing interest, particularly since the financial scandals at the beginning of 2000 and even more the global financial crisis of 2008, after which the number of studies on the topic has greatly increased becoming a significant area of study within the field of management and corporate finance (Shi and Li, 2019). However, investigations into predicting corporate crises date back a long time. Indeed, a significant amount of research has focused on the prediction of corporate financial distress since Altman's influential introduction of his bankruptcy prediction model in 1968 [5]. Altman found that predicting bankruptcy can be done by using discriminant analysis and liquidity, profitability, productivity, leverage and asset turnover ratios to establish the so-called Z-score. The Z-score is calculated using five financial ratios assessing a company's liquidity, profitability, efficiency, solvency and turnover, thereby providing a comprehensive view of its financial health. A higher Z-score indicates better financial strength and stability, while a lower score suggests higher bankruptcy risk. Altman pioneered a field of studies that aimed to describe the financial variables that lead to the default of companies during different years. After Altman, other models have been particularly influential. Ohlson (1980) for instance investigated the bankruptcy prediction for American firms from 1970 to 1976 using the logistic regression model and nine financial ratios. Begley *et al.* (1996) investigated bankruptcy in three of the major stock markets in the United States (NYSE, AMEX and NASDAQ), observing that the Altman model performed better than the Ohlson model for data from 1980 to 1989. Some other papers went beyond the use of financial variables. Hu and Sathye (2015) for instance observed financial distress in the Hong Kong Growth Enterprise Market from 2000–2010 and found that a logistical model that used financial, non-financial and macroeconomic variables overperformed the other models. Liang *et al.* (2016) used the combination of financial ratios and corporate governance indicators for bankruptcy prediction, finding that combining such ratios and indicators is more efficient than using only financial data (Liang *et al.*, 2016).

The main techniques employed following the seminal contribution of Altman and the subsequent influential contribution mainly aim to distinguish firms into bankrupt or non-bankrupt and include multivariate discriminant analysis, logit, probit and neural networks (Bellovary *et al.*, 2007). However, analysis of the most recent literature on anticipating business failure reveals a wide array of models employed that extend far beyond the ones observed by the review of Bellovary. This diversity stems from advancements in statistical techniques and information technology over time that have tried to establish more accurate bankruptcy prediction models compared to earlier attempts, aiming to contribute to firms in their crisis prevention decisions.

In particular, information technology-based techniques have been developed since the 1990s, after which neural networks have been the most widely used methods to predict corporate crises. Obviously, in the initial stages of using this technology, the models adopted were less complex than the more recent ones. Indeed, in the 1990s some AI models were developed (Tam and Kiang, 1992; Wilson and Sharda, 1994), followed by subsequent models in the succeeding decade. For instance, in the 2000s Atiya (2001) showed that neural network models performed well in predicting bankruptcy for credit risk. Shin *et al.* (2005) investigated bankruptcy prediction in Korea by using Support Vector Machines (SVMs) and a back-propagation neural network (BPN). They found that the SVM performed better than BPN when the training set size got smaller. Tsai and Wu (2008), in another study, show that single neural networks perform better than multiple neural networks. Nanni and Lumini (2009) reported that the ML models outperformed the traditional statistical analysis methods in predicting bankruptcy in three credit markets (Australian, German and Japanese). In the following decade, there was an increase in studies on the prediction of corporate crises, particularly considering that the negative effects on businesses caused by the global financial crises exacerbated and underscored the gravity of this phenomenon. Barboza *et al.* (2017) show that ML models have a higher capacity for predicting bankruptcy compared to Artificial Neural Network (ANN), Logistic Regression (LR) and Multiple Discriminant Analysis (MDA) models for data from 1985 to 2013. Also, Mai *et al.* (2019) used ML models with non-financial variables to predict bankruptcy. Jabeur *et al.* (2020) studied the bankruptcy prediction of French companies from 2014 to 2016 using fuzzy convolutional neural networks (FCNNs). They concluded that FCNN performs better than neural networks, logistic regression, partial least square discriminant analysis, SVMs or discriminant analysis.

As a matter of fact, the use of AI provided a higher explanatory power in crisis prediction in comparison to a deterministic model based on financial ratios. Considering this superiority, a fight for the best technology-based approach started. The vast amount of research has led in recent years to the use of highly advanced AI techniques to predict corporate crises, leading up to the models characterising this research trend in the last two years. In a recent study, Kim *et al.* (2022) used textual sentiment analysis Bidirectional Encoder Representations from Transformers (BERT) to predict bankruptcy. They found that BERT-based analysis performed better than dictionary-based analysis and Word2Vec-based analysis combined with a convolutional neural network for data from 1995 to 2020. Yang *et al.* (2023) show that the Hierarchical Deep Neural Network (HDNN) algorithm was a good solution for higher dimensional corporate credit risk during the entire sample period (from 1 January 2009 to 31 December 2019). Chen *et al.* (2023) investigated the corporate bankruptcy prediction of U.S. firms in the period from 1994 to 2018 by including the text-based communicative value of annual reports in four ML models. They reported improvements in the performance of XGBoost and Random Forest models. They confirmed the importance of text-based annual reports for banks' corporate loan underwriting decisions. Charalambous *et al.* (2023) observed the U.S. public firms for data from 1990 to 2015 and found that structural models like the Black-Scholes-Merton and the Down-and-Out option models perform better than a standard neural network. Dube *et al.* (2023) used ANNs to investigate the financial distress models on the Johannesburg Stock Exchange (JSE) between 2000 and 2019. They found that ANN had good accuracy and predicted financial distress for up to five years for the financial services and manufacturing companies. Kim *et al.* (2022) found that from January 2007 to December 2019 the RNN and long short-term memory (LSTM) increased the performance of bankruptcy prediction compared to the use of logistic regression, SVM and random forest methods. They concluded that the RNN and LSTM methodologies cannot detect the importance of each explanatory variable for bankruptcy prediction. Elhoseny *et al.* (2022) in another study found that combining the DL and Whale optimisation algorithm (AWOA-DL) overperformed the Teaching-Learning-Based Optimization (TLBO-DL), Deep Neural Network (DNN), LR and Radial Basis Function (RBF) models in predicting bankruptcies and assessing credit risk. Du Jardin (2023) found that the convolutional neural network CNN performed better compared to the traditional model.

Despite the attention on crisis prediction from both academics and the community in general, no superior model has emerged among the others to forecast corporate crises. Every year researchers develop models that aim to be more capable of predicting corporate failure better than others, but these efforts have not led to the development of a universal model used by all companies today. Veganzones and Severin (2021) highlight that the way researchers design experiments is a crucial factor since it can have a significant impact on the outcomes. They believe that differences among the key elements (definition of failure, sample size, prediction methods, variables, evaluation metrics and performance) of such kinds of analysis are at the core of different outcomes.

Thus, here comes into play the need to develop a model that can encompass as much information as possible to predict corporate crises more accurately than prior contributions. With this in mind, we try to fill this research gap by investigating bankruptcy prediction using a mix of explainable AI techniques among the most recent and advanced solutions. Indeed, we use ML and DL models at the same time, while other papers use just one technique. In doing so, we pay a lot of attention to variable selection and data characteristics, using the Orbis database provided by Bureau Van Dijk. Moreover, Italian studies on the topic are very few and use a shorter timespan or a lower sample size. The Italian context is well suited for this analysis as in Italy there are significant differences among provinces in terms of institutional development.

### *2.1 Artificial intelligence application*

*2.1.1 Neural networks.* Neural network is one of the most popular DL methods. The neural network is inspired by the human brain function and structure, by using interconnect nodes called neurons in a layered structure that resembles a graph. In each layer, several neurons use the outputs of all neurons in the previous layer as inputs, such that all neurons interconnect with each other through the different layers. Each neuron is typically assigned a weight that is adjusted during the learning process by a decrease or an increase. A neural network can learn from data, so it can be trained to recognise patterns, classify data and forecast future events. It breaks down the input into layers of abstraction and defines a wide range of models characterised by an extremely high number of parameters, especially in the so-called deep models, which can be based on supervised or unsupervised learning paradigms. In the supervised learning approach, a neural network employs a sample of data consisting of corresponding inputs to outputs. By manipulating input parameters, the neural network finds the best non-linear predictive model that generates output consistent with the sample. This model has generalisation properties, which means that it can be used to predict an output when we add a new set of inputs that the model has never seen. This approach is typically used to solve regression and data classification problems. Instead, the unsupervised learning approach provides the computational model with a sample that does not include output information. In this case, it identifies statistical structures within the sample, such as correlations or associations, producing an output that describes such relationships. The unsupervised strategy is typically applied to solve clustering problems and it is a useful tool to assess industry similarities and data analysis in the financial field. There exist different types of neural networks.

