Decision trees to identify companies' distress: the AI at work

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Abstract

Frame of the research: *The main subject of investigation is represented by the valuation of a company's distress, adopting decision trees, a well-established artificial intelligence methodology to automatically identify a combination of attributes to explain two target variables of interest, that is the zone of discrimination and cut off. The proposed methodology allows for the representation of decision processes according to paths on the tree's branches, or through a set of easily browsable if-then rules.*

Objectives: *The study aims to examine whether and how artificial intelligence (AI) may facilitate the joint comprehension of corporate distress and corporate legality. The main subjects of investigation are both represented by the valuation of the company's distress, as well as by the legality rating (LR), which is a measure of the company's degree of legality. The combination of a new set of variables, allows to understand - within a given range of accuracy - the company's financial health, and conversely, the company's distress, regardless of the Altman Z-score.*

Methodology*: The dataset is composed of companies in possession of legality ratings. Two experimental settings, which make use of decision trees, allow us in this study to automatically identify the unique combination of variables from the dataset that explains two target variables - 'zone of discrimination' and 'cut off' - from the standpoint of a unique perspective; one that is not considered by the Altman Z-score.*

Findings*: AI allows for the identification of a new 'basket' of variables, one different from those employed by the Altman Z–score. These variables may be used to determine a company's level of distress. The experiments test the 'ability' of the algorithm to identify a combination of variables to predict the target value. It is thereby possible to analyse in which way these variables operate alongside one another to produce with accuracy the correct identification of the target variable. In light of this scenario, the contribution of the study is the identification of two algorithms able to determine two settings of if-then rules that produce the same outcomes obtainable through the application of the Altman Z-score model, without directly using the model itself.*

Research limits: *The methodology described above was required to determine a plausible interval for the variables identified by the decision trees. The current development of the research, however, reveals that the methodology still needs to be adapted in order to determine the plausible intervals for the variables identified by the decision trees. In fact, the dimensionality of the dataset could benefit from resampling the variables for the proposed methodology, which suffers from certain degrees of skew.*

Practical implications: *The AI methodology can process large amounts of records within a given dataset, thereby allowing for the testing of the effectiveness of LR in the assessment of creditworthiness.*

Originality of the study: *The recognition and composition of the new variables can be interpreted as a tool to strengthen the comprehension of the company's distress.*

Key words: company's distress; legality rating; artificial intelligence; decision tree; Z-score

1. Introduction

The study aims to examine whether and how *artificial intelligence* (AI) may suggest and facilitate a different joint comprehension of *distress* (Vulpiani, 2014) and *legality* within the business context.

The *legality rating* (LR) system is employed to measure the company's *degree of legality*. It was introduced by the Italian legal system through the Legislative Decree n.1/2012, and it measures a company's compliance along a scale of values - from '*' to '***' (see Section 2)- in relation to the different levels of achieved legality. The current Italian regulatory framework suggests that companies, in possession of a LR, can benefit from certain advantages when accessing credit both from public administrations and banks.

This study evaluates the financial performance of the Italian companies in possession of a LR, by examining their *distress*, using as a benchmark the *Altman Z-score*, which is a *bankruptcy prediction model*.

The novelty of the paper is represented by the employment of *decision trees* (*DTs*), a well-established artificial intelligence methodology (Quinlan, 1993; Mitchell, 1997; Witten, 2011; Barile *et al.*, 2019; D'Avanzo *et al.*, 2018), to automatically identify a combination of *attributes* (from 2 to 7, out of 101 variables) to explain two target variables of interest; that is, the *zone of discrimination* and *cut off*. The proposed method uses a new 'basket of variables', different from those employed by the *Altman Z-score*, in order to identify a company's *distress zone*s'. The proposed methodology allows for the representation of decision processes according to *paths* on the *tree's* branches, or through a set of easily browsable *if-then* rules (Anderson *et al.*, 2015; Masías *et al.*, 2015).

The recognition and composition of these new variables, which were previously not considered by Altman's formulation, can be interpreted as a tool to reinforce understanding of a company's *distress*. In fact, the new variables and attributes consider other aspects of the company's financial profile, which collectively can be translated into a model for understanding said company's financial health.

The paper is organised as in the follows. Section 2 reports on the *LR, companies' distress*, and *Altman's Z-score*; these factors represent the benchmark for the subsequent analysis. Section 3 contains a description of the artificial intelligence methodology employed. Section 4 reports on the experimental settings - describing, respectively, how DTs identify *zones of discrimination* and *cut off* targets. The final section discusses the results and depicts the conclusion.

2. Background

Company's distress and its evaluation

Analysts usually differentiate between *financial* and *operational distress* (Vulpiani, 2014). The former occurs when the values of *equity* and *debt* show probabilities of default. The latter is related to sporadic events or factors, such as economic downturns, employee turnover, and so on.

Bankruptcy is recognized as the last *threshold of distress* (Pratt, 2010; Damodaran, 2002), whereas *financial distress* is usually considered the last step before bankruptcy, as it is present when it is impossible to generate revenues or incomes to meet or to pay financial obligations.

