A state-of-the-art appraisal of bankruptcy prediction models focussing on the field's core authors: 2010–2022

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Abstract

Purpose – The primary purpose of this paper is to identify the so-called core authors and their publications according to pre-defined criteria and thereby direct the users to the fastest and easiest way to get a picture of the otherwise pervasive field of bankruptcy prediction models. The authors aim to present state-of-the-art bankruptcy prediction models assembled by the field's core authors and critically examine the approaches and methods adopted.

Design/methodology/approach – The authors conducted a literature search in November 2022 through scientific databases Scopus, ScienceDirect and the Web of Science, focussing on a publication period from 2010 to 2022. The database search query was formulated as "Bankruptcy Prediction" and "Model or Tool". However, the authors intentionally did not specify any model or tool to make the search non-discriminatory. The authors reviewed over 7,300 articles.

Findings – This paper has addressed the research questions: (1) What are the most important publications of the core authors in terms of the target country, size of the sample, sector of the economy and specialization in SME? (2) What are the most used methods for deriving or adjusting models appearing in the articles of the core authors? (3) To what extent do the core authors include accounting-based variables, non-financial or macroeconomic indicators, in their prediction models? Despite the advantages of new-age methods, based on the information in the articles analyzed, it can be deduced that conventional methods will continue to be beneficial, mainly due to the higher degree of ease of use and the transferability of the derived model.

Research limitations/implications – The authors identify several gaps in the literature which this research does not address but could be the focus of future research.

Practical implications – The authors provide practitioners and academics with an extract from a wide range of studies, available in scientific databases, on bankruptcy prediction models or tools, resulting in a large number of records being reviewed. This research will interest shareholders, corporations, and financial

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institutions interested in models of financial distress prediction or bankruptcy prediction to help identify troubled firms in the early stages of distress.
Social implications – Bankruptcy is a major concern for society in general, especially in today's economic environment. Therefore, being able to predict possible business failure at an early stage will give an organization time to address the issue and maybe avoid bankruptcy.
Originality/value – To the authors' knowledge, this is the first paper to identify the core authors in the bankruptcy prediction model and methods field. The primary value of the study is the current overview and analysis of the theoretical and practical development of knowledge in this field in the form of the construction of new models using classical or new-age methods. Also, the paper adds value by critically examining existing models and their modifications, including a discussion of the benefits of non-accounting variables usage.
Keywords Review, Business failure, Machine learning, Bankruptcy prediction models, Core authors
Paper type Research paper

Introduction

Since the creation of the first bankruptcy prediction models in the 1960s, scholars have developed numerous different models worldwide. Shareholders, corporations and financial institutions are interested in models of financial distress prediction or bankruptcy prediction to help identify troubled firms in the early stages of distress (Sun *et al.*, 2014a, b). The literature in this area has grown significantly and the global financial crisis made it grow even more. Historically, scholars employed various methods to devise bankruptcy prediction models. Karas and Režňáková (2017) argue that we must pay attention to the method choice, because it predetermines the method's discrimination ability to a large extent. However, the models differ in the methods used and the type of explanatory variables. Moreover, each model emerged in the specific condition of the individual country or is dedicated to a particular branch. Furthermore, the sample of companies usually consisted of companies from various economic categories. When choosing an appropriate model, all of these criteria require consideration.

We found several studies that provided an overview of bankruptcy models, their methods and predictors, including the frequency of their use in the literature, and discussed their advantages and disadvantages (Adnan Aziz & Dar, 2006; Alaka *et al.*, 2018; du Jardin, 2018; Kovacova *et al.*, 2019a, b). Alaka *et al.* (2018) prepared a framework for model selection and systematically reviewed 49 journal articles published between 2010 and 2015. Based on 13 key criteria, their research showed how eight popular methods perform: accuracy, result transparency, fully deterministic output, data size capability, data dispersion, variable selection method required and variable types applicable. However, the research did not mention the review's limitations nor did it reflect on acknowledged and area-dedicated authors.

We could not find any review in ScienceDirect, Web of Science, or Scopus that identified the field's core authors. What are their methods and other study features, i.e. which articles should we study if the focus is only on the core fields? The above reasons led us to provide practitioners and academics with an extract from a wide range of studies from the scientific databases on bankruptcy prediction models or tools, resulting in a large number of reviewed records (over 7300).

Given the current economic situation, the focus of this research is highly topical. Many companies seek to review and assess their business to predict future development, often considering whether to stay in business or not. Although most previous studies prefer endogenous to exogenous causes (Jones, 2017), some authors ask which approaches to bankruptcy prediction to use and also consider non-financial variables and macroeconomic variables.

We aimed to identify the so-called core authors and their publications according to pre-defined criteria and thereby direct the users to the fastest and easiest way to get a picture of the otherwise pervasive field of bankruptcy prediction models. We focused on core authors to find the most recognized and dedicated authors in the area of bankruptcy prediction. Although some studies connect a core status only to the citation status, scientometric studies suggest another approach combining various criteria (Gu, Li, Li, & Liang, 2017; Ouyang *et al.*, 2018; Wang, Wang, & Yang, 2017). Hence, we adopted a combination of impact reflection techniques, wherein the minimum required number of articles in the research accompanied citations and dedication to the research.

We analyzed the core authors' publications with emphasis on the target country, the sample structure, the type of explanatory variables, the methods applied and other characteristics. We aimed to answer the following research questions:

RQ1. What are the most important publications of the core authors in terms of the target country, the sample size, the economy's sector and SME specialization?

RQ2. What are the most used methods for deriving or adjusting models appearing in the articles of the core authors?

RQ3. To what extent do the core authors include accounting-based variables, non-financial or macroeconomic indicators, in their prediction models?

Following the introduction, the article will focus on the research methodology, including the search strategy, eligibility criteria and methods classification. The next sections will present the results and discussion, and, finally, the conclusion and future research recommendations.