*2.1.2 Recurrent neural networks.* An RNN is a neural network that adopts the following principle: it processes sequences by iterating through the sequence elements and maintaining a state containing information relative to what it has seen so far. An RNN is a type of neural network that has an internal loop. Unlike traditional neural network algorithms which are limited in their ability to handle ordered data, such as time-series data, music or sentences, RNNs can manage such data by exploiting these loops in their structure.

The state of the RNN is reset between processing two different, independent sequences, so you still consider one sequence a single data point: a single input to the network. What changes is that this data point is no longer processed in a single step; rather, the network internally loops over sequence elements. There exist different ways to implement an RNN. The easiest one is simple RNN, but it is never used in practice because it suffers from the vanishing gradient problem, as you keep adding layers to a network the network will struggle to remember information many timesteps before, so long-term dependencies are impossible to learn. The LSTM and Gated Recurrent Unit (GRU) layers are designed to solve this problem. Indeed, they work similarly: they save information for later, thus preventing older signals from gradually vanishing during processing.

*2.1.3 SHapley Additive exPlanation.* We employed SHapley Additive exPlanation (SHAP) to elucidate the interpretability of neural network models. SHAP values, derived from cooperative game theory, were used to quantify the contribution of individual features to the model's predictions. By calculating Shapley values for each input feature, we discerned their impact on the neural network's output, thereby enhancing the interpretability of complex model decisions. This approach facilitated a comprehensive understanding of the neural network's behaviour, offering insights into the relative importance of features in driving predictions, thereby contributing to the transparency and interpretability of our model.

## 3. Materials and methods

### *3.1 Data and variables*

The data used in this study were collected from the Orbis European database by Bureau Van Dijk. We collected annual accounting data from 2012 to 2020. The dataset counts about 4,172,046 Italian firm-year observations, 66,226 of which experienced bankruptcy. In this dataset, each financial index is collected for 9 years from 2012 to 2020. From such a dataset we extracted sequences of annual accounting data for different periods, considering period length from 2 to 9 years. The dataset consists of 22 indexes of financial performance: Intangible Assets; Non-current Plant and Equipment; Inventories; Current Assets; Trade Receivables, Cash and Cash Equivalents; Total Assets; Equity; Share Capital; Long-term Indebtedness; Non-current Liabilities; Current Liabilities; Debts; Trade Payables; Total Value of Production, Revenue, Sales and Services; Operating Profit [EBIT]; Financial Income; Financial Charges; Total Taxes; Profit/Loss for the Year [Net Profit]; Inventory Rotation; Cash-out times (days); Payment times (days). In this dataset, we distinguish between two classes: Class 0 is the set of firms for which bankruptcy occurred (66,226 firms), while Class 1 is the set of firms in good health (4,105,820 firms). This dataset is characterised by unbalanced classes, meaning that the number of firms in Class 0 is lower than the number of healthy businesses. However, our number and percentage (on the whole sample) of companies that went bankrupt is sufficient in light of the sample size in other recent research studies on the topic (e.g. Kim *et al.*, 2022; Chen *et al.*, 2023; Charalambous *et al.*, 2023).

*3.2 Preprocessing*

Along with the need for large amounts of data, DL models and, in particular, neural networks, need to work with data values distributed in a well-defined range and with data balanced among the classes. For this reason, we first normalised each variable in the range [0, 1] and then re-balanced the classes by generating synthetic data samples (firms). We augmented Class 0 by using the Synthetic Minority Over-sampling Technique (SMOTE) by Bower and Gilson (2003). Thanks to this technique, new synthetic instances are created starting from existing ones that are in the minority class, and small perturbations are added to the new data points.

*3.3 Experiments and models*

In this section, we discuss the development of optimisation of an RNN model for predicting bankruptcy. We conducted experiments on four RNN architectures by considering different numbers and types of recurrent layers. We selected the best-performing model over these in terms of accuracy and subsequently performed an automated model selection process with cross-validation to ensure the robustness and generalisation capabilities of the selected model across different data partitions. Finally, we used an explainable AI method called SHAP to explain the contribution of each financial index to the prediction.

*3.4 Training and hyperparameter optimisation*

In the development of bankruptcy prediction models, we implemented and evaluated a set of four models, each characterised by a distinct set of hyperparameters. Our dataset comprised 84,000 actual data instances, augmented by 26,000 synthetically generated samples using SMOTE. The dataset was partitioned into training (80%) and test (20%) sets, with the test set being exclusively constituted of real (non-synthetic) samples. All the models shared the following configuration. First, as a loss function, we used Binary Cross-Entropy, suited to the binary classification nature of the bankruptcy prediction task. Second, the Metric Accuracy is defined as the proportion of correct predictions out of the total predictions made. Finally, we used Adam as an optimiser.

The architectural details of the models used are as follows:

*Model 1:* 2 subsequent LSTM layers of 128 and 64 blocks respectively, followed by 3 fully connected layers of 64,128,64 neurons with dropout.

*Model 2:* 3 subsequent Conv1D layers of 64 blocks respectively, followed by 3 BatchNormalization of 64 blocks, and finally GlobalAveragePooling1D of 64 blocks.

*Model 3:* 2 subsequent LSTM layers of 256 and 128 blocks respectively, followed by 2 fully connected layers of 256 and 128 neurons with dropout.

*Model 4:* 2 subsequent GRUs of 128, followed by 2 fully connected layers of 128 and 128 neurons with dropout.

Model 1 performed best, with the best accuracy in each test. We trained it several times by varying the input data, exploring models with fixed sequence lengths (FSLs; from lengths 2 to 9) as well as models with variable sequence lengths. To properly evaluate its performance, we used the K-fold cross-validation technique with $K = 10$.

*3.5 Metrics*

In this work, different models were created by varying the input data. As evaluation metrics, we used Accuracy which is the ratio between the number of correct predictions and the total number of observations and Receiver-operating characteristic (ROC) curve.

## 4. Results

This section reports the performance of Model 1 in two cases: (1) When the model is trained and tested on FSLs; and (2) When the model is trained and tested on sequences of variable lengths.

*4.1 Fixed sequence length models*

As the first report, we want to compare results between models in which input data are only data with fixed lengths. We will refer to these as FSL models. Each of these models is specialised for input sequences of fixed length, so a model whose input data length is 2 learns from data with complete information only for 2012 and 2013, and accordingly, a model whose input data length is nine learns from data with complete information from 2012 to 2020. Each FSL model has been trained and tested on 15,000 firms. Specifically, 90% of the data were used for train and validation and 10% of the samples were used for testing their performances. Training and testing were performed by using a cross-validation approach with ten iterations.

We can notice that as the length of the sequence increases (i.e. the information becomes more complete), the performances of the neural networks increase. This difference is more evident between the "low-length model" and the "high-length model". Indeed, as shown in the confusion matrices of Figure 1, and the ROC curve in Figure 2, the best FSL model with length nine is much more accurate than the length 2 model.

Moreover, the AUC of the length 2 model is smaller than the other areas. For length >5 we can report a small difference in terms of ROC-AUC score and accuracy between the different FSL models.