To assess the severity of business *distress*, most of the time one employs bankruptcy prediction models, which, usually, are divided into 'accounting-ratio-based', 'market-based', and 'hybrid-based'.

Altman's Z-score, and its subsequent variants, belong to the category of an accounting-ratio-based model, which works with information and data collected from the financial statements[1].

According to Altman's formulation, the 'zone of discrimination' allows for the classification of the companies into three zones: *safe zone, grey zone*, and *distress zone*, whereas the 'cut off' divides the companies according to the zone of *possible distress* and the zone of *potential solvency*. In other words, a zone of discrimination identifies companies with a well-defined financial profile (namely, s*olvent, insolvent,* and *to be determined*), while a cut off deals with uncertainty, since it allows for a better understanding of the conduct of companies falling into the *grey zone*, defined by the zone of discrimination. In other words, the cut off establishes a demarcation line of the financial behaviour, suggesting when the zone of discrimination is grey.

Legality rating: general features

The LR is a measure of the *degree of legality*, valid only within the Italian legal system. It is a voluntary rating, granted by the Italian Competition Authority (AGCM) at the request of the interested party.

To obtain a LR, companies must comply with the following requirements:
- operational headquarters in Italy;
- a minimum turnover of two million euros in the last financial year closed by the time of the request for the rating - this stands for a single company or group which has requested the rating, and evidence provided must come from a financial statement approved and published under the law;
- at the date of the LR request, the business must have been registered for at least two years;
- compliance with the other substantive requirements of the AGCM.

The base score of LR is '*', one star, granted to companies that comply with all the substantive legislative requirements. In fact, these basic

1 See 'Supplementary materials' published online on www.sijm.it' for a detailed explanation about the three models.

requirements refer both to the legal persons requesting the rating, and and to the individuals they represent.

This type of requirements include, for instance, the absence of precautionary measures or penal sentences for convictions related to crimes against national and European Institutions, social security, as well as a history of compliance with law provisions.

The base score may be increased by a '+' for each additional requirement which the company meets. For instance, one additional requirement[2] is the adoption of protocols or legal agreements aimed at preventing and counteracting the infiltration of organised crime into the legal economy. Another requirement is represented by the use of payment tracking systems which include the tracking of payments of sums of amounts lower than those required to be tracked by law, or another involves the adoption of organisational models for the prevention of and defence against corruption.

The achievement of three '+' rewards the attribution of an additional '*', up to a maximum score of '***' (i.e. three stars).

Tab. 1: Legality rating - Requirements

Purpose	Requirements
Request of LR	Cumulatively: • operational headquarters in Italy • turnover ≥ € 2 million • registered in the business register for at least two years
'*' Achievement	Compliance with the other substantive requirements
'+' increase	Compliance with an additional requirement
'*' increase	Compliance with three additional requirements

Source: authors' elaboration on LR requirements, AGCM.

The possible combinations of LR in relation to their requirements are summarised in the following table.

Tab. 2: Legality rating scores

Rating	Requirements
*	Basic requirements
*+	Basic requirements and 1 additional requirement
*++	Basic requirements and 2 additional requirements
**	Basic requirements and 3 additional requirements
**+	Basic requirements and 4 additional requirements
**++	Basic requirements and 5 additional requirements
***	Basic requirements and 6 additional requirements

Source: authors' elaboration on LR requirements, AGCM.

A LR lasts two years from the date of issuance, is renewable on request, and is free of charge.

2 See 'Supplementary materials' for the full list of the additional requirements.

Company's distress and legality rating

As mentioned above, the adoption of a LR allows firms to benefit from certain advantages when accessing credit. For instance, both public administrations and banks, when granting loans, consider the company's LR. Companies, when seeking loans from public administrators, enjoy at least one of the following rewards if they have a respectable LR:

- preference in ranking;
- attribution of a higher credit rating;
- share reserve of the financial resources allocated.

Regarding access to bank credit, the potential benefits of LR while dealing with banks should include the reduction of the investigation time, better economic conditions when requesting or renegotiating the loan, and the reduction of investigation costs.

In relation to the access to bank credit, the Italian legal system actively encourages Italian financial institutions to consider LR among the parameters in assessing a company's creditworthiness.

In fact, Italian banks are encouraged to define and formalise internal procedures to regulate the use of LR. Financial institutions take LR into account to determine loans' conditions of disbursement whenever relevant.

In light of these considerations, LR is related to the company's creditworthiness, and by consequence, to the company's distress. In fact, the higher the creditworthiness, the lower the likelihood of bankruptcy.

3. Methodology and data

Since LR is a measure of the degree of legality, valid only within the Italian legal system, the dataset employed in the following experiments is exclusively composed of Italian companies. In particular, it involves qualitative and quantitative information of 6,005 Italian companies, extracted from the Bureau van Dijk database, AIDA. All of the companies under investigation have their own LR.

The sample includes companies whose LR was conferred for the first time, or renewed by the Italian Competition Authority (AGCM) and updated on 12/10/2018. The list of companies is publicly available on the AGCM website. Companies have been classified into four geographical areas (*North East, North West, Centre, South, and Insular*) according to the NUTS 1 (Nomenclature of Territorial Units for Statistics at the first level - subdivision for Groups of Regions), based on the region of the operational headquarters. In cases lacking this information, the companies were classified based on the legal headquarters with which they had registered.