Research methodology

Search strategy

We conducted a literature search in November 2022 through scientific databases Scopus, ScienceDirect and the Web of Science. Our database search query was "Bankruptcy Prediction" and "Model or Tool." We intentionally did not specify any model or tool to make the search non-discriminatory. We performed the Web of Science search with the search tag ALL and ScienceDirect and the Scopus search with the title, abstract and keywords options. Because we focused on the core but recent authors in the business research area, we set the search criteria as follows:

(1) Publication timespan: 2010 to 2022;

(2) Document type: journal article;

(3) Research or subject area: business;

(4) Written in English.

Eligibility criteria

A team of six researchers assessed the articles to determine whether they met eligibility criteria. In addition to the above search/eligibility criteria, the researchers excluded articles:

(1) Focused on company credit scoring;

(2) Focused on personal bankruptcy prediction;

(3) Focused on an accounting perspective;

(4) Focused on a macroeconomics and government policy perspective;

(5) Written by anyone other than a core author.

The last eligibility criterion required us to analyse who are core authors. We should not mistake them for the primary authors (first- or second-listed author) or corresponding authors. The designation “core” stands for the relation to the field of study. Initially, Wang, Qiu, & Yu (2012) claimed that there was no report on any standard for identifying core authors in a scientific field, but in a later scientometric article (Wang *et al.*, 2017), they adopted criteria of inclusion of authors who published five or more papers and received ten or more citations. We find a similar approach of citing and authorship analysis in other scientometric studies, for example, literature co-citation and the innovation path analysis of a research field (Gu *et al.*, 2017), number of articles and network density analysis (Castro & Parreiras, 2018), or co-authorship frequency (Ouyang *et al.*, 2018). Therefore, we adopted criteria based on a dedication to the field of study and audience response, as cited by Wang *et al.* (2017). We applied the criteria after the screening phase and content eligibility criteria analysis. For this article’s purpose, a core author published five or more articles in our screened and eligibility-criteria-reduced sample and achieved ten or more citations from articles included in our filtered sample.

The final part of the analysis focused on the most impactful articles on the reviewed topic so as not to miss any highly relevant articles and verify if the core authors were among those most impactful ones. We found that some authors significantly overlapped with the computer science research area. Therefore, we employed the field-weighted citation impact (FWCI) indicator to normalize citations to see which articles and authors received more citations than typical in the given field in a given year. Field-weighted citation impact is based on a normalization suggested by Lundberg (2007) and elaborated in greater detail by Waltman, van Eck, van Leeuwen, Visser, and van Raan (2011). We assessed the FWCI indicator for articles that met all eligibility criteria except criterion “e” regarding core authors. We found 70 articles to be adequate. We then acquired these articles and studied them following a pragmatic research approach (Lefley, 2006) (Figure 1).

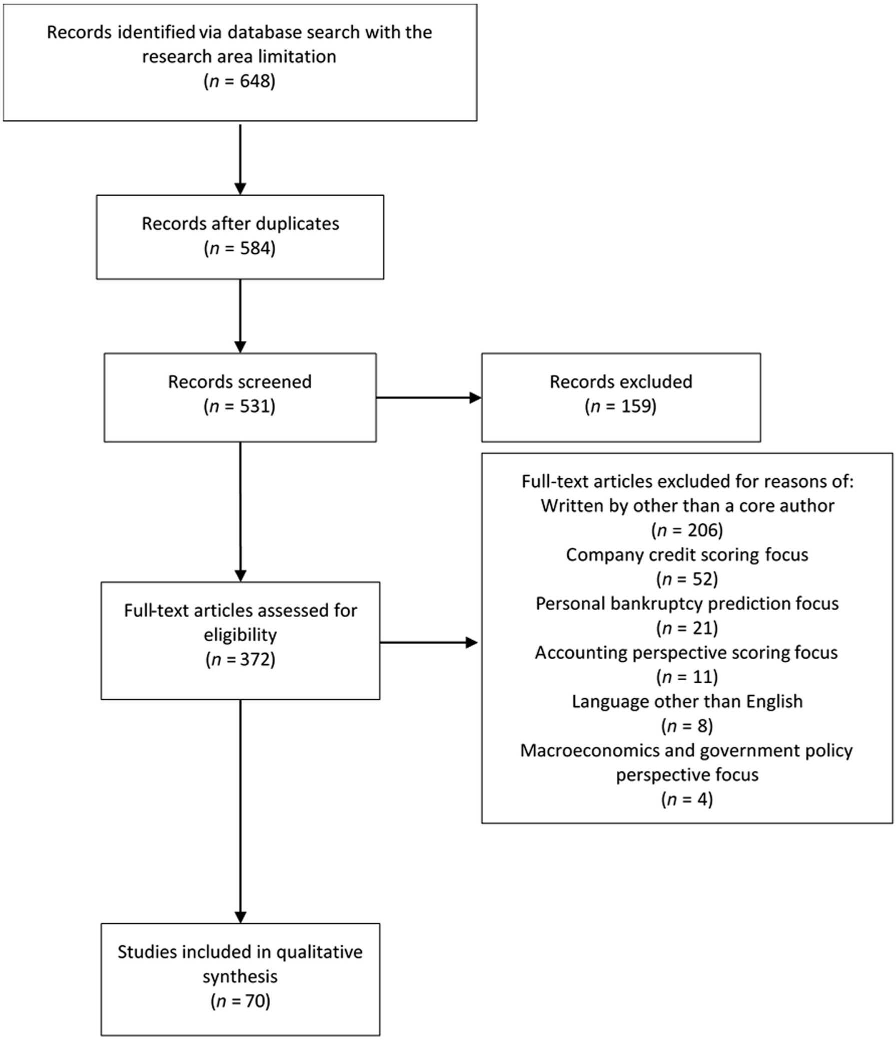
Methods classification

The bankruptcy model creation process employs various methods as a stand-alone method, combined in an ensemble model and also when modified for an application of machine learning. It has different tasks, but the most important is the modelling technique. Other roles, such as optimizing method, a genetic algorithm in machine learning, pre-analysis sample preparation and mixed sample approach, also play their part. However, we focused solely on the techniques that constitute the model’s basis. We may find two main groups among the bankruptcy prediction models:

(1) Conventional statistical methods:

- Cluster analysis: it assesses if we may meaningfully summarize a data set in terms of a relatively small number of clusters (groups) of objects or individuals that resemble each other and are different in some respects from individuals in other clusters (In Everitt, 2011). The classification is successful if the objects within clusters are close together when plotted geometrically and different clusters are far apart (Meloun & Militký, 2012). Moreover, we may employ it to segment cases, such as companies (Lukason & Laitinen, 2019) or explanatory variables, e.g. primary groups of financial indicators (Kovacova *et al.*, 2019a, b).