*4.2 Variable sequence length models*

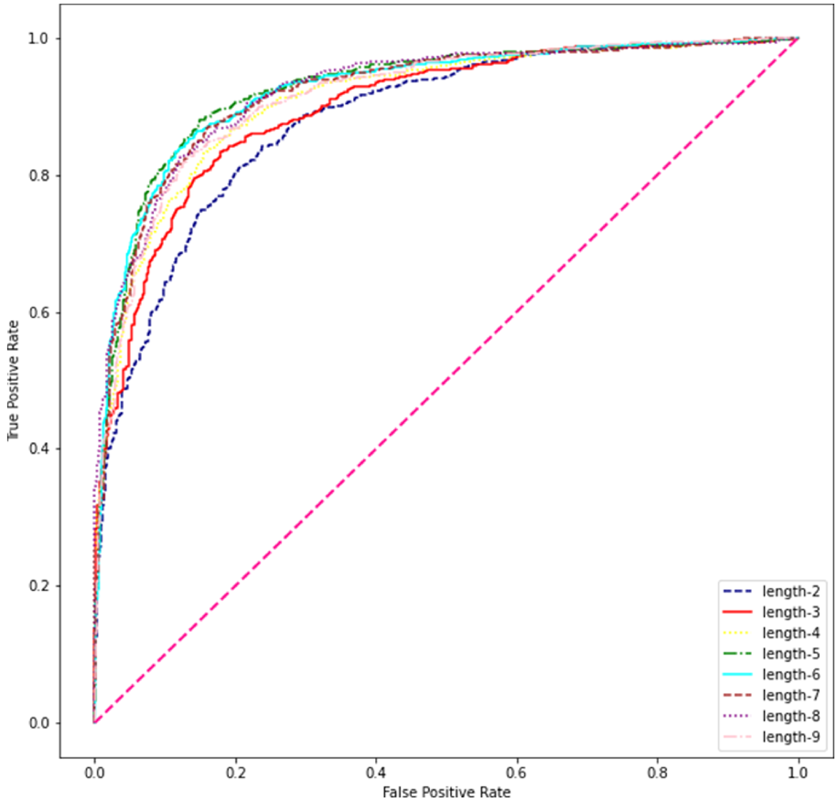
Now we want to compare results between models whose input data are mixed, so as to have more flexible models that can perform with sequences of different lengths, which we refer to as Variable Sequence Length (VSL) models. Each VSL model has been trained and tested on a different dataset where 90% of data were used for train and validation and 10% of samples were used for testing. Training and testing were performed by using a cross-validation approach with ten iterations.

In Table 2, we highlight the performance of the best VSL model, which is the one trained on sequences with complete information and time series that comprises data in the ranges: 2012–2017, 2012–2018, 2012–2019 and 2012–2020 (see Table 1). In Figure 3 we show the ROC curve to compare the results of the different VSL models and the confusion matrix of the best-performing model on the test set.

It is possible to notice how the model trained with sequences of lengths 3, 4 and 5 is the worst model in this case, and this can be explained by the fact that it is the model with less complete information than all the other models, so it is more likely to be wrong in its predictions. In Figures 4 and 5 we show the results of the exploitability method over the best-performing Variable Sequence Length (VSL) model.

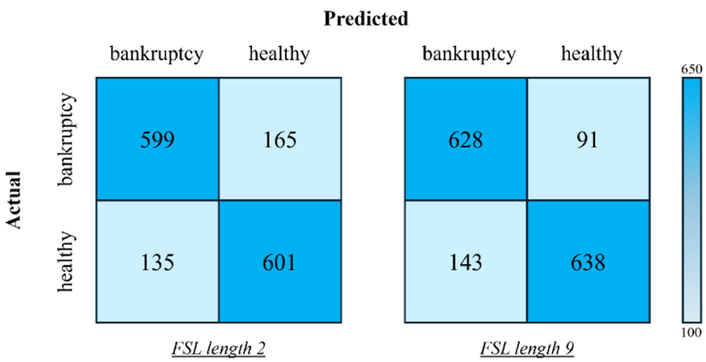
It is possible to notice that the most important feature in bankruptcy prediction is the inventory, and the firms with higher inventory have less chance of financial distress. This result can be explained because firms that have an important purchase-transformation-sale cycle with high stock levels are able to work well and survive within the market.

Moreover, the right inventory management system can save a company time and money. We also observe that a firm with a higher net profit has a lower probability of financial distress. This




**Source(s):** Figure created by authors

**Figure 1.** ROC curve




**Source(s):** Figure created by authors

**Figure 2.** Confusion matrix of the fixed length best models for length 2 and length 9 of the sequence

**Table 1.** Results of the FSL models on test sets

| Input sequence length | Accuracy | 95% C.I. | ROC-AUC |
|---|---|---|---|
| 2 (2012–2013) | 0.802 | [0.778, 0.794] | 0.880 |
| 3 (2012–2014) | 0.826 | [0.792, 0.816] | 0.897 |
| 4 (2012–2015) | 0.836 | [0.799, 0.821] | 0.910 |
| 5 (2012–2016) | 0.862 | [0.831, 0.846] | 0.926 |
| 6 (2012–2017) | 0.859 | [0.844, 0.853] | 0.924 |
| 7 (2012–2018) | 0.851 | [0.823, 0.838] | 0.924 |
| 8 (2012–2019) | 0.850 | [0.832, 0.845] | 0.924 |
| 9 (2012–2020) | 0.844 | [0.826, 0.841] | 0.914 |

**Note(s):** Each model has been tested by using 1500 samples of the same sequence length. The table reports the accuracy of the best model (over cross-validation) on the bankruptcy binary classification, followed by the confidence interval of accuracy over the results of cross validation and the ROC-AUC score of the best performing model
**Source(s):** Table created by the authors

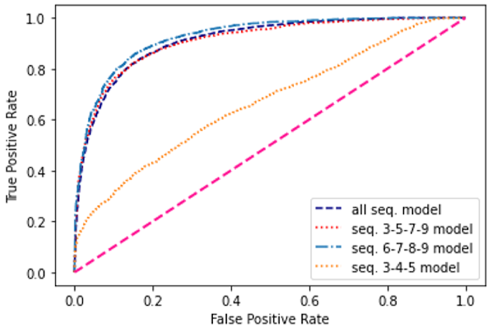
**Table 2.** Results of the VSL models on test sets

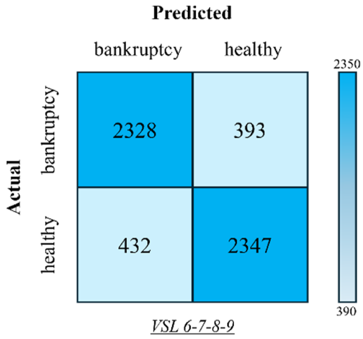
| Number of firms | Input sequence length | Accuracy | 95% C.I. | ROC-AUC |
|---|---|---|---|---|
| 110k | all lengths | 0.835 | [0.829, 0.832] | 0.912 |
| 55k | 6-7-8-9 | 0.850 | [0.828, 0.842] | 0.927 |
| 43k | 3-4-5 | 0.834 | [0.816, 0.828] | 0.908 |
| 54k | 3-5-7-9 | 0.836 | [0.812, 0.827] | 0.910 |

**Note(s):** Each model has been trained and tested by using the number of firms in the first column. The table reports the accuracy of the best model (over cross-validation) on the bankruptcy binary classification, followed by the confidence interval of accuracy over the results of cross validation and the ROC-AUC score of the best performing model
**Source(s):** Table created by the authors

result indicates that those companies that succeed in having revenues significantly higher than costs presumably are less subject to face situations of difficulty. When the value of inventory turnover is high the chance of financial distress increases, and this can be explained by the fact that if this ratio is high in difficult periods the company might not have the stock necessary to supply the production department or the points of sale in a timely manner. Moreover, a higher turnover of inventory could make the company riskier. Another important variable is the share capital. Higher values are related to higher default probability, indicating that the economic contribution of shareholders is not sufficient to guarantee proper resource management. Despite this, we interestingly notice that the higher the equity the lower the financial distress. Typically, firms with a capital structure having prevailing equity are stronger because throughout the years the company has achieved high profits which became reserves. It seems that reserves play a key role in survival more than the liquidity invested by shareholders in the form of share capital.