The size-class of a company considers three parameters, and defines four categories of companies: *micro, small, medium,* and *big*[3].

[3] This classification is borrowed from the Italian Legislative Decree n. 139/2015, which distinguishes the limited companies (società di capitali) based on quantitative parameters

Tab. 3: Size-classes

Size-class	Parameters (at least two out of three)		
	Total Assets	Sales Revenues	Employees
Micro	≤ € 175,000	≤ € 350,000	≤ 5
Small	≤ € 4,400,000	≤ € 8,800,000	≤ 50
Medium	≤ € 20,000,000	≤ € 40,000,000	≤ 250
Large	> € 20,000,000	> € 40,000,000	> 250

Source: Legislative Decree n. 139/2015

As said above, in order to better grasp the peculiarities of the Italian business context, this research uses Altman's Z-Score as a corporate bankruptcy prediction model[4]. This choice originates from the main intrinsic features of the Z-score, which are suitable for non-listed companies. This characteristic allows the Z-score to fit with the companies within our sample. The data used to calculate the Z-score refers back to the 2016 financial year.

The *cut off* corresponds to a Z-score equal to 2.675 (Altman, 2013). Compared to this value, companies with a higher Z-score fall into the *potential solvency* category, while companies with a lower Z-score fall into the *possible distress* category. However, it is undisputed that when Z-score is lower than 1.23, companies are surely in the *distress zone*, and when Z-score is higher than 2.90 companies are surely in the *safe zone*. Consequently, the *cut-off* analysis allows us to better understand the performance of companies with a Z-score from 1.23 to 2.90, which fall into the *grey zone*. In other words, the *cut-off* could be interpreted as a measure of uncertainty.

After having illustrated the main features of the sample, and the criteria referring to the profiling of the *zone of discrimination* and the *cut-off,* it would be suitable to highlight the key concepts related to the AI methodology used in the research.

Decision trees are a classification scheme, widely employed both to represent and to run decision processes (Anderson *et al.*, 2015), which themselves generate a *tree* and a set of rules from a given dataset (Witten and Frank, 2011). They represent a useful graphical tool, as they allow for an intuitive understanding of a problem, and can aid decision-making, since they are interpretable through *if-then* rules by any professional - including trainees, even if he or she is not trained in computer applications. Users can refer to rules generated by the DT in order to make decisions, since such rules are based on a short-ordered list of features (also referred to as attributes).

Experiments introduced below employ an implementation of the *C4.5 DT algorithm*, developed by Quinlan (1993). The C4.5 DT algorithm classifies instances (i.e. companies' records) by sorting them down from the *root* to some *leaf nodes*. It provides the classification of the *instances* according to the values of a given *target attribute* (e.g. a *cut-off* that can assume two values: *possible distress* and *potential solvency*). Nodes of the DT specify a testing of some features describing the instances, such as

[4] See 'Supplementary materials' for a more complete discussion.

Return on Assets (*ROA*) at the root node of the DT, shown in Figure 5. Branches descending from nodes correspond to one of the possible values the *attribute* may assume; for instance, in the case of the tree depicted in Figure 6, the *root* attribute may assume two sets of possible values: 21.54%, and > 21.54%. The same process is repeated for the sub-tree rooted at the new node. Looking at Figures 5 and 6, after testing *ROA* at the root node, the C4.5 DT algorithm jumps on the right and left branches, based on the two sets of value the root feature may assume, and, if this is the case, then the algorithm tests other variables (e.g., *Total Debt%* on the left branch); otherwise, it stops. The process is repeated until a *leaf node* is reached, where the class label is present, such as in the tree represented in Figure 6, where it corresponds to *possible distress* and *potential solvency*.

As a feature selection methodology - i.e. which feature/attribute is to be tested at each node of the tree - used in the experiments introduced below, *Information Gain* has been employed (Mitchell, 1997). Information Gain is strictly related to *Entropy* (Mitchell, 1997), or an index of the purity of a dataset, since it only represents the expected reduction in entropy that results from the partition of the examples according to this attribute.

Experiments performed have been tested using different evaluation metrics (Fawcett, 2006). As a first evaluation metric, *accuracy* has been employed. This measures how often the DT makes the correct prediction by calculating the ratio between the number of correct predictions and the total number of predictions. *Accuracy*, however, does not distinguish between false-positives and false-negatives. For such a kind of evaluation, the *confusion matrix* was employed, showing a detailed breakdown of correct and incorrect classifications for each class; such sorts of information would otherwise be lost just looking at the overall accuracy.

A *precision* score estimates how many cases are needed so that the DT assigns an extraction target, while *recall* allows for the determining of how many cases are found to be true by the DT, out of all the true cases.

4. AI at work

Preliminary considerations on the sample

This section reports on some preliminary considerations on the features of the sample dataset employed.

An analysis from descriptive statistics has allowed for the exploring of certain macro aspects, such as *legality rating*, *zone of discrimination,* and *cut-off*, concerning four geographic areas.