- Multiple discriminant analysis: it aims to understand group differences and predict the likelihood that an entity (individual or object) will belong to a particular class or group based on several metric-independent variables (Hair, 2014). Multiple discriminant analysis and logit analysis are the most common statistical models for bankruptcy prediction, (see, e.g. Altman, 2018).



Source(s): Own elaboration

Figure 1. Flowchart

- Logistic regression: often referred to as logit models, combines multiple regression, in which one or more independent variables serve to predict a single dependent variable, and multiple discriminant analysis, in which a dependent variable is nonmetric (In Hair, 2014). It is one of the most frequent methods employed to classify/separate companies for which bankruptcy is likely from those for which it is not (Kovacova *et al.*, 2018).
- Decision tree: used in classification, it detects criteria for dividing the individuals of a population into n predetermined classes. Criteria are variables that provide the best separation of the individuals in a class, containing the largest possible proportion of individuals (Tufféry & Tufféry, 2011). The result is a network of

questions that forms a treelike structure with the ends of the tree as "leaf" nodes (Nisbet, 2017). Financial ratios are the most common criteria/variables (Korol, 2013).

- Fuzzy logic: a method for reasoning with logical expressions describing membership in fuzzy sets. Rather than considering uncertainty about the truth of well-defined propositions, fuzzy logic handles vagueness – its propositions have a degree of truth between 0 and 1 (Russell & Norvig, 2021). This way, fuzzy logic treats problems that arise from bivalent logic. Fuzzy logic does not replace other conventional or machine-learning statistical methods. It rather adds rules induction applicable in decision systems or processes combined with other statistical methods (Nisbet, 2017). See Korol (2018) for fuzzy logic applied to financial ratios.

(2) Machine learning methods:

- Neural network: an algorithm inspired by neurons (units) and their synapses (weights). Each input variable corresponds to a unit at a first level, called the input layer. On the opposite side stands a final level called the output layer. Units belonging to an intermediate level are the hidden layer or layers (Tufféry & Tufféry, 2011). The learning occurs in the hidden layer(s). It expresses a nonlinear function by assigning weights to the input variables to produce an output value (Nisbet, 2017). A neural network can handle a high amount of input variables, both traditional; financial and non-traditional, structure and ownership (Jones, 2017).

- Decision tree: the classification task remains the same as in the case of the conventional decision tree. However, it differs in learning. Contrary to a neural network, during learning, the decision tree method conveys effects by developing methods to find rules that allow the evaluation of input values for categorizing them into distinct groups, without directly expressing the functional relationship (Nisbet, 2017). There are various algorithms applied to decision trees (Sun *et al.*, 2018). Although it is a conventional statistical method, it frequently serves as a base classifier in a machine-learning combination of models (du Jardin, 2021).

- Support vector machine: the method is based on a concept of decision planes that define decision boundaries. In their simplest form, such boundaries resemble a separating line which ideally separates objects with different class memberships (Nisbet, 2017). Therefore, some authors call the lines margin separators (Russell & Norvig, 2021). Separation can use the main function types: linear, polynomial and sigmoid. Li and Sun (2011d) give examples of various support vector machine models.

- K-nearest neighbour: this method classifies each individual by searching among previously classified individuals for the class of the k individuals, which are its nearest neighbours, in terms of Euclidean distance or other distance metrics (Tufféry & Tufféry, 2011). Scholars will choose the k value so as to obtain the best possible classification. Regarding the output, after an algorithm finds the set of neighbours, it takes the most common output value (Russell & Norvig, 2021). A study by Li and Sun (2010) shows an influence of different k values. The methods are applicable in both conventional and machine learning models.

Results and discussion

Based on the above methodological procedure, we selected 70 journal articles with full texts available through open-source and premium access. We present the list of articles in the

Table A1. We listed the articles according to the core author criteria, FWCI, target region, the article's aim, survey period and sample size. Concerning our research questions and the overall goal of the article, Tables 1–5 contain the key summary findings obtained based on the analysis of the 70 articles.

From Table 1, we may observe that in the monitored period, core authors focused primarily on the European region (including various groupings from independent states to more expansive areas), followed by the region comprising China and Taiwan. Core authors gave little or no specific attention to Africa, South America, or Southeast Asia. It appears that many authors frequently focus on their home region (10 out of 15 of the core authors identified by this current research are active in Europe). Altman, Iwanicz-Drozdowska, Laitinen and Suvas (2017) tested the hypothesis about the influence of country-specific differences (economic environment, legislation, culture, financial markets and accounting practices) on the accuracy of the model.

Considering the research sample's size (right side of Table 1) that founds the models for determining a company's bankruptcy, the category "0–999 companies" was the most represented. This usually corresponds to the derivation of a model for the national economy (Jabeur, Gharib, Mefteh-Wali, & Arfi, 2021). The largest samples are typically involved in international comparisons (Altman *et al.*, 2017). Based on public or private databases to obtain data due to mandatory reporting of data to local authorities [in Slovakia – the Register of Financial Statements (Kovacova & Kliestik, 2017), in V4 countries (Czech Republic, Slovakia, Poland and Hungary) – the Amadeus database (Karas & Režňáková, 2017; Kliestik, Vrbka, & Rowland, 2018), in France – the Orbis database (Jabeur, Gharib, Mefteh-Wali, & Arfi., 2021), or the Bureau van Dijk Amadeus database for various European countries (Lukason & Laitinen, 2019)].