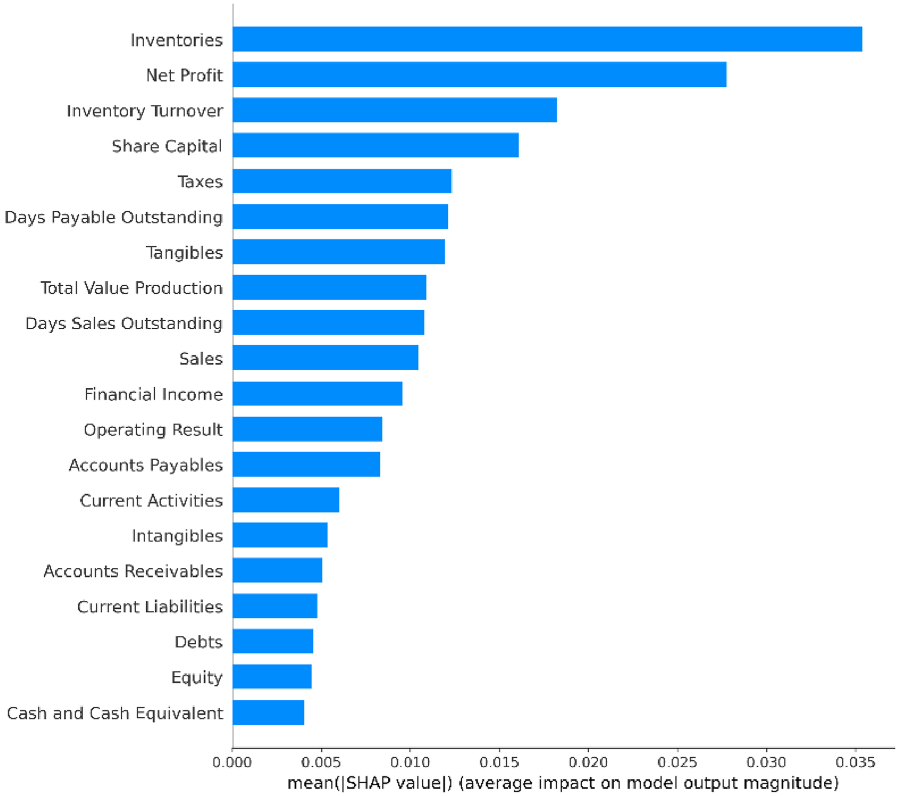
Additionally, when taxes are low this means that the company was good at leveraging the tax shield and saving cash to invest. The higher the value of days payable outstanding the higher the probability of financial distress, and this can be explained by the fact that taking a lot of time to pay bills and invoices of trade suppliers could make them dissatisfied with receiving the money with so much delay, leading them to undertake adverse conduct towards the company. The higher the tangibles the lower the financial distress, as firms having higher values of physical and measurable assets have more resources to be competitive in today's dynamic markets. More assets are also linked to a higher availability of collateral, which is useful to get loans and receive the cash necessary to pay debts to prevent bankruptcy. The higher the total value production the lower the financial distress. This means that businesses that are able to sell as much and add value



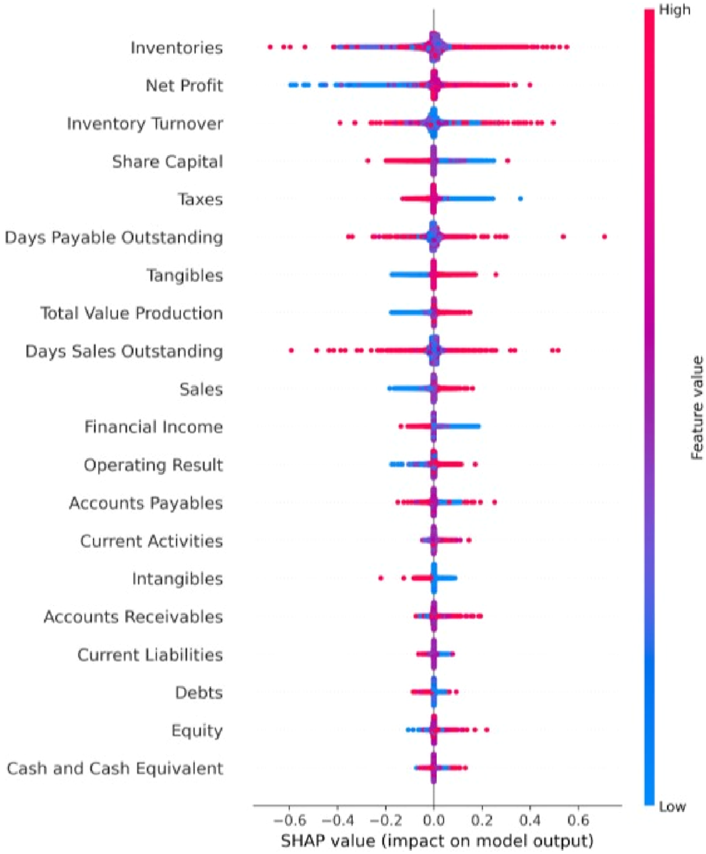

**Source(s):** Figure created by authors

**Figure 3.** ROC curve comparison over the VSL models (on the left), and confusion matrix of the best VSL model on the test set




**Source(s):** Figure created by authors

**Figure 4.** Global feature importance plot




**Source(s):** Figure created by authors

**Figure 5.** Global summary plot

to production costs are less likely to fail. Similarly, the higher the sales the lower the financial distress because firms with no difficulty selling products or services undoubtedly have a competitive advantage in the market. Additionally, the higher the days sales outstanding the higher the risk of bankruptcy because if the average number of days taken by a firm to collect payment from their customers after the completion of a sale is excessive the company might not have cash buffers both for current activities and new investments that are crucial to surviving. The lower the financial income the higher the financial distress, indicating that the revenue generated by the cash invested in financial investments could play an important role. This interesting finding suggests that non-operating activities also matter. The higher the operating result the lower the financial distress. Operating results are an essential metric for investors to understand how much money a company is potentially capable of generating from its core business; moreover, it shows the ability to generate profit from operating activities that can remunerate both debtholders and shareholders. The higher the accounts payables the higher the probability of default, if the amount of money that the company owes to suppliers is high, suppliers could be dissatisfied and might decide to interrupt the supply or not grant deferred payment when the firm needs it. We also observe that the higher the current assets the lower the financial distress because a firm that operates in the market using many resources could potentially have a competitive advantage. The lower the intangible assets the higher the financial distress. The intangibles allow growth opportunities in the market and increase corporate value. In the current context, patents, managerial skills and know-how are essential to survive. The higher the accounts receivables the lower the financial distress, meaning that the company that converts accounts receivables to cash faster can use such cash for growth purposes. The higher the current liabilities the higher the financial distress; we explain this result by the fact that if a firm needs to pay debts within the next 12 months it could need more money in the short run and if the cash is not available it could suffer from financial constraints. Moreover, as expected, the higher the debts the higher the financial distress, as the most indebted companies may have difficulty coping with their debts and subsequently go into crises. Finally, cash is negatively related to default, as firms with more liquidity have a greater possibility to make investments in order to grow and pay their debts of any nature, avoiding corporate crises.

## 5. Exploitability

In this section, SHAP results will be reported and interpreted. SHAP was used to interpret the output of the best model with a variable sequence length. Interpretation is very important in order to get practical implications from the research conducted. For each SHAP plot, in this section, we show the top 20 variables that most affected the model's prediction.

### *5.1 Global feature importance*

Figure 4 shows a waterfall plot of absolute mean SHAP values, reporting the average importance of each financial index in the model, and hence the contribution of each to the predictions, evaluated by using SHAP. Indexes are reported in order of importance. For example, the model was strongly influenced by “inventories” and “net profit”, moderately influenced by “tangibles” and poorly influenced by the others below.

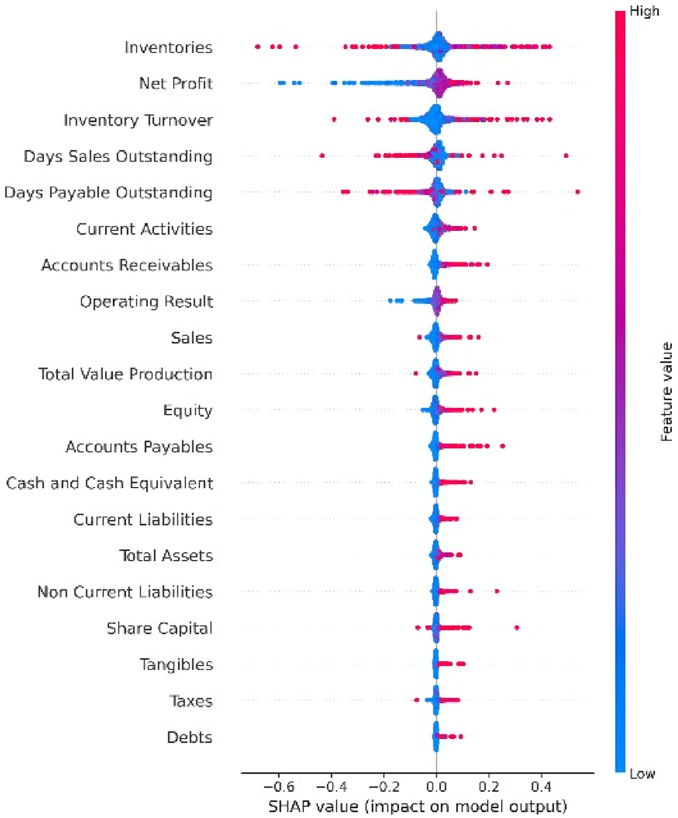
The feature importance plot is useful but contains no information beyond global importance. For a more informative plot, see the global summary plot reported in Figure 5.

