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Review article

A bibliometric study on intelligent techniques of bankruptcy prediction for corporate firms

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ABSTRACT

Bibliometric analysis is an effective method to carry out quantitative study of academic output to address the research trends on a given area of investigation through analysing existing documents. This paper aims to explore the application of intelligent techniques in bankruptcy predictions so as to assess its progress and describe the research trend through bibliometric analysis over the last five decades. The results indicate that, although there is a significant increase in publication number since the 2008 financial crisis, the collaboration among authors is weak, especially at the international dimension. Also, the findings provide a comprehensive view of interdisciplinary research on bankruptcy modelling in finance, business management and computer science fields.

The authors sought to contribute to the theoretical development of bankruptcy prediction modeling by bringing new knowledge and key insights. Artificial intelligent techniques are now serving as important alternatives to statistical methods and demonstrate very promising results. This paper has both theoretical and practical implications. First, it provides insights for scholars into the theoretical evolution and intellectual structure for conducting future research in this field. Second, it sheds light on identifying under-explored machine learning techniques applied in bankruptcy prediction which can be crucial in management and decision-making for corporate firm managers and policy makers.

1. Introduction

Over the past 50 years, bankruptcy prediction has been a field of increasing interest to researchers all around the world. Many academic studies have been dedicated to exploring the corporate failure prediction model with better accuracy. Since the breakthrough in the bankruptcy prediction model was introduced by Altman in 1968, a large body of research has focused on the prediction of corporate financial distress. In most cases, authors tend to use the ultimate failure (bankruptcy) as the dividing line when they distinguish between failed and non-failed firms.

Since different sectors require different bankruptcy prediction models, researchers use distinctive methods and variables to construct models for each sector. The diversity on this subject led to the appearance of some influential comparative and review studies (Ravi Kumar and Ravi, 2007; Balcaen and Ooghe, 2006; Dimitras et al., 1996; Gissel et al., 2007). However, most of these review studies focus on statistical method-based models. Meanwhile, along with the development of computer science and artificial intelligent technology, some researchers started to apply machine learning techniques to the construction of bankruptcy prediction models (Pan, 2012; Min and Lee, 2005; Shin et al., 2005; Wilson and Sharda, 1994; Zhang et al., 1999). do Prado et al. (2016) pioneered to adopt bibliometric analysis to identify the use of multivariate techniques in bankruptcy research. Some others compare particularly two or three machine learning techniques for bankruptcy prediction modeling (Jo et al., 1997; Alfaro et al., 2008; Boyacioglu et al., 2009). However, to the best knowledge of the authors, there is no comprehensive bibliometric analysis studying the evolution of artificial intelligent techniques application in bankruptcy prediction and the authors sought to fill the gap in this area of research. The rationale for this paper lies in its recognition that this research field has been expanding dramatically in recent years and it is important to assess its progress and describe the research trend through bibliometric analysis and visualization.

Given the importance of this topic, the current study aims to explore the existing academic literature regarding bankruptcy predictions using intelligent techniques and the specific objectives are as follows:

1. To describe how this area of research is organized and progressed in terms of publications, authors, and journals, and identify the bibliometric trends (co-authorship, geographical area of authors, co-

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citation, co-occurrence and text mining, etc.) of bankruptcy prediction applying intelligent techniques.
2. To present an overview study bringing together research work classified in business, finance and management fields with the computer science field so as to have a multidisciplinary research in bankruptcy prediction modelling.
3. To discuss, based on results and knowledge obtained, the under-explored areas and reflect on possible future research opportunities to gain a more profound insight and understanding of this research topic.

This study has been conducted based on relevant search using the Web of Science database from 1968 (the year when Altman published the Z-score model) to 2018. Eighteen keywords (6 primary and 12 secondary) are identified to carry out the literature search and the sample consists of 413 academic publications in this study. The bibliometric approach contributed significantly to exploring and describing the existing academic literature on bankruptcy prediction modelling.

This paper is structured as follows. Section two starts with the literature review of bibliometric studies and bankruptcy prediction so as to collect principal methods that have been widely used by authors. Section three presents the research methodology based on the bibliometric approach and descriptive data analysis. The main research findings are discussed in section four. Conclusions, limitations and future research are presented in section five.