Region				Number of companies in the analyzed dataset			
Category	Number of studies	%	Top article, according to the FWCI	Category	Number of studies	%	Top article, according to the FWCI
V4[1]	16	23	Kliestik *et al.* (2017)	0–999	30	44	Jabeur *et al.* (2021)
EU[2]	19	27	Jabeur *et al.* (2021)	1000–9999	14	21	Jones *et al.* (2017)
Europe[3]	2	3	Korol (2018)	10,000–999,999	16	23	Kliestik *et al.* (2017)
Other country groupings[4]	7	10	Altman *et al.* (2017)	1M and more	4	6	Altman *et al.* (2017)
Not assigned to a specific region	4	6	Altman (2018)	No real data/NA	4	6	Sun *et al.* (2014a, b)
China/Taiwan	15	21	Liang *et al.* (2016)	_	–	–	–
North America	6	8.5	Barboza *et al.* (2017)	_	–	–	–
Australia	1	1.5	Peat and Jones (2012)	_	–	–	–
Total	*70*	*100*		*Total*	*68[4]*	*100*	

Note(s): [1]Visegrad countries (V4) together or separate; [2]EU as a whole and other EU countries without V4; [3]European countries meaning EU countries and other non-EU countries together; [4]two articles deal with the comparison of already created models
Source(s): Own elaboration

Table 1. Articles by target region and number of companies in the analyzed dataset

Sector				Size of the company in the dataset			
Category	Number of studies	%	The top article, according to the FWCI	Category[1]	Number of studies	%	The top article, according to the FWCI
Agriculture	2	3	Karas *et al.* (2017)	Small and medium-sized	9	13	Altman *et al.* (2020)
Manufacturing	5	7	Lukason and Laitinen (2019)	Large	1	1.5	Jones and Wang (2019)
Construction	3	4.5	Karas and Režňáková (2017)	Medium and large	1	1.5	Muñoz-Izquierdo *et al.* (2020)
Accommodation and food service activities	1	1.5	Li and Sun (2011)	All or N/A	59	84	Kliestik *et al.* (2017)
Two and more sectors together	10	14	Kliestik *et al.* (2018)	–	–	–	–
N/A	49	70	Kliestik *et al.* (2017)	–	–	–	–
Total	*70*	*100*		*Total*	*70*	*100*	

Note(s): [1]the categorization of businesses by size is based on the methodology of individual articles
Source(s): Own elaboration

Table 2.
Articles by sector and size of the company in the data set

Category	Number of studies	%	Top articles according to the FWCI
New model	48	69	Kliestik *et al.* (2017)
Existing model in a new environment[1]	6	9	Sun *et al.* (2014)
Existing model with modifications	6	9	Altman *et al.* (2017)
Others[2]	10	14	Kliestik *et al.* (2020)
Total	*70*	*100*	

Note(s): [1]transferability of the model; [2]comparison of the models; predictors' analysis without model construction
Source(s): Own elaboration

Table 3.
Outputs of the articles

Category	Method	Number of studies	%	Top article according to the FWCI
Conventional method	Cluster analysis	8	11	Kliestik *et al.* (2020)
	Discriminant analysis	35	50	Kovacova and Kliestik (2017)
	Regression analysis (Logit, Probit)	44	63	Valaskova *et al.* (2018)
	Decision tree	12	17	du Jardin (2016)
Machine learning method	Artificial neural network	16	23	Jones *et al.* (2017)
	Support vector machines	23	33	Barboza *et al.* (2017)
	Decision tree	9	13	Carmona *et al.* (2019)
	K-nearest neighbour	5	7	Li and Sun (2009)

Source(s): Own elaboration

Table 4.
Methods employed in selected articles

Table 2 shows that only a minority of the included studies deal with a specific economic sector, either independently (16%) or within the framework of an inter-industry comparison (14%). The vast majority of articles (70%) do not consider the different conditions in the industry as essential. If the authors derive a model for a specific region, they work with all enterprises in the given region as a whole or do not provide more detailed information about the sample. We may similarly interpret the right side of Table 2, which focuses on the size of the enterprises in the research sample. Noteworthy, 13% of the considered studies addressed the SME environment. However, the vast majority of publications do not comment specifically on the companies' size in the research sample they work with.

Table 3 illustrates that among the monitored articles from the core authors, 69% focused on developing new models. The top-rated articles, as determined by FWCI, include Kliestik, Misankova, Valaskova, and Svabova (2017), Valaskova *et al.* (2018) and Jabeur *et al.* (2021). In the field of bankruptcy prediction models, the academic community also debates whether the models are transferable, i.e. whether they are applicable in any environment other than where they emerged (Sun *et al.*, 2014a, b). Gavurova, Packova, Misankova, and Smrcka (2017) validated four models (Altman model, Ohlson model, and indices IN05 and IN01) for the Slovak business environment, and Karas *et al.* (2017) analysed the accuracy of four traditional models in the field of agriculture. Many authors (Gavurova *et al.*, 2017; Karas, Režňáková, & Pokorný, 2017; Režňáková & Karas, 2015) conclude that the prediction accuracy of bankruptcy models falls when applied to a different branch, period, or economic environment and that such models need validation in the other conditions. When authors changed the original model (whether it was an adjustment of weights, variables, or boundary bands), we included the given article in the category "existing model with modifications."

Altman *et al.* (2017) offer a comprehensive international analysis by investigating the performance of the z-score model for firms from 31 European and three non-European countries using different modifications of the original model. Altman *et al.* (2017) conclude that the general z-score model works reasonably well for most countries (the prediction accuracy was approximately 0.75), and using country-specific estimation that incorporates additional variables can further improve classification accuracy (above 0.90).

In total, 14% of publications deal with the predictors' analysis (Karas & Režňáková, 2017; Kliestik, Valaskova, Lazaroiu, Kovacova, & Vrbka, 2020), methods' comparison (Barboza, Kimura, & Altman, 2017), comparison of existing models (Kovacova *et al.*, 2019a, b), or comparison of models' performance or efficiency (Altman, Iwanicz-Drozdowska, Laitinen, & Suvas, 2020; Liang, Lu, Tsai, & Shih, 2016).