Moreover, as shown in (right), higher values of profit/loss inventories are associated with positive SHAP values, meaning that they will increase the prediction towards 1 (healthy firms). Moreover, lower values of the variable are associated with negative SHAP values, meaning that they will decrease the prediction towards 0 (bankruptcy). Conversely, for the taxes lower values are associated with positive SHAP values, increasing the prediction toward 1. Higher values of the latter index, instead, are associated with negative SHAP values, meaning they will decrease the forecast towards 0, which means bankruptcy.

### *5.2 Summary plot for each time step*

We analysed the impact of variables at each different time step. As can be seen, each time step ranks features. In particular, it is interesting to notice the changing impact of some key variables over time. Inventories are the most impacting feature at a global level, and this is confirmed by data of time steps 2017–2018 (Figures 6 and 7), although a slight reduction in its relevance in 2019–2020.

As shown by time step 7 (Figure 8), the feature net profit is the most impacting one. This feature indicates the net profit of the company, and its contribution is directly related to the output of the model: it means that as the value of the feature increases, the firm is pushed towards a status of health. In other words, a company whose net profit assumes a high value tends to be in financial health and vice versa. Also, the relevance of net profit decreases in 2020. In time step 8 (Figure 9), the feature Taxes occupies the first position. As noted previously, the contribution of this item is inversely related to the value of the prediction: as the value of the feature increases, the output tends to be negative. In other words, a company with a lot of taxes to pay is more likely to fail. The feature sales shows a slight increase in importance from time steps 5 to 8, placing it among the top 5 variables during that period. Similar




**Source(s):** Figure created by authors

**Figure 6.** Global summary plot for time step 5 (2017)

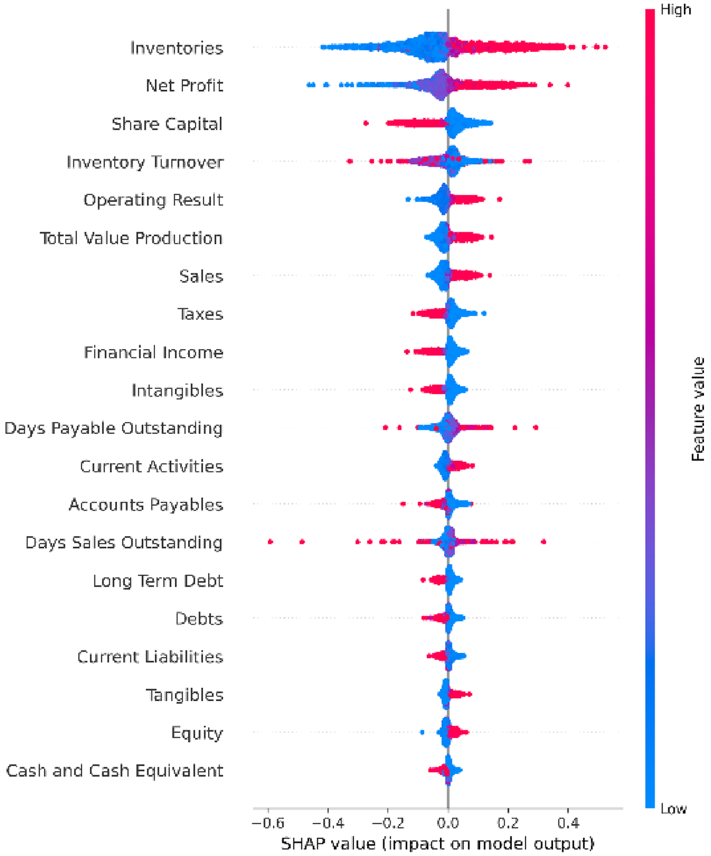
behaviour can be observed for the variable total value production, whose relevance increases over time. For both variables, higher values correspond to a status of health. Also, the feature cash and cash equivalent seems to be less important in step 8. On the contrary, the feature tangibles is located in the third-to-last position in the initial two steps instead moves to the third position in the two final steps.

These findings not only prove that SHAP is also useful at the local level to understand better what happens time step after time step but also shed the light on the potential impact of Covid-19 crisis that in 2020 affected companies. They thus provide useful insights for future research directions that investigate the role of the Covid-19 crisis years.

## 6. Discussion, managerial contribution and conclusions

This work presented a DL approach for bankruptcy prediction, utilising the RNN technique. Notably, our best model outperformed other architectures, and we explored fixed and variable sequence length models, ultimately selecting a variable sequence length model with an accuracy of 0.85 and an ROC-AUC score of 0.927 as the optimal predictor. Leveraging the SHAP method, we explained the impact of each feature on model predictions, enhancing the results' interpretability to obtain managerial implications.

Our findings demonstrate the viability of RNNs in bankruptcy prediction, offering a valuable tool for decision-making in financial contexts.

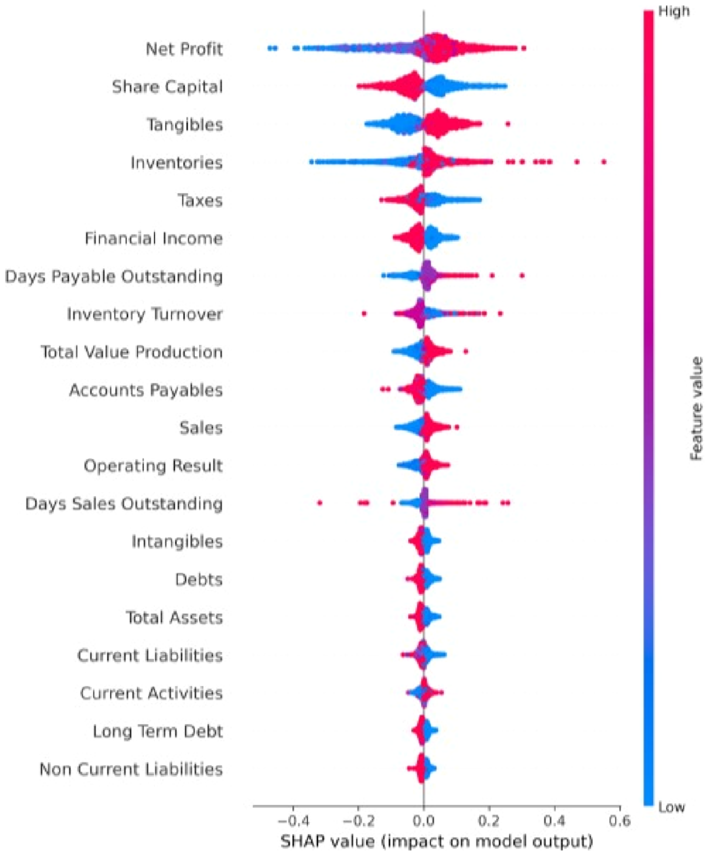



**Source(s):** Figure created by authors

**Figure 7.** Global summary plot for time step 6 (2018)

First of all, the use of a long time-series allows us to understand how many years before the crises there were signals of possible financial distress. Moreover, the changes from one year to the next can be useful for promptly dealing with them. It is important to know in large advance the probability of default of companies. It becomes a sort of alert that allows earlier changes or turnaround in strategies and business activities. In particular, turnaround strategies should focus on improving those critical areas where poor performance may lead to potential failure. Therefore, business activities can be intensified to mitigate the negative impact of specific factors that are at the core of bankruptcy. Taken in advance, these light changes can solve problems that, otherwise, could cause later distress and bankruptcy of difficult solutions.