2. Literature review of bibliometric study and bankruptcy prediction

The term *bibliométrie* was first used by Otlet (1934). He defined it as "the measurement of all aspects related to the publication and reading of books and documents." Pritchard (1969) introduced firstly the anglicized version *bibliometrics*, defining it as an area of study that applies mathematical and statistical methods to examine and quantify books and other media of communication. Historically, bibliometric methods have been used to trace relationships among academic journal citations (Schaer, 2013). Nowadays, it can also be applied in quantitative research assessment exercises of academic output in order to address the trends on a given area of study, through analyzing existing documents, such as books, reports, theses, dissertations, published articles, etc. More specifically, the bibliometric studies aim to detect the intellectual networks among scholars or identify and map the intellectual structure of an area of study (Pinto et al., 2014).

Bibliometric studies may examine an array of different objects and have been used in different disciplines, such as information systems, knowledge management, marketing, innovation, entrepreneurship, etc. (Pinto et al., 2014). In the research field of bankruptcy prediction, do Prado et al. (2016) conducted a bibliometric study on the knowledge field of credit risk and bankruptcy, with the purpose of identifying and describing the use of multivariate data analysis techniques, as well as presenting the publications tendencies, the outstanding journals, the authors and their structures of co-citation and co-authorship. Klopotan et al. (2018) provided knowledge and key insights into the bibliometric research trends in the area of early warning systems in management, economics, public administration and business finance fields.

Since there is an increasing number of papers published related to business failure prediction in the recent years, some other authors shed light on carrying out comparative studies or provide overviews of business failure prediction models. Hillegeist et al. (2004) compared two accounting-based models, Altman's (1968) Z-score and Ohlson's (1980) O-score, with a market-based measure they developed based on the Black-Scholes-Merton option-pricing model, showing that the latter can provide significantly more information than the former two. Kim (2011) compared the functional characteristics of multivariate discriminant analysis, logistic, artificial neural network and support vector machine models by analysing their overall classification, prediction accuracy and relative error cost ratios. He concluded that an artificial neural network was the most recommended technique for the Korean hotel sector due to its high accuracy and small relative error costs. de Llano Monelos et al. (2016) compared the effectiveness of eight popular prediction methods, pointing out that different methodologies used in each study did not show significant influence on the results, and they suggested focusing on improving the quality of informational context of variables rather than designing sophisticated analysis techniques. Jabeur and Fahmi (2017) compared two financial distress prediction statistical methods (discriminant analysis and logistic regression) with the machine learning model (random forest), concluding that random forest is the most robust and efficient method with better results.

As for the overview studies, Dimitras et al. (1996) conducted a survey of literature on business failure, introducing a new framework to discuss the findings. This new framework includes classification of studies by country, method and industrial sector. Balcaen and Ooghe (2006) undertook an overview of classic statistical methodologies during the last 35 years (1969–2004), seeking to understand their features as well as their related problems. Ravi Kumar and Ravi (2007) presented a review on bankruptcy prediction in banks and firms based on statistical and intelligent techniques during 1968–2005, highlighting the source of data sets, financial ratios used, country of origin, time line of study and accuracy comparison of each technique. Gissel et al. (2007) analyzed 165 bankruptcy prediction studies published during 1965–2007 aiming to reveal trends in model development based on different methods, number and variety of factors, and specific uses of models.

In the literature related to intelligent techniques used in bankruptcy prediction, Tam (1991) believes that a neural network is a competitive instrument for evaluating the financial condition of a bank, so his study contributes a discussion regarding the potential and limitation of a neural network as a general modeling tool for financial applications. Min and Lee (2005) state that a number of studies have shown that machine learning techniques achieved better performance than transitional statistical ones. They intend to suggest a new bankruptcy prediction model with better explanatory power and stability by applying a support vector machine. After comparing with multiple discriminant analysis, logistic regression analysis and three layers fully connected back-propagation neural network, the support vector machine was declared to outperform the other methods. Dimitras et al. (1999) used a rough set to weaken limitations of previous models and confirm that the rough set approach can discriminate between financially healthy and failing firms with encouraging results.