Category	Number of studies	%	Top article, according to the FWCI
Financial ratios[1]	70	100	Kliestik *et al.* (2017)
Nonfinancial indicators[2]	10	14	Liang *et al.* (2016)
Macroeconomic indicators			
GDP/GDP per capita	5	7	Jones (2017)
Inflation rate	2	3	Jones (2017)
Unemployment	2	3	Jones (2017)
Others	2	3	Jones (2017)

Note(s): [1]accounting-based variables and market-based variables; [2]corporate governance indicators, other industry and firm-specific indicators
Source(s): Own elaboration

Table 5. Articles according to the type of variable used

Logit and discriminant analysis are the most often used methods (Table 4), not just as a method by itself but as a benchmark to which scholars compare other predictive tools' performance rates. A very wide range of authors used these two methods. The decision tree method is specific, because it serves as a conventional method providing results on its own or as a first-stage method in machine learning. The second-stage method is usually an artificial neural network that uses variables preselected through the decision tree or trees. By trees, we mean a group/ensemble of trees (tree boosting) to mitigate the disadvantages of a single decision tree. A similar case is the k-nearest neighbour method which, scholars can employ conventionally or as a part of the learning process. Among the machine learning methods, the one most common in the sample was the support vector machines, which we found mainly in articles by four authors collective around Du Jardin, Tsai, Li and Sun.

Since the 1960s, bankruptcy prediction models designed have been primarily based on financial ratios, for example, accounting-based variables (Altman, 1968; Kliestik *et al.*, 2017; Ohlson, 1980; Zmijewski, 1984). Some authors (Jones, 2017) argue that accounting-based variables report past business performance and recommend using market-based variables (see also Atiya, 2001; Beaver, 1966). The current research also shows that financial ratios are the primary predictors of bankruptcy in all monitored articles (Table 5). Accounting-based variables derive from firm income statements and balance sheets; these data are readily available, offer good discrimination ability (Altman, 1968) and are well standardized. The market-based variables are, for example, market capitalization, market-to-book, or price volatility (Jones, 2017). du Jardin, Veganzones and Séverin (2019) indicate that accounting-based variables can be "manipulated." However, their article suggests a way to overcome the deteriorated model performance resulting from firms manipulating the figures of their annual accounts.

In recent years, researchers have addressed the importance of non-financial variables (Jones, 2017; Liang *et al.*, 2016). In most cases, they did it in conjunction with accounting-based variables. In the current research, we used non-financial indicators in 14% of cases. As non-financial indicators, we considered governance indicators (Jones, 2017) and other industry and firm-specific indicators (Doumpos, Andriosopoulos, Galariotis, Makridou, & Zopounidis, 2017; Jones, Johnstone, & Wilson, 2017), which may provide additional power in bankruptcy prediction. According to Shailer (2004), corporate governance includes the mechanisms, processes and relations that control and direct corporations.

Tsai *et al.* (2021) classify corporate governance indicators into five categories: board structure, ownership structure, cash flow rights, the key person retained and others. Their research aimed to assess the prediction performance obtained by combining seven different categories of financial ratios and five different categories of corporate governance indicators. Our results show that financial ratios of solvency and profitability and the corporate governance indicators of board structure and ownership structure are the most important features in bankruptcy prediction.

We may consider macroeconomic factors (GDP per capita, GDP growth, the CPI index, interest rate levels, and public debt to GDP) as non-financial indicators as well, but in the current research, we monitored such factors separately. Among the monitored studies, few articles use macroeconomic indicators. In the case of the use of GDP-based indicators, there are five studies, and in the case of other macroeconomic indicators, only two studies. According to FWCI, the best-rated article using macroeconomic indicators is the one by Jones (2017), in which he uses the gradient boosting model, which accommodates very large numbers of predictors. Based on their overall predictive power, we can rank-order these predictors from best to worst. Among other indicators, Jones also includes exogenous variables, i.e. real GDP and real GDP growth, CPI index, unemployment rate and others. However, his research concludes that macroeconomic variables are the weakest predictors, together with variables such as analyst recommendations/forecasts and industry-specific variables.

Conclusions and future research recommendations

This article addressed three research questions:

> RQ1. What are the most important publications of the core authors in terms of the target country, the sample size, the economy's sector and SME specialization?

We present our findings based on the 70 articles itemized in the Appendix, showing the core author criteria, FWCI, target region, the article's aim, survey period and sample size. We support it with the data presented in Tables 1–3. We presented the core authors' most important publications in bankruptcy prediction models.

> RQ2. What are the most used methods for deriving or adjusting models appearing in the articles of the core authors?

Conventional methods are the most used compared to the less used machine learning methods. Despite the advantages that new age methods offer, based on the information in the analyzed articles, we deduce that conventional methods will continue to be beneficial, mainly due to the higher degree of ease of use and the transferability of the derived model.

> RQ3. To what extent do the core authors include accounting-based variables, non-financial or macroeconomic indicators, in their prediction models?

While all of our core authors indicated the usage of "financial ratios" and, to a lesser extent "non-financial indicators" and "macroeconomic indicators," we were able to show the growing importance of corporate governance and other industry and firm-specific indicators.

This study primarily contributes by providing a contemporary overview and analysis of the theoretical and practical advancements in the field. It achieves this by constructing new models through classical or new-age (machine learning) methods, as well as by evaluating existing models and their adaptations. It also engages in a discussion regarding the advantages of incorporating non-accounting variables. Furthermore, it identifies the core/lead authors who systematically dealt with bankruptcy models in the given period and thus developed the given field. To the best of our knowledge, this is the first study to focus on the systematic work of lead, respectively, core authors with required citation responses. This study further connects the outputs of the core authors with the value of the bibliographic indicator FWCI. It thus provides an overview of the attractiveness of these outputs, actually the attractiveness of the approaches of the core authors. Therefore, in this study, we devoted considerable attention to methods for model derivation.

Concluding, our research shows that current core authors work with bankruptcy models from various, often very complex, perspectives regarding work with the research sample, either from the point of view of its structure or the environment of research sample's location. Moreover, conventional and new-age methods are frequently used in a modifying capacity. Despite the advantages that new age methods offer, based on the information in the articles analyzed, we may deduce that conventional methods will continue to be beneficial, mainly due to the higher degree of ease of use and the transferability of the derived model. Nevertheless, the accuracy of models decreases when they are used differently in time and space.

We identified several gaps left to be answered by future research.