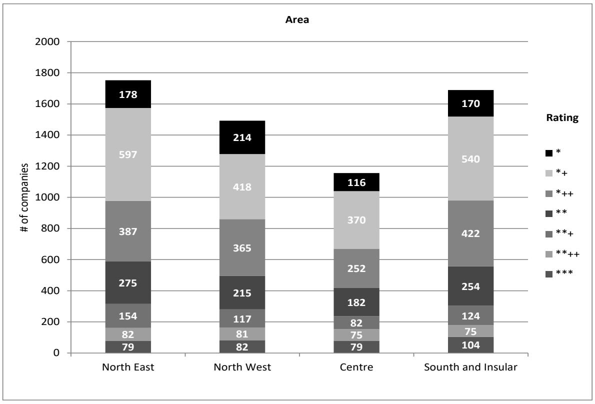
Companies are classified by their geographic areas, and in comparison to this variable, other variables are assessed. First and foremost, the sample's geography shows an uneven composition: the number of firms belonging to the Centre and the North East regions are, respectively, 24% lower than the average, and 16% higher than the average.

Concerning the LR, cross-region trends arise: the most recurring LR is '*+', present in almost one-third of the sample. The higher the LR ('**++' or '***'), the lower the diffusion within the sample (about 5%).

Moreover, in all geographic areas, the LR featured by '*' (and its variants - '*+' and '*++') amounts to two-thirds of the whole sample.

The relative frequency of each LR-class, assessed by geographic area, does not differ significantly from the average value. It can be therefore derived that the four geographic areas show the same average LR regardless of distribution.

Fig. 1: Legality rating vs. geographic area



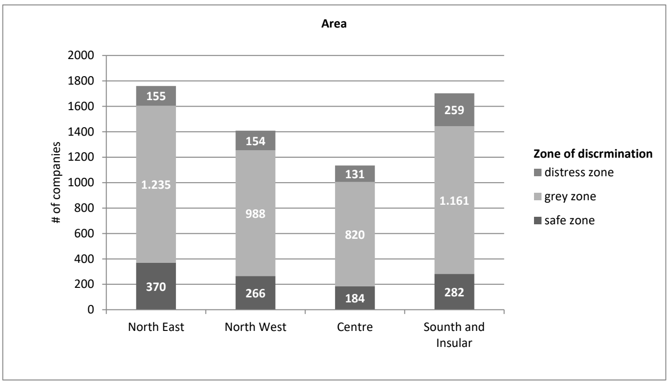
Source: authors' elaboration

Secondly, a common cross-geographical trend emerges also around the *zones of discrimination* (as derived from Z-score). This means that in all four areas, roughly the same percentages for each zone of discrimination applied: *safe zone* - around 20%; *grey zone* - around 70%; and *distress zone* - around 10%. It is relevant to note that a consistent portion of the sample is composed of companies featuring an uncertain financial profile.

Moreover, companies in the *distress zone* were situated mainly in the South (37%), whereas those marked as within the *safe zone* were significantly present in the North East.

In the following chart, these considerations are expressed in relation to absolute frequencies.

Fig. 2: Zone of discrimination vs. geographic area



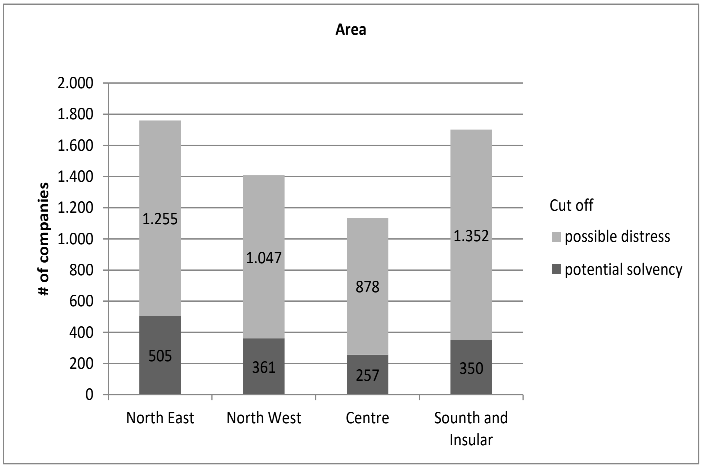
Source: authors' elaboration

An additional analysis leads to the comparison between *cut-off* and geographic area.

It is useful to state a brief reminder that the *cut-off* point (Z-score equal to 2.675) allows for the distinguishing of companies marked as within *possible distress*, from those companies marked by *potential solvency*. Regional differences then emerge: in the North east, *possible distress* is three times as common as *potential solvency*; in the South, the *possible distress* is four times as frequent as *potential solvency*.

Furthermore, an overall analysis of the sample shows that the *possible distress* is prevalent in the South (about 30%), whereas the *potential solvency* is mainly depicted in the North East (34%).