Moreover, we have identified potential variables with a higher predictive power, to prevent corporate financial crises. The identification of the most relevant drivers of financial crisis is a second relevant output of the research. In particular, we observed that firms with higher inventories, net profit, sales, value of production and operating results have a lower probability of distress, and being successful in the market. Our findings interestingly highlight that having a lot of inventory left over can be a sign of good health. We also find that management of net working capital is also important, as having too many trade debts (or paying such debts with delay) could make suppliers dissatisfied and having too many receivables (or collecting such receivables with a delay) could bring cash difficulties. We also find that having reserves (and




**Source(s):** Figure created by authors

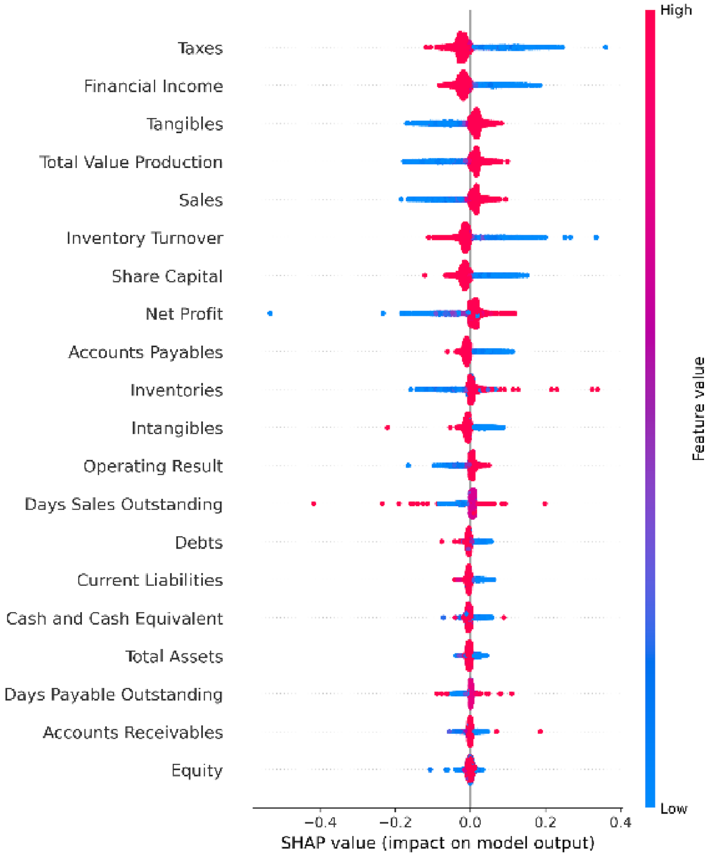
**Figure 8.** Global summary plot for time step 7 (2019)

so positive net profits throughout the years) is more important for survival than the amount of money provided by shareholders in terms of share capital. It indicates that leaving liquid resources within the company is crucial to increase the probability of survival and to enable the company to seize growth opportunities.

Concerning potential practical implications, the first important one is to provide a model/tool that assesses a possible business crisis in advance through a monitoring and alert system. In this way, it is possible to provide indications on the critical business areas and exploit an easy-to-use management support tool.

Another important application is for policymakers, who can use our research's output as a tool to combine with current credit-scoring systems and to assess the effectiveness of the new corporate crisis reforms that are upcoming in many European countries. This would favour public and private collaboration. An example of the practical application of our model involves understanding whether and to what extent the variables that generate a low credit score for a firm are related to a real risk of bankruptcy. In this way, firms that receive low scores will be able to implement specific strategies aimed at safeguarding their financial health, and in turn, improving their scores in the future.

In addition, it would support the current control system of the business crisis, reducing and making the assessments more efficient. For example, in Italy such a model would make it




**Source(s):** Figure created by authors

**Figure 9.** Global summary plot for time step 8 (2020)

possible to improve the "assisted settlement of the crisis", a system introduced in Italy through Legislative Decree 14/2019. More generally, the model can more effectively support the entire Italian control system, with regard to managers and corporate crisis organisation. Our model can also be used by Italian financial institutions to elaborate the existing Indices of Reliability for companies, going beyond the techniques currently employed.

A further advantage of the model is its greater simplicity in forecasting crises. With this model, it is possible to avoid/mitigate the negative consequences of socio-economic effects from business failure, such as less time spent by the courts on insolvency proceedings, lower unemployment, fewer social consequences for entrepreneurs whose project fails, fewer psycho-emotional reactions and personal traumas that often characterise "failed" entrepreneurs. Therefore, the potential practical/technological applications are considerable, and the tool can be available to companies in order to reduce corporate crises with important socio-economic benefits.

The results of our research can also be useful to banks, public entities and consulting firms that interact with companies and are interested in the evaluation of a firm's financial health and stability using tools provided by digital transformation (Wu *et al.*, 2023). Banks could, for example, benefit from using AI to assess the creditworthiness of their customers. Thanks to this, it will be possible to facilitate access to credit for high-quality businesses and discriminate against those of poor quality.

Another important application can be found in the educational setting. Our user-friendly tool can be used by educators at the university level or for advanced courses, allowing students to understand the mechanisms behind corporate crises and how to manage them long before they begin their professional careers.

To sum up, our results additionally provide implications with a strong impact on the scientific/technological community at the international level, as it represents the starting point of new challenges in technological innovation aimed at applying AI techniques to predictive models of business strategies, such as investments, financial decisions, marketing choices and so on. It is possible to start a new line of scientific and technological research that would lead to the use of AI in various areas of management, exploiting DL techniques for applications that guide the entrepreneur not only toward the correct quantitative choices but also provide support for strategic/qualitative decisions, with a consequent strong impact on business and economic growth. Combining the strengths of both approaches could lead to their joint use.

Future research prospects could involve the integration of governance, ESG and social media information into our RNN model which could provide real-time insights, overcoming the limitations of delayed financial reporting and improving predictive accuracy. It could thus be important to combine data from different sources and with different meanings. Utilising LSTM for processing unstructured text from governance indicators, ESG social media and news articles holds promise for capturing economic trends, thus enhancing the overall predictive capabilities of neural networks in identifying risky business situations and signalling potential financial distress. Indeed, ESG factors, social media and news are increasingly crucial for most companies, and their impact on bankruptcy prediction can be significant. Future developments in our research could integrate social intelligence with AI. Our model already demonstrates great accuracy, and we aim to further boost this accuracy by incorporating additional non-accounting data. However, these pieces of information often overlook managerial insight, which is crucial for a company's success. Therefore, future advancements in this research could include managerial perceptions and feelings, which, like social media data, can be systematised, analysed through our AI techniques and used to support bankruptcy prediction. Such advancements could help establish critical thresholds to better distinguish between healthy and unhealthy firms. Additionally, the research could be extended to provide industry- or firm-specific support by applying it to specific sectors, countries or groups of companies.

This research thus opens avenues for accurate and timely bankruptcy prediction methodologies, crucial in today's dynamic economic landscape. A research limitation consists of the fact that this paper is based only on accounting data and that for this reason, we suggest to use of other non-financial variables to further improve accuracy.

**Notes**

1. Failure, insolvency, default and bankruptcy are essentially the four terms used to characterise those unsuccessful businesses (Altman and Hotchkiss, 2011).

2. For example, the recent Italian reform of bankruptcy law by the Business Crisis and Insolvency Code (Legislative Decree no. 14–12 January 2019), effective 15 June 2022, corroborates the attention to this phenomenon. This reform is in line with EU Directive 2019/1023 on Preventive Restructuring Frameworks, on Discharge of Debt and Disqualifications, and on Measures to Increase the Efficiency of Procedures Concerning Restructuring, Insolvency and Discharge of Debt.

3. https://www.bvdinfo.com/en-gb/

4. https://single-market-economy.ec.europa.eu/smes/sme-definition_en

5. Before Altman, Beaver in 1966 was the first to investigate corporate bankruptcy using financial ratios to predict default (Beaver, 1966)

## References


Acebo, E., Miguel-Dávila, J.A. and Nieto, M. (2022), "Do financial constraints moderate the relationship between innovation subsidies and firms' R&D investment?", *European Journal of Innovation Management*, Vol. 25 No. 2, pp. 347-364, doi: 10.1108/EJIM-07-2020-0286.

Altman, E.I. (1968), "The prediction of corporate bankruptcy: a discriminant analysis", *The Journal of Finance*, Vol. 23 No. 1, p. 193, doi: 10.2307/2325319.

Altman, E.I. and Hotchkiss, E. (2011), "Corporate financial distress and bankruptcy: predict and avoid bankruptcy", *Analyze and Invest in Distressed Debt*, Vol. 289, doi: 10.1002/9781118267806.

Atiya, A.F. (2001), "Bankruptcy prediction for credit risk using neural networks: a survey and new results", *IEEE Transactions on Neural Networks*, Vol. 12 No. 4, pp. 929-935, doi: 10.1109/72.935101.

Barboza, F., Kimura, H. and Altman, E. (2017), "Machine learning models and bankruptcy prediction", *Expert Systems with Applications*, Vol. 83, pp. 405-417, doi: 10.1016/j.eswa.2017.04.006.

Beaver, W.H. (1966), "Financial ratios as predictors of failure", *Journal of Accounting Research*, Vol. 4 No. 1966, pp. 71-111, doi: 10.2307/2490171.