First, regarding the methods, machine learning methods can be transferable, although the process is more complex than, for example, logistic regression. No author who employed the machine learning method provided means for doing so. Verification, application of their models on other data, or simply reproducing the results is impossible. Therefore, it would be helpful – not only for the field of bankruptcy models – to agree on a reporting method and its means. This task is similar to the widely-used PRISMA methodology for systematic reviews.

Thus, future research should focus on the transferability of machine learning model results, which includes the identification of the model framework and the hyperparameter file. This would be equivalent to conventional methods with model procedures (like logit or MDA) and equation variables (constant and explanatory variable values). In the best-case scenario, the results would be uploaded to a service such as Kaggle or Google Colab, so that the model can run without the help of an expert IT.

Second, regarding the characteristics of the samples involved in deriving the models, researchers focus on Europe, the USA and China from a regional perspective. We did not identify a systematic approach to other economies, especially developing ones, including traditional and "new age" methods. Similarly, the majority of studies disregard the differentiation of input data required for formulating models, specifically concerning the scale of enterprises and the economic sector in which these enterprises are active.

Third, in terms of both theoretical and practical aspects, conducting a study that compares the model's accuracy at the macroeconomic level with its accuracy in various specific economic sub-sectors would be beneficial. In our research sample, we inadequately address the matter of incorporating national characteristics, represented by non-accounting indicators, when the model encompasses a broader array of diverse economies. In this area, in further research, it is possible to build on Altman *et al.* (2017), who propose the inclusion of a variable expressing national specifics in the construction of the model. This field would benefit from a broader discussion of appropriate variables defining these national specificities.

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(The Appendix follows overleaf)

Appendix

Table A1.
Focus overview of analyzed articles

Core author(s)	Article	FWCI	Target region	Aim of the article	Survey period	Sample size
Kliestik, Kovacova (Misankova), Valaskova	Kliestik *et al.* (2017)	*28.44*	Slovakia	To design and assess a novel tool for bankruptcy prediction	2012–2015	265,347
Kliestik, Kovacova	Kovacova and Kliestik (2017)	7.25	Slovakia	To construct models for the bankruptcy prediction of Slovak companies and compare the overall predictive ability of the two developed models	2015	1,000
Kliestik, Kovacova	Kovacova *et al.* (2018)	2.25	Slovakia	To test the validity of prediction models developed as partial results of our research project	2015–2016	27,029
Kliestik, Kovacova, Valaskova	Valaskova *et al.* (2018)	26.19	Slovakia	To assess the financial risks of Slovak entities, realized by identifying significant factors and determinants affecting the prosperity of Slovak companies	2015	62,533
Kliestik, Kovacova, Valaskova, Vrbka	Kliestik *et al.* (2020)	*15.44*	Slovakia, the Czech Republic, Poland, Hungary, Romania, Lithuania, Latvia, Estonia, Croatia, Russia, Ukraine and Belarus	To analyse and compare financial ratios used in the models of transition countries	1993–2018	*180 models (not companies) were analyzed*
Kliestik, Vrbka	Kliestik *et al.* (2018)	4.47	V4 (Czech Rep., Hungary, Poland, Slovakia)	To develop a model to reveal the unhealthy development of the enterprises in V4 countries, which is done by the multiple discriminant analysis	2015–2016	449,781
Kovacova (Misankova)	Gavurova *et al.* (2017)	3.92	Slovakia	Assessment of four bankruptcy prediction models to determine the most appropriate model	2009–2014	700

(*continued*)

Core author(s)	Article	FWCI	Target region	Aim of the article	Survey period	Sample size
Kovacova, Valaskova	Kovacova *et al.* (2019)	N/A	V4 (Czech Rep., Hungary, Poland, Slovakia)	To provide deep insight and analyse the bankruptcy prediction models developed in countries of Visegrad four, emphasizing methods applied and explanatory variables used in these models, and evaluate them through appropriate statistical methods	Not stated	*103 prediction models developed in V4 countries*
Kovacova, Vrbka	Podhorska *et al.* (2020)	N/A	Emerging markets including 17 countries from Europe	To create a comprehensive prediction model of enterprise financial distress based on decision trees under emerging market conditions. The model also contains three dummy variables (country, size of enterprise and NACE classification) and countries' GDP data	2015–2016	2,359,731
Valaskova	Valaskova *et al.* (2020)	N/A	Slovakia	To portray the bankruptcy models (eight) developed in conditions of the Slovak republic, especially in the agriculture sector, verify their predictive ability using divergent statistical methods, and explore the importance of financial ratios in the prediction of financial stability	2016–2018	3,329
Altman, Laitinen	Altman *et al.* (2017)	*18.03*	31 European + 3 non-European countries (USA, China, Colombia)	To deliberate on categorizing the Z-Score model in terms of forecasting bankruptcy	2002–2010	2,640,778
Altman, Laitinen	Altman, Iwanicz-Drozdowska, Laitinen, and Suvas (2016)	1.25	Finland	To evaluate the effectiveness of financial and nonfinancial variables in the long-term perspective	2004–2013	59,099
Altman	Barboza *et al.* (2017)	14.88	North America	To test machine learning models to predict bankruptcy one year before the event, and compare their performance with other models	1985–2013	41,741
Altman	Altman (2018)	2.41	Not mentioned	To assess the fundamental and stats elements of Altman's Z-score model presented in 1968	1968–2018	No real data

(*continued*)

Table A1.

Table A1.