Fig. 3: Cut off vs. geographic area



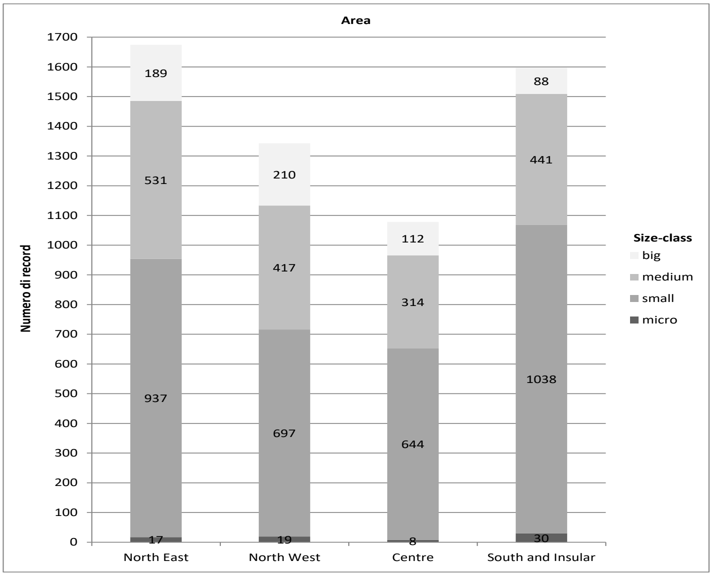
Source: authors' elaboration

Lastly, the assessment of companies' size-classes shows the clear predominance of small companies, as such typology includes approximately two-thirds of the sample. Moreover, small and medium firms together compose about 90% of the sample.

Size classes are distributed in the same order across geographic areas; namely small, followed by medium, then large, and lastly micro. Despite maintaining the same order, however, the geographical areas show different concentrations of companies' in relation to their size-classes: large companies are gathered in the North West (16% of the regional total); medium companies are gathered in the North East (32% of the regional total); and small and micro companies are gathered in the South (respectively, 65% and 2% of the regional total).

The same territorial differences are also maintained, as evidenced in the analysis of the deviations from the average values for each size class. Comparing against the total number of large companies, the North West and South regions register respectively +5% and -5% more or less than the average for this size-class. Similarly, against the total number of medium companies, North East and South show respectively +2% and -2% more or less than the average of the size-class. Conversely, regarding the total of small companies, the North West and South regions mark respectively -6% and +7% more or less than the average for this size-class. Lastly, against the total number of micro-companies, the Centre and South regions display divergent dynamics (respectively -1% and +1% more or less than the average of this size class).

Fig. 4: Size-class vs. geographic area



Source: authors' elaboration

The inquiry is composed of two experiments aimed at analysing two different target variables; respectively, the zone of discrimination (experiment 1) and cut off (experiment 2).

In this section, we illustrate the experimental setting, the *if-then* rules, the metrics, and the DTs of each experiment.

The rules shown in both the experiments are those generated in the training phase, and, therefore, each of the counts refer to this step. It may be appropriate to generate everything in the test phase, so as to align with the measurement metrics.

Experiment 1: DT to identify 'zone of discrimination' target

The first experiment assesses the 'zone of discrimination' as the target variable - the values of which, in relation to the Z-score, can be: *safe zone*, *grey zone*, and *distress zone*.

The goal of the experiment is to test the ability of the algorithm to identify a combination of variables, used then to predict the target without considering the pre-written variables of 'cut off' and 'Z-score' in the dataset.

The experimental setting for the first experiment is described in the following table.

Tab. 4: Experimental setting (experiment 1)

Number of initial records	6,005
Number of records after the elimination of 'N/A' values	5,726
Target variable	Zone of discrimination
Values of the target variable	DISTRESS ZONE GREY ZONE SAFE ZONE
Features of the experimental setting	The variables 'cut off' and 'Z-score' are eliminated in order to test the ability of the algorithm to identify a combination of variables to predict the target.
Data partition for training and testing	Training set: 4,580 Test set: 1,146 Total: 5,726
Feature selection method	Gain ratio
Pruning method	Minimal Description Length

Source: authors' elaboration

This experiment identifies eight *if-then* rules (R1 - R8), and consequently, the best practices that generate the respective DT. Before illustrating each rule and its outcome, in the following table an explanation of the financial meaning of the variables involved in the first experiment is provided.

Tab. 5: Financial meaning of the rules (experiment 1)

Variable	Financial meaning
Total Debt%	Total debt/Total liabilities and equity
ROA	ROA (Return on Assets)
EBIT	EBIT (Earnings Before Interest and Taxes)
Non-current assets %	Non-current assets/Total Assets
Sales	Sales

Source: authors' elaboration

R1 is made up of two variables; Total Debt% and ROA. The outcome of the first rule is the prediction of the *safe zone*.

R2 is made up of four variables that predict the distress zone. The variables are EBIT, Non-current assets %, Total Debt%, and ROA.

R3 predicts the *safe zone* thanks to five variables: Total Assets, ROA, EBIT, Non-current assets %, Total Debt%, and ROA.

Five variables Sales, Total Assets, ROA, EBIT, Non-current assets %, Total Debt%, and ROA are featured in R4, which predicts the *distress zone*.