Begley, J., Ming, J. and Watts, S. (1996), "Bankruptcy classification errors in the 1980s: an empirical analysis of Altman's and Ohlson's models", *Review of Accounting Studies*, Vol. 1 No. 4, pp. 267-284, doi: 10.1007/BF00570833.

Bell, T.B. (1997), "Neural nets or the logit model? A comparison of each model's ability to predict commercial bank failures", *International Journal of Intelligent Systems in Accounting, Finance and Management*, Vol. 6 No. 3, pp. 249-264, doi: 10.1002/(sici)1099-1174(199709)6:3<249::aid-isaf125>3.0.co;2-h.

Bellovary, J., Giacomino, D. and Akers, M. (2007), "A review of bankruptcy prediction studies: 1930 to present", *Accounting Faculty Research*, Vol. 33, pp. 1-42.

Bower, J. and Gilson, S. (2003), "The social cost of fraud and bankruptcy", *Harvard Business Review*, Vol. 81 No. 12, p. 20.

Carruthers, B.G. (2015), "The history of bankruptcy: economic, social and cultural implications in early modern Europe", *The Journal of Economic History*, Vol. 75 No. 2, pp. 597-599, doi: 10.1017/s0022050715000819.

Charalambous, C., Martzoukos, S.H. and Taoushianis, Z. (2023), "A neuro-structural framework for bankruptcy prediction", *Quantitative Finance*, Vol. 23 No. 10, pp. 1445-1464, doi: 10.1080/14697688.2023.2230241.

Charitou, A., Neophytou, E. and Charalambous, C. (2004), "Predicting corporate failure: empirical evidence for the UK", *European Accounting Review*, Vol. 13 No. 3, pp. 465-497, doi: 10.1080/0963818042000216811.

Chen, T.K., Liao, H.H., Chen, G.D., Kang, W.H. and Lin, Y.C. (2023), "Bankruptcy prediction using machine learning models with the text-based communicative value of annual reports", *Expert Systems with Applications*, Vol. 233, 120714, doi: 10.1016/j.eswa.2023.120714.

Deakin, E.B. (1972), "A discriminant analysis of predictors of business failure", *Journal of Accounting Research*, Vol. 10 No. 1, p. 167, doi: 10.2307/2490225.

du Jardin, P. (2023), "Designing topological data to forecast bankruptcy using convolutional neural networks", *Annals of Operations Research*, Vol. 325 No. 2, pp. 1291-1332, doi: 10.1007/s10479-022-04780-7.

Dube, F., Nzimande, N. and Muzindutsi, P.F. (2023), "Application of artificial neural networks in predicting financial distress in the JSE financial services and manufacturing companies", *Journal of Sustainable Finance and Investment*, Vol. 13 No. 1, pp. 723-743, doi: 10.1080/20430795.2021.2017257.

Elhoseny, M., Metawa, N., Sztano, G. and El-Hasnony, I.M. (2022), "Deep learning-based model for financial distress prediction", *Annals of Operations Research*, Vol. 23, pp. 1-23, doi: 10.1007/s10479-022-04766-5.

Ellul, A. and Pagano, M. (2019), "Corporate leverage and employees' rights in bankruptcy", *Journal of Financial Economics*, Vol. 133 No. 3, pp. 685-707, doi: 10.1016/j.jfineco.2019.05.002.

Fasano, F. and Deloof, M. (2021), "Local financial development and cash holdings in Italian SMEs", *International Small Business Journal: Researching Entrepreneurship*, Vol. 39 No. 8, pp. 781-799, doi: 10.1177/02662426211011554.

Fasano, F. and La Rocca, T. (2023a), "Does the bank-firm human relationship still matter for SMEs? The game-changing role of digitalization", *Small Business Economics*, Vol. 62 No. 1, pp. 0123456789-123457178, doi: 10.1007/s11187-023-00758-2.

Fasano, F. and La Rocca, M. (2023b), "Local versus national banking development in Europe: who is the winner?", *Eurasian Business Review*, Vol. 14, pp. 1-30, doi: 10.1007/s40821-022-00233-0.

Fuertes-Callén, Y., Cuellar-Fernández, B. and Serrano-Cinca, C. (2022), "Predicting startup survival using first years financial statements", *Journal of Small Business Management*, Vol. 60 No. 6, pp. 1314-1350, doi: 10.1080/00472778.2020.1750302.

Graham, J.R., Kim, H., Li, S. and Qiu, J. (2023), "Employee costs of corporate bankruptcy", *The Journal of Finance*, Vol. 78 No. 4, pp. 2087-2137, doi: 10.1111/jofi.13251.

Heo, J. and Yang, J.Y. (2014), "Bankruptcy forecasting model using AdaBoost: a focus on construction companies", *Journal of Intelligence and Information Systems*, Vol. 4866 No. 1, pp. 35-48.

Hosaka, T. (2019), "Bankruptcy prediction using imaged financial ratios and convolutional neural networks", *Expert Systems with Applications*, Vol. 117, pp. 287-299, doi: 10.1016/j.eswa.2018.09.039.

Hu, H. and Sathye, M. (2015), "Predicting financial distress in the Hong Kong growth enterprises market from the perspective of financial sustainability", *Sustainability*, Vol. 7 No. 2, pp. 1186-1200, doi: 10.3390/su7021186.

Huang, Z., Chen, H., Hsu, C.J., Chen, W.H. and Wu, S. (2004), "Credit rating analysis with support vector machines and neural networks: a market comparative study", *Decision Support Systems*, Vol. 37 No. 4, pp. 543-558, doi: 10.1016/S0167-9236(03)00086-1.

Jabeur, S.B., Sadaaoui, A., Sghaier, A. and Aloui, R. (2020), "Machine learning models and cost-sensitive decision trees for bond rating prediction", *Journal of the Operational Research Society*, Vol. 71 No. 8, pp. 1161-1179, doi: 10.1080/01605682.2019.1581405.

Jackson, R.H.G. and Wood, A. (2013), "The performance of insolvency prediction and credit risk models in the UK: a comparative study", *The British Accounting Review*, Vol. 45 No. 3, pp. 183-202, doi: 10.1016/j.bar.2013.06.009.

Jang, Y., Jeong, I.-B., Cho, Y.K. and Ahn, Y. (2019), "Predicting business failure of construction contractors using long short-term memory recurrent neural network", *Journal of Construction Engineering and Management*, Vol. 145 No. 11, pp. 1-9, doi: 10.1061/(asce)co.1943-7862.0001709.

Kim, H., Cho, H. and Ryu, D. (2022), "Corporate bankruptcy prediction using machine learning methodologies with a focus on sequential data", *Computational Economics*, Vol. 59 No. 3, pp. 1231-1249, doi: 10.1007/s10614-021-10126-5.

Kliestik, T., Misankova, M., Valaskova, K. and Svabova, L. (2018), "Bankruptcy prevention: new effort to reflect on legal and social changes", *Science and Engineering Ethics*, Vol. 24 No. 2, pp. 791-803, doi: 10.1007/s11948-017-9912-4.

La Rocca, M., Fasano, F. and Sanchez-Vidal, J.F. (2022), "The role of government policies for Italian firms during the COVID-19 crises", *Finance Research Letters*, Vol. 50, doi: 10.1016/j.frl.2022.103273.

Levratto, N. (2013), "From failure to corporate bankruptcy: a review", *Journal of Innovation and Entrepreneurship*, Vol. 2 No. 1, p. 20, doi: 10.1186/2192-5372-2-20.

Liang, D., Lu, C.C., Tsai, C.F. and Shih, G.A. (2016), "Financial ratios and corporate governance indicators in bankruptcy prediction: a comprehensive study", *European Journal of Operational Research*, Vol. 252 No. 2, pp. 561-572, doi: 10.1016/j.ejor.2016.01.012.

Lin, W.Y., Hu, Y.H. and Tsai, C.F. (2012), "Machine learning in financial crises prediction: a survey", *IEEE Transactions on Systems, Man, and Cybernetics – Part C: Applications and Reviews*, Vol. 42 No. 4, pp. 421-436, doi: 10.1109/TSMCC.2011.2170420.

Lundberg, S. and Lee, S. (2017), "A unified approach to interpreting model predictions", *Advances in Neural Information Processing Systems*, Vol. 16 No. 3, pp. 426-430.