Core author(s)	Article	FWCI	Target region	Aim of the article	Survey period	Sample size
Altman	Altman (2018)	2.03	Not mentioned	To discuss many implementations of the Z-score	1968–2018	No real data
Altman, Laitinen	Altman *et al.* (2020)	1.93	Finland	To compare the accuracy and efficiency of five different estimation methods for predicting the financial distress of small and medium-sized enterprises	2004–2013	48,916
Laitinen	Laitinen and Lukason (2014)	1.89	Finland, Estonia	Considering "the novel topic of comparing firm failure processes between different countries."	2002–2009	140
Laitinen	Laitinen and Suvas (2016)	2.07	EU–26	The objective is to investigate the influence of Hofstede's original cultural dimensions on financial distress prediction	2002–2010	1,278,362
Laitinen	Lukason and Laitinen (2019)	1.36	EU (Italy, France, Spain, Romania, Hungary)	The paper aims to extract firm failure processes (FFPs) by using failure risk and ranking the importance of failure risk contributors for different stages of FFPs	N/A	1,234
Laitinen	Muñoz-Izquierdo *et al.* (2020)	1.86	Spain	To empirically analyse the usefulness of combining accounting and auditing data to predict corporate financial distress. Concretely, to examine whether audit report information incrementally predicts distress over a traditional accounting model: the Altman's Z-Score model	2004–2014	808
Jabeur	Jabeur *et al.* (2021)	*8.30*	France	To propose a new gradient boosting technique for bankruptcy prediction, namely, CatBoost	2014–2016	133
Jabeur	Ben Jabeur (2017)	2.03	France	To improve the LR in the presence of highly correlated data, by using a PLS-LR that offers a significant alternative by allowing, among other advantages, in considering the action of the existing correlation	2006–2008	800
Jabeur	Jabeur and Fahmi (2018)	*1.82*	France	To present a model to predict financial distress in French companies	2006–2008	800

(*continued*)

Table A1.

Core author(s)	Article	FWCI	Target region	Aim of the article	Survey period	Sample size
Jabeur	Stef and Jabeur (2018)	*0.53*	France	To determine if nonfinancial variables such as the number of new firms can represent a useful tool for forecasting a firm's liquidation	2006–2008	825
Jabeur	Ben Jabeur, Stef, and Carmona (2022)	4.44	France	An improved Extreme Gradient Boosting (XGBoost) algorithm based on feature importance selection (FS-XGBoost) is proposed to predict corporate failure	2014–2017	1,850
Tsai	Liang *et al.* (2016)	*6.17*	Taiwan	To assess the prediction performance obtained by combining multiple financial ratios and corporate governance indicators	1999–2009	478
Tsai	Tsai and Cheng (2012)	1.41	Australia, Germany, Japan	To examine the performance of bankruptcy prediction models after removing several outlier volumes	N/A	4,778
Tsai	Tsai and Hsu (2013)	1.14	Australia, Germany, Japan	To present a meta-learning framework to predict bankruptcy	N/A	2,343
Tsai	Liang, Tsai, and Wu (2015)	2.78	Australia, Germany, Taiwan, China	A comprehensive study examines the effect of performing filter and wrapper-based feature selection methods on financial distress prediction. In addition, the impact of feature selection on the prediction models obtained using various classification techniques is also investigated	N/A	2,818
Tsai	Liang *et al.* (2020)	1.65	USA	To construct a bankruptcy prediction model based on multiple financial ratios and corporate governance indicators	1996–2014	286
Tsai	Tsai *et al.* (2021)	1.41	Not exactly specified	To compare the performance of three feature selection algorithms, three instance selection algorithms, four classification algorithms, and two ensemble learning techniques	N/A	242,429

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Table A1.

Core author(s)	Article	FWCI	Target region	Aim of the article	Survey period	Sample size
Jones	Jones *et al.* (2017)	*6.16*	USA	Based on a large sample of US corporate bankruptcies, we examine the predictive performance of 16 classifiers, ranging from the most restrictive classifiers (such as logit, probit and linear discriminant analysis) to more advanced techniques such as neural networks, support vector machines (SVMs) and "new age" statistical learning models including generalized boosting, AdaBoost and random forests	2000–N/A	3,111
Jones	Peat and Jones (2012)	N/A	Australia	The study adds to current debates by investigating the performance of N.N.s in the context of forecast combination. Furthermore, to test the performance of the N.N. model with the most widely used discrete choice model in the bankruptcy literature, logistic regression	Period 1: 2000–2002, Period 2: 2003+	558 max/period (different samples for different periods)
Jones	Jones (2017)	3.91	USA	To outline a conspicuous trend in the literature by applying the gradient boosting model	1987–2013	1,115
Jones	Cheng, Jones, and Moser (2018)	0.27	USA	To examine the trading behaviour of U.S. corporate insiders and certain groups of institutional investors (short-term, transient, top-performing, and those with fiduciary responsibility) in the eight quarters leading up to a U.S. firm bankruptcy filing	1992–2012	610
Jones	Jones and Wang (2019)	2.16	Whole world	The study utilizes an advanced machine learning method known as TreeNet(R) (Salford Systems, 2017) to predict various private company failure states, ranging from binary settings (i.e. failed vs non-failed) to more complex multi-class settings with up to five states of failure	2009–2013	4,922,271

(*continued*)

Core author(s)	Article	FWCI	Target region	Aim of the article	Survey period	Sample size
Jones	Alam, Gao, and Jones (2021)	0.97	North America	To propose a deep learning model of firm failure prediction and compare it to the traditional prediction model	2001–2018	641,667
Li, Sun	Sun, Li, Huang, and He (2014)	*5.97*	China	To compile a complete summary, analysis and evaluation of the current literature on financial distress prediction (FDP)	N/A	No real data
Li, Sun	Li and Sun (2009)	2.06	China	To construct of hybrid case-based reasoning model and to test the performance	N/A	153
Li, Sun	Li and Sun (2011a)	N/A	China	To explain the data mining technique of two-step clustering; to introduce a new mining method	N/A	266
Li, Sun	Li and Sun (2011b)	1.30	China	To explain the necessity to base such case-based reasoning ensemble (CBRE) prediction technique on random similarity functions (RSF)	N/A	313
Li, Sun	Li and Sun (2011c)	1.52	China	To construct a principal-component case-based reasoning ensemble (PC-CBR-E) model	N/A	270
Li, Sun	Li and Sun (2011d)	0.36	China	To compare different models using SVM techniques	N/A	153
Li, Sun	Li, Lee, Zhou, and Sun (2011)	1.17	China	To construct a new model based on random subspace binary logistic regression analysis	N/A	270
Li, Sun	Li and Sun (2012)	1.01	China	To compare the CBR ensemble with MDA, logistic regression, and classical CBR algorithm	N/A	153
Li, Sun	Li, Hong, He, Xu, and Sun (2013)	0.40	China	To construct a small sample-oriented case-based kernel predictive method (SSOCBKPM)	N/A	200
Li, Sun	Li, Li, Wu, and Sun (2014)	2.42	China	To verify statistically a performance of statistic-based wrapper based on SVM methods	N/A	668
Li, Sun	Sun *et al.* (2014)	0.97	China	To explore the "imbalanced FDP based on SVM."	Sample 1: 2010–2012 Sample 2: 2012–2013	427

(*continued*)

Table A1.