R5 has six variables - Sales, Total Assets, ROA, EBIT, Non-current assets %, Total Debt%, and ROA - that predict the *grey zone*.

R6 comprises of four variables, ROA, EBIT, Non-current assets %, and Total Debt%, and predicts the *safe zone*.

R7 has three variables, namely Non-current assets %, Total Debt%, and ROA, that predict the *distress zone*.

Lastly, R8 is made up of one variable, ROA, which predicts the *safe zone*.

In order to better explain the results expressed above, a brief summary of the *if-then* rules, their outcomes, the record count, and the number of correct cases is presented in the following table.

Tab. 6: If-then rules (experiment 1)

	if-then rules (best practices)	Outcome	Record count	Number of correct cases
R1	IF Total Debt% ≤ 18.204271574863533 AND ROA ≤ 22.86	Safe zone	112	95
R2	IF EBIT ≤ -374.7615 AND Non-current Assets% ≤ 76.30784360563888 AND Total Debt% > 18.204271574863533 AND ROA ≤ 22.86	Distress zone	106	71
R3	IF Total Assets ≤ 1138.336 AND ROA ≤ 15.934999999999999 AND EBIT > -374.7615 AND Non-current Assets% ≤ 76.30784360563888 AND Total Debt% > 18.204271574863533 AND ROA ≤ 22.86	Safe zone	101	65
R4	IF Sales ≤ 1633.301 AND Total Assets > 1138.336 AND ROA ≤ 15.934999999999999 AND EBIT > -374.7615 AND Non-current Assets% ≤ 76.30784360563888 AND Total Debt% > 18.204271574863533 AND ROA≤ 22.86	Distress zone	101	55
R5	IF Sales > 1633.301 AND Total Assets > 1138.336 AND ROA ≤ 15.934999999999999 AND EBIT > -374.7615 AND Non-current Assets% ≤ 76.30784360563888 AND Total Debt% > 18.204271574863533 AND ROA ≤ 22.86	GREY ZONE	3,731	2,997
R6	IF ROA > 15.934999999999999 AND EBIT > -374.7615 AND Non-current Assets% ≤ 76.30784360563888 AND Total Debt% > 18.204271574863533 AND ROA ≤ 22.86	Safe zone	202	139
R7	IF Non-current Assets% > 76.30784360563888 AND Total Debt% > 18.204271574863533 AND ROA ≤ 22.86	Distress zone	109	82
R8	IF ROA > 22.86 AND TRUE	Safe zone	118	113
Total			4,580	3,617

Source: authors' elaboration

In order to give a complete illustration of the first experiment, its metrics are outlined in two tables.

Tab. 7: Metrics - Part 1 (experiment 1)

Zone of discrimination	GREY ZONE	Safe zone	Distress zone
GREY ZONE	736	35	33
Safe zone	115	95	1
Distress zone	85	2	44

Source: authors' elaboration

Tab. 8: Metrics - Part 2 (experiment 1)

Correct classified	875
Wrong classified	271
Accuracy	76,353%
Error	23,65%
Cohen's Kappa	0,406

Source: authors' elaboration

The decision tree corresponding to this experimental setting can be viewed in the supplementary material file.

Experiment 2

The second experiment assesses the cut off as the target variable - the value of which, in relation to Z-score, can be: *potential solvency*, or *possible distress*.

The goal of the experiment is to test the ability of the algorithm to identify a combination of variables, later used to predict the target without considering the pre-determined variables of 'zone of discrimination' and 'Z-score' in the dataset.

The experimental setting for the second experiment is described in the following table.

Tab. 9: Experimental setting (experiment 2)

Number of initial records	6,005
Number of records after the elimination of 'N/A' values	5,726
Target variable	Cut off
Values of the target variable	Potential solvency Possible distress
Features of the experimental setting	The variables 'Z score' and 'Zone of discrimination' are eliminated in order to test the ability of the algorithm to identify a combination of variables to predict the target.
Data partition for training and testing	Training set: 4,580 Test set: 1,146 Total: 5,726
Feature selection method	Gain ratio
Pruning method	Minimal Description Length

Source: authors' elaboration

This experiment identifies nine *if-then* rules (R1 - R9), and consequently the *best practices*, which generate a respective DT.

An explanation of the financial meanings of the variables involved in the second experiment is presented in the following table. In relation to the use of the symbol "" in the name of the variable, the same considerations of the previous experiment are applied.

Tab. 10: Financial meaning of the rules (experiment 1)

Variable	Financial meaning
Total Debt%	Total Debt % (Total Debt/Total liabilities and equity)
ROA	ROA (Return on Assets)
Total Assets	Total Assets
Long-term Debts	Total debt due beyond the financial year
Labour cost%	Labour cost/Sales

Source: authors' elaboration

R1 is made up of two variables; Total Debt% and ROA. The outcome of the first rule is the prediction of the *potential solvency*.

R2 has three variables, namely Total Assets, ROA, Total Debt%, and predicts the *potential solvency*.

R3 predicts the *potential solvency* thanks to three variables: Total Debt%, Total Assets, ROA.

Five variables are featured in R4: Long-term Debts, Labor cost%, ROA, Total Debt%, and Total Assets. The outcome of the fourth rule is the prediction of the *potential solvency*.