However, none of the previous work has carried out a complete and comprehensive study applying bibliographic and bibliometric methods, in order to analyze and address the evolution of major intelligent techniques-based methods used in the field of bankruptcy prediction. Therefore, this paper contributes to the existing literature by studying and analyzing the evolution of machine learning techniques in bankruptcy predictions so as to provide new academic and empirical insights. Moreover, it adopts an inclusive research criterion (not limiting itself to a specific discipline or group of journals) aiming to obtain a more comprehensive picture of research on bankruptcy prediction modelling.

3. Research methodology and descriptive data analysis

The literature searching covers the journal articles and reviews from the database of Web of Science (core collection) published during 1968–2018. Initial search for identifying the international academic papers related to the research topic were carried out by using a set of keyword combinations as searching criteria. Such criteria is based on a previous systematic literature review conducted by the authors (Shi and Li, 2019) providing the following combination of primary keywords: **Bankruptcy Prediction** (Altman et al., 1994; Hillegeist et al., 2004;

Wilson and Sharda, 1994; Fletcher and Goss, 1993; Lee et al., 1996; Serrano-Silva et al., 2018); **Default Prediction** (Tserng et al., 2014; Peresetsky et al., 2011); **Financial Failure** (Altman and Hotchkiss, 2006); **Financial Distress** (Pan, 2012; Jones and Hensher, 2004; Sun and Li, 2008; Xiao et al., 2012); **Insolvency** (Langford et al., 1993; Lepetit and Strobel, 2013; Jackson and Wood, 2013); and **Business Failure** (Dimitras et al., 1996).

Given the aforementioned search criteria, the authors have consulted numerous previous studies (Ravi Kumar and Ravi, 2007; Dimitras et al., 1996; Gissel et al., 2007) in order to set the scope of the intelligent techniques used for bankruptcy prediction and the most frequently applied artificial intelligent techniques are: neural network, support vector machine, decision tree, genetic algorithm, fuzzy, rough set, data mining, case-based reasoning, DEA (data envelopment analysis), Adaboost, K-nearest neighbors, Bayesian network. Therefore, the combination of searching keywords design is displayed in Figure 1.

The searching process has been carried out by introducing the established keywords, where field terms are used in TITLE searching and intelligent techniques keywords are applied in TOPIC searching, and the two are combined with the connective word AND. After introducing such keywords, results are refined by considering only scientific articles and reviews. As for language options, none of the languages has been delimited, although the majority of results are written in English. No filter on disciplines is placed since the authors sought to provide a comprehensive view of research undertaken across distinct disciplines. The search is restricted to the period 1968 (when the first paper of bankruptcy prediction was published) to 2018. After screening out the duplicates and irrelevant papers, the final retrieved results are 413 international academic papers.

3.1. Overview of statistical and intelligent-based technique methods in bankruptcy prediction

Referring to bankruptcy prediction models, two families of techniques are generally applied as statistical techniques and artificial intelligent/soft computing techniques. Altman (1968) pioneered to use the statistical method as multivariate discriminant analysis to forecast business failure. Since then, the statistical approach has been majorly applied for the development of bankruptcy prediction models. Neural network as intelligent technique has been adopted widely after 1990s (Tam, 1991; Lee et al., 1996). Ravi Kumar and Ravi (2007) concluded logistic regression and discriminant analysis as statistical techniques. They also covered neural network, decision tree, case-based reasoning, rough sets, data envelopment analysis, support vector machine and fuzzy logic as intelligent techniques in their review study.

Reviewing a large number of studies published during 1968–2018, where various statistical and intelligent techniques were applied to solve bankruptcy prediction problems in different sectors including manufacturing and industrial firms, banks, etc., the authors contribute to elaborating a summary of models that are based on the aforementioned two methods (see Table 1).