Table A1.

Core author(s)	Article	FWCI	Target region	Aim of the article	Survey period	Sample size
Li, Sun	Sun *et al.* (2016)	0.79	China, world	To propose an approach for dynamic evaluation and prediction of financial distress based on the entropy-based weighting (EBW), the support vector machine (SVM) and an enterprise's vertical sliding time window (VSTW)	2006–2010	5
Li, Sun	Sun *et al.* (2019)	0.56	China	To replicate the Campbell, Hilscher, and Szilagyi (2008) bankruptcy prediction model and add additional terms for the absolute value of changes in the percentage ownership by corporate insiders over the previous six months or changes in ownership by specific groups of institutional investors	2000–2015	486
Li	Li, Hong, Zhou, and Yu (2015)	0.12	China	To compare pure SVM, hybrid SVM, SVM ensemble, and hybrid SVM ensemble	N/A	551
Li	Li, Xu, and Yu (2017)	0.57	China	To provide a "feasible approach to handle possible mixed information caused by oversampling; mixed sample modelling (MSM)."	N/A	No real data
du Jardin	du Jardin (2016)	*3.51*	France	To present a new model of bankruptcy prediction based on ensembles of models	2002–2012 Learning samples 2002–2011 (one set per year), testing samples 2003–2012 (one set per year)	337,400
du Jardin	du Jardin and Séverin (2012)	0.82	France	To introduce a new way of using a Kohonen map as a prediction model	Period 1: 1998–2000, period 2: 2000–2002, period 3: 2002–2004	11,540

(continued)

Core author(s)	Article	FWCI	Target region	Aim of the article	Survey period	Sample size
du Jardin	du Jardin (2018)	1.62	France	To propose a new bankruptcy prediction model that relies on estimating failure patterns that are quantified with ensembles of Kohonen maps	2007–2014	6,120
du Jardin	du Jardin *et al.* (2019)	1.35	France	To present a new measure that helps improve bankrupt models' accuracy by using a method to embody earnings management	Period 1: 2006–2007, Period 2: 2009–2010, Period 3: 2011–2012	14,220 max (different samples for different periods)
du Jardin	du Jardin (2021)	1.25	France	To present a new method of bankruptcy prediction based on modelling firms' history with a self-organizing map. To propose an approach that relies on a particular modelling of firm history using self-organizing neural networks and segmentation of the data space, which makes it possible to typify subsets of firms that share a common evolution of their financial situation over time	Period 1: 2000–2003, Period 2: 2004–2007, Period 3: 2007–2011, Period 4: 2011–2015	293,840
du Jardin	du Jardin (2021)	2.82	France	To present a new firm-failure forecasting method using an ensemble of self-organizing neural networks	2008–2015	470,330
Korol	Korol (2013)	*2.61*	Poland, Latin America (Mexico, Argentina, Brazil, Chile, Peru)	To compare "the effectiveness of twelve different early warning models."	Poland 2000–2007, Latin America 1996–2009	245
Korol	Korol and Kolodi (2011)	1.15	Poland	To present a fuzzy logic-based system	1999–2005	132

(*continued*)

Table A1.

Table A1.

Core author(s)	Article	FWCI	Target region	Aim of the article	Survey period	Sample size
Korol	Korol (2018)	0.16	7 EU countries, ten non-EU countries	To evaluate the effectiveness of the 13 fuzzy logic models	Sample 1: 1999–2007, Sample 2: 2000–2009, Sample 3: 1999–2009	166
Korol	Korol (2019)	N/A	EU	To develop and evaluate dynamic bankruptcy prediction models for European enterprises	2004–2017, the period ten years before bankruptcy	600
Karas, Režňáková	Karas and Režňáková (2017)	*1.84*	Czech Republic	To verify whether bankruptcy predictors are specific in terms of industry or time	2004–2013 (the concerned companies went bankrupt 2008–2013)	34,533
Karas, Režňáková	Režňáková and Karas (2015)	0.97	V4 (Czech Rep., Hungary, Poland, Slovakia)	To test the predictive capability of the original version of the Altman model in an environment different from the environment of its origin and to explore its transferability to a different economic environment	2007–2012	5,977
Karas, Režňáková	Karas *et al.* (2017)	0.50	Czech Republic	To analyse the current accuracy of four traditional bankruptcy prediction models (the revised Z-score model, Altman-Sabato's model in both versions – with unlogged and logged predictors, and IN 05 model) in agriculture	2011–2014	475
Karas, Režňáková	Karas and Režňáková (2017)	1.16	Czech Republic	To create a bankruptcy prediction model based on the data from construction companies in the Czech Republic	2011–2014	654
Karas, Režňáková	Karas and Režňáková (2018)	0.53	Czech Republic	To analyze the usefulness of information about the past development of a company's financial situation in predicting bankruptcy	2011–2014	1,355

(*continued*)

Core author(s)	Article	FWCI	Target region	Aim of the article	Survey period	Sample size
Karas	Karas and Srbová (2019)	0.52	Czech Republic	To test the current accuracies of five selected bankruptcy models in predicting the bankruptcy of construction companies and to create a new model designed specifically for this branch	2006–2015 (the concerned companies went bankrupt 2011–2015)	4,420
Karas, Režňáková	Karas and Režňáková (2020)	0.41	Czech Republic	To introduce a new hybrid model incorporating solely cashflow-based indicators (three model versions were derived)	2013–2018	4,350
Karas, Režňáková	Karas and Režňáková (2021)	1.25	EU-28	Construct a default prediction model incorporating factors considered internal or external manifestations of the financial constraint situation. For example, authors use the Cox semiparametric model, leaving the baseline hazard rate unspecified and employing macroeconomic variables as explanatory variables	2014–2019	213,731

Note(s): By core authors within the period 2010–2022; sorted in descending order by the FWCI indicator
Source(s): Appendix created by authors

Table A1.

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