R5 has five variables that predict the *possible distress*. The variables involved are: Long-term Debts, Labor cost%, ROA, Total Debt%, and Total Assets.

R6 predicts the *possible distress*. In order to produce this outcome, four variables are involved: Labor cost%, ROA, Total Debt%, Total Assets.

R7 comprised of three variables: ROA, Total Debt%, and Total Assets. The outcome is the prediction of the *potential solvency*.

R8 has two variables, ROA and Total Debt%, that predict the *potential solvency*.

Lastly, R9 is defined by one variable, ROA, which predicts the *potential solvency*.

In the following table, in relation to the second experiment, a brief summary of the *if-then* rules, their outcomes, their record count, and their number of correct cases, is presented.

Tab. 11: If-then rules (experiment 2)

	if-then rules (best practices)	Outcome	Record count	Number of correct cases
R1	IF Total Debt% ≤ 18.196832168335906 AND ROA ≤ 21.54	Potential solvency	125	116
R2	IF Total Assets ≤ 1241.238 AND ROA ≤ 16.055 AND Total Debt% > 18.196832168335906 AND ROA ≤ 21.54	Potential solvency	149	99
R3	IF Total Debt% ≤ 25.066864783615408 AND Total Assets > 1241.238 AND ROA ≤ 16.055 AND Total Debt% > 18.196832168335906 AND ROA ≤ 21.54	Potential solvency	101	63
R4	IF Long-term Debts ≤ 318.2925 AND Labor cost% ≤ 4.276964813170087 AND ROA ≤ 13.614999999999998 AND Total Debt% > 25.066864783615408 AND Total Assets > 1241.238 AND ROA ≤ 16.055 AND Total Debt% > 18.196832168335906 AND ROA ≤ 21.54	Potential solvency	137	79
R5	IF Long-term Debts > 318.2925 AND Labor cost% ≤ 4.276964813170087 AND ROA ≤ 13.614999999999998 AND Total Debt% > 25.066864783615408 AND Total Assets > 1241.238 AND ROA ≤ 16.055 AND Total Debt% > 18.196832168335906 AND ROA ≤ 21.54	Possible distress	157	119
R6	IF Labor cost% > 4.276964813170087 AND ROA ≤ 13.614999999999998 AND Total Debt% > 25.066864783615408 AND Total Assets > 1241.238 AND ROA ≤ 16.055 AND Total Debt% > 18.196832168335906 AND ROA ≤ 21.54	Possible distress	3,497	3,085
R7	IF ROA > 13.614999999999998 AND Total Debt% > 25.066864783615408 AND Total Assets > 1241.238 AND ROA ≤ 16.055 AND Total Debt% > 18.196832168335906 AND ROA ≤ 21.54	Potential solvency	112	66
R8	IF ROA> 16.055 AND Total Debt% > 18.196832168335906 AND ROA ≤ 21.54	Potential solvency	177	134
R9	IF ROA > 21.54	Potential solvency	125	120
Total			4,580	3,881

Source: authors' elaboration

In order to give a complete illustration of the first experiment, its metrics are outlined in two tables.

Tab. 12: Metrics - Part 1 (experiment 2)

Cut off	Possible distress	Potential solvency
Possible distress	807	57
Potential solvency	113	169

Source: authors' elaboration

Tab. 13: Metrics - Part 2 (experiment 2)

Correctly classified	976
Wrongly classified	170
Accuracy	85.166%
Error	14.83%
Cohen's Kappa	0.572

Source: authors' elaboration

The decision tree corresponding to this experimental setting can be viewed in the supplementary material file.

5. Conclusion

The experiments performed show reveal an algorithm capable of identifying a combination of variables used later to predict the target, without considering the two variables of, respectively 'cut off' and 'Z-score' (experiment 1), and 'zones of discrimination' and 'Z-score' (experiment 2), in the dataset.

Two different settings of *if-then* rules are featured in the experiments: the first identifies eight rules able to predict the values of the 'zones of discrimination', while the second determines nine rules, the outcomes of which are related to the values of the cut off.

Despite the unique targets typical of each experiment, and the different combinations of variables involved, the key role of the variable ROA - that is, *Return on Assets* - emerges in both cases. In fact, in both experiments, ROA is at the root node of the decision tree.

It should be noted that ROA corresponds with the variable X3 ((EBIT)/ Total Assets) of the Altman Z-score, connected to which is the highest weighting coefficient within the linear combination. This means that both the AI algorithms and the Altman Z-score model confer a pivotal role towards the same variable.

ROA (or EBIT/ Total Assets) represents a profitability ratio that suggests how a company can conduct business activity, regardless of the form of financing. In other words, this ratio depicts the ability of a company to create value through internal assets: the higher the ROA, the greater the ability to enhance the resources. It can be derived that ROA gives stakeholders an idea of management's efficiency at using assets to generate earnings.

Both experiments share the use of one other variable - which, unlike the previous one, is not mentioned in the Altman Z-score model. This variable is Total Debt%, which is equal to total debt divided by total liabilities and equity.