Mai, F., Tian, S., Lee, C. and Ma, L. (2019), "Deep learning models for bankruptcy prediction using textual disclosures", *European Journal of Operational Research*, Vol. 274 No. 2, pp. 743-758, doi: 10.1016/j.ejor.2018.10.024.

Nanni, L. and Lumini, A. (2009), "An experimental comparison of ensemble of classifiers for bankruptcy prediction and credit scoring", *Expert Systems with Applications*, Vol. 36 No. 2 PART 2, pp. 3028-3033, doi: 10.1016/j.eswa.2008.01.018.

Narvekar, A. and Guha, D. (2021), "Bankruptcy prediction using machine learning and an application to the case of the COVID-19 recession", *Data Science in Finance and Economics*, Vol. 1 No. 2, pp. 180-195, doi: 10.3934/dsfe.2021010.

Ohlson, J.A. (1980), "Financial ratios and the probabilistic prediction of bankruptcy", *Journal of Accounting Research*, Vol. 18 No. 1, p. 109, doi: 10.2307/2490395.

Ooghe, H. and De Sofie, P. (2008), "Failure processes and causes of company bankruptcy: a typology", *Management Decision*, Vol. 46 No. 2, pp. 223-242, doi: 10.1108/00251740810854131.

Perboli, G. and Arabnezhad, E. (2021), "A Machine Learning-based DSS for mid and long-term company crises prediction", *Expert Systems with Applications*, Vol. 174, 114758, doi: 10.1016/j.eswa.2021.114758.

Prusak, B., Morawska, S., Łukowski, M. and Banasik, P. (2022), "The impact of bankruptcy regimes on entrepreneurship and innovation: is there any relationship?", *The International Entrepreneurship and Management Journal*, Vol. 18 No. 1, pp. 473-498, doi: 10.1007/s11365-021-00773-3.

Shi, Y. and Li, X. (2019), "An overview of bankruptcy prediction models for corporate firms: a systematic literature review", *Intangible Capital*, Vol. 15 No. 2, pp. 114-127, doi: 10.3926/ic.1354.

Shin, K.S., Lee, T.S. and Kim, H.J. (2005), "An application of support vector machines in bankruptcy prediction model", *Expert Systems with Applications*, Vol. 28 No. 1, pp. 127-135, doi: 10.1016/j.eswa.2004.08.009.

Tam, K.Y. and Kiang, M.Y. (1992), "Managerial applications of neural networks: the case of bank failure predictions", *Management Science*, Vol. 38 No. 7, pp. 926-947, doi: 10.1287/mnsc.38.7.926.

Tsai, C.F. and Wu, J.W. (2008), "Using neural network ensembles for bankruptcy prediction and credit scoring", *Expert Systems with Applications*, Vol. 34 No. 4, pp. 2639-2649, doi: 10.1016/j.eswa.2007.05.019.

Tung, F. (2005), "Is international bankruptcy possible?", *SSRN Electronic Journal*. doi: 10.2139/ssrn.309779.

Veganzones, D. and Severin, E. (2021), "Corporate failure prediction models in the twenty-first century: a review", *European Business Review*, Vol. 33 No. 2, pp. 204-226, doi: 10.1108/EBR-12-2018-0209.

Wilson, R. and Sharda, R. (1994), "Bankruptcy prediction using neural networks", *Decision Support Systems*, Vol. 11 No. 5, pp. 545-557, doi: 10.1109/ICISC.2018.8399072.

Wu, Y., Li, H., Luo, R. and Yu, Y. (2023), "How digital transformation helps enterprises achieve high-quality development? Empirical evidence from Chinese listed companies", *European Journal of Innovation Management*, Vol. 27 No. 8, doi: 10.1108/EJIM-11-2022-0610.

Yang, S.A., Birge, J.R. and Parker, R.P. (2015), "The supply chain effects of bankruptcy", *Management Science*, Vol. 61 No. 10, pp. 2320-2338, doi: 10.1287/mnsc.2014.2079.

Yang, M., Lim, M.K., Qu, Y., Li, X. and Ni, D. (2023), "Deep neural networks with L1 and L2 regularization for high dimensional corporate credit risk prediction", *Expert Systems with Applications*, Vol. 213, 118873, doi: 10.1016/j.eswa.2022.118873.

Zhao, Z., Xu, S., Kang, B.H., Kabir, M.M.J., Liu, Y. and Wasinger, R. (2015), "Investigation and improvement of multi-layer perception neural networks for credit scoring", *Expert Systems with Applications*, Vol. 42 No. 7, pp. 3508-3516, doi: 10.1016/j.eswa.2014.12.006.

Zhou, B., Jin, J., Zhou, H., Zhou, X., Shi, L., Ma, J. and Zheng, Z. (2023), "Forecasting credit default risk with graph attention networks", *Electronic Commerce Research and Applications*, Vol. 62, 101332, doi: 10.1016/j.elerap.2023.101332.

Zmijweski, M.E. (1984), "Methodological issues related to the estimation of financial distress prediction models", *Journal of Accounting Research*, Vol. 22, pp. 59-82, doi: 10.2307/2490859.

**About the authors**

Francesco Fasano is an adjunct professor with a tenure track at the University of Calabria. At LUISS University, Rome, research fellow of the "Strategic Change" Research Center and adjunct professor for courses on "Advanced Corporate Finance", "Management of SMEs" and "Research Project Design". Research experiences abroad at the Universities of Cartagena (Spain), Antwerp (Belgium), Osnabrück (Germany) and Nottingham (UK). Lectured at the Manhattan Institute of Management in New York, earned the title "Doctor Europaeus" and received 3 best papers in conferences. Scientific research dealing with entrepreneurship and management presented at over 30 international or national conferences/seminars and published in leading journals. Francesco Fasano is the corresponding author and can be contacted at: francesco.fasano@unical.it

Carlo Adornetto is a PhD Student in Computer Science at the University of Calabria. His research is focused on machine learning and AI-based methodologies and applications. He is currently a visiting student at Massachusetts Institute of Technology – MIT Media Lab in the CityScience group, working on innovative methodologies for AI Agent-based simulations, focused on advancing our comprehension of human behaviour within urban environments. He served as the main lecturer and teaching assistant for several Deep Learning and Computer Science courses at the University of Calabria, and he has recently been awarded a special mention in the Italian "National Innovation Award".

Zahid Iliess is a PhD student in the second year of Business and Economics at the University of Calabria. He has two master's degrees: the first in Actuarial Sciences and Financial Markets, and the second in Finance and Insurance. He has a robust background in financial market insurance and data analysis and is also proficient in programming. He speaks multiple languages: French, English, Italian and Arabic. He is currently at the University of Western Ontario in Canada, conducting research with the Department of Statistics and Finance. He is interested in exploring the application of AI in business.

Maurizio La Rocca is a Full Professor in Management and Finance at the University of Calabria (Italy). He has been a Visiting Professor at the University of Cartagena, the University of Nanterre and the University of Antwerp. He was a PhD Visiting scholar at the University of Chicago (2002 and 2003), at the University of Temple (2003), and at the Master's in Economics and Finance (University of Napoli Federico II – winter 2002). He has many awards as Best Paper. He has more than 50 papers on International Journals such as: Entrepreneurship Theory and Practice, Global Strategic Journal, International Small Business Journal, Small Business Economics, Management Decision and many others.

Luigi Montaleone is a Research Assistant in Computer Science at the University of Calabria, specialising in Data Science and Artificial Intelligence. He holds a Master's degree in Artificial Intelligence and Data Science, and his research focuses on machine learning and AI-based methodologies and applications.

Gianluigi Greco is a Full Professor of Computer Science at the University of Calabria, where holds the position of Department Director of Mathematics and Computer Science. He is the President of the Italian Association for Artificial Intelligence. He is also a member of the Board of Directors of the Italian Society for the Ethics of Artificial Intelligence. With over 200 scientific publications in the field of AI, he has received numerous awards and recognitions, including the AAIA Fellowship, the EurAI Fellowship and the Kurt Gödel Fellowship Award. He is a member of the editorial boards of numerous computer science journals.

Alfio Cariola was a Full Professor of Business Economics and Management at the University of Calabria. Since 2018, he has been the Director of the Department of Business and Legal Sciences at Unical and a member of the Academic Senate. From 2013 to 2018, he served as a Member of the Board of Directors of Unical and previously held numerous other positions within the university's governance. He has numerous monographic contributions and international and national publications. He was a speaker at national and international conferences, a lecturer in University Masters and Advanced Training Courses, and a consultant.