This ratio is related to the company's financial structure, and it expresses the weight of the total debt over the invested capital. According to another perspective, this ratio is complementary to the financial-independence index, equal to equity over invested capital. This comparison allows for the examination of the relationship between risk capital (equity) and debt capital, as well as allows the considering of the relationships between the remuneration of the former and the cost of the latter. Therefore, with the same invested capital, the higher the total debt, the lower the equity. It follows, then, that companies will prefer to use third-party capital, rather than their own capital.

From this brief explanation of the financial meaning of this variable emerges the conclusion that, despite its absence within the Altman Z-score model, Total Debt% works as a good predictor of the features associated with the company's financial structure. For this reason, it is plausible that it may be used as a measure to represent both of the target variables ('zone of discrimination' and 'cut off').

However, both experiments are marked by the presence of other variables missing in Altman's Z-score model.

In particular, the first experiment also includes the following variables: Sales, EBIT, and Non-current assets %, which represents the non-current assets ratio.

Sales and EBIT are both items of the income statement, and so they pertain to the analysis of the company's economic situation. Each express different sides of profitability: while sales refers to the value of a company's sales of goods and services, where the revenue or income process begins, EBIT is a company's net income before income tax expense and interest expenses have been deducted. Although EBIT is also present in the ROA formula, it is in this case considered to represent ROA's absolute value. It represents a good indicator with which one can analyse the performance of a company's core operations without considering the impact on profit of the costs of the capital structure and tax expenses.

The non-current assets ratio is given by the weight of non-current assets (fixed, intangible, and financial) over total assets, and it indicates the long-term methods involved in business operations to generate income.

This ratio pertains to the assessment of the financial position, and is complementary to the current asset ratio. This means that, when total assets are equal, the higher the value of fixed assets the lower the value of current assets - and by extension a higher number of assets are not expected to be consumed or converted into cash in the short period.

The second experiment considers three variables not included in Altman's Z-score model: Total Assets (total assets), Long-term Debts (total debt due beyond the financial year), and Labor cost% (personnel costs ratio). These variables pertain to two different sides of evaluation: the first two are related to the financial assessment, while the second to economic analysis.

Total assets represent the total amount of invested capital, and so the variable gives a measure of the resources with economic value that are able to generate cash flow, reduce expenses, or improve sales. Total assets are given by the sum of all non-current assets (fixed, intangible, and financial) and all current assets, which are the short-term resources expected to be converted into cash within one year.

Total debt due beyond the present financial year represents the non-current liabilities, and so the liabilities to be paid over the medium to long period.

The personnel costs ratio is given by the personnel costs (salary and wage expenses) on sales. Personnel costs are included within the operating costs - a negative component that contributes to determining the operating result. It can be derived that, when sales are equal, the higher the personnel costs are the lower are the operating costs and, consequently, the net income.

In light of this scenario, the contribution of the study is the identification of two algorithms able to determine two settings of *if-then* rules that produce the same outcomes obtainable through the application of the Altman Z-score model, without directly using the model itself.

It derives that, thanks to the combination of a new set of variables, it is possible to understand - within a given range of accuracy - the company's financial health, and conversely, the company's distress, regardless of the Altman Z-score.

The current development of the research reveals that the methodology still needs to be adapted in order to determine the plausible intervals for the variables identified by the decision trees. In fact, the dimensionality of the dataset could benefit from resampling the variables for the proposed methodology, which, even using high-quality software and hardware, suffers from certain degrees of skew.

However, the identified algorithms are a powerful tool that strengthens the comprehension of a companies' financial profile. Since they work with large amounts of data, they are even more significant.

This algorithm is thus an asset of great value, when used in relation to the peculiarities of the sample under investigation, as all the companies are in possession of a LR.

The practical implications related to this finding may be addressed uniquely to various actors.

For example, banks may wish to employ a methodology, which is different to the Altman Z-score model, to monitor companies' financial profiles. In detail, financial institutions may perform comparative evaluations when granting loans to companies in possession of legality ratings: the financial health of these kinds of companies may be assessed *vis-à-vis* the financial profile of the other companies seeking bank credit. In addition to the company's individual financial assessment, banks may benefit from a set of rules to monitor the comprehensive financial status of the above-mentioned forms of companies.

Furthermore, companies themselves may be the recipients of this research's achievement. Management can monitor competitor companies requesting for legality ratings (the companies' list is freely available on the

AGCM website), and their financial performance. So, from a perspective of competition, by virtue of an AI methodology, management may make a relative self-evaluation of its own company in relation to a set benchmark. It can be derived that a virtuous circle is triggered by avoiding downward competition.

Moreover, the policy-maker may take advantage of the AI methodology in order to assess the coherence of law provisions on legality rating, and the ratings' concrete impacts. It may allow the testing of the effectiveness of LR in the assessment of creditworthiness, and may potentially encourage amendments aimed to align the regulation's intent with the real bank-company relationship.

In consideration of the link between LR and a company's distress, the AI toolbox is able to process large amounts of records within a given dataset, thus allowing for the testing of the effectiveness of LR in the assessment of creditworthiness.

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