Meanwhile, there are also authors who applied more than one method to establish a bankruptcy prediction model. These methods are presented as hybrid methods. Wang et al. (2017) applied the hybrid of logistic regression and Bayesian probabilistic networks to establish a bankruptcy prediction model. Li and Sun (2011b) proposed a hybrid method integrating principal component analysis with multivariate discriminant analysis and logit. Cao and Chen (2013) presented a fuzzy membership for the fuzzy support vector machine combined with case-based reasoning for predicting financial distress of Chinese listed

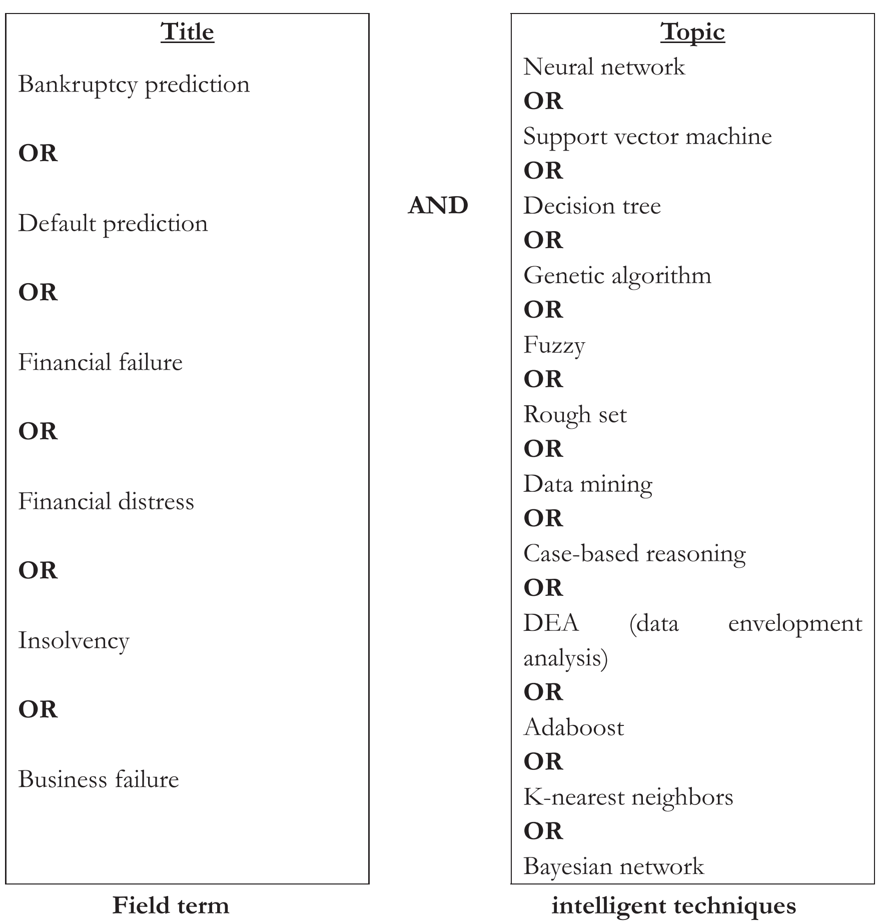

Figure 1. Combination of searching keywords.

Table 1. Summary of models based on statistical methods & intelligent techniques.

Statistical methods	
logistic regression/logit:	Makeeva and Khugaeva (2018); Cohen et al., (2017); Yerdelen et al., (2016); Xu et al., (2014); Chen (2011); Premachandra et al. (2009); Lawrence et al., (2009)
Probit	Kovacova and Kliestik (2017); Ahmadpour-Kasgari et al., (2012)
Discriminant analysis	Altman (1968); Deakin (1972); Xie et al., (2010)
Hazard model	Eling and Jia (2018); Tudor et al., (2015); Dang (2013)
Partial least squares	Serrano-Cinca and Gutiérrez-Nieto (2013); Ben Jabeur (2017)
Intelligent techniques	
Neural network	Atiya (2001); Tam (1991); Lee et al., (1996).
Support Vector Machine	Min and Lee (2005); Shin et al., (2005); Li and Sun (2009b); Li and Sun (2011a); Li et al., (2014); Lee et al., (2011)
Data Mining	Sun and Li (2008); Yerdelen et al., (2016); Geng et al., (2015)
Decision Tree	Gepp et al., (2009); Kim and Upneja (2014); Chen (2011)
Genetic algorithm	Shin and Lee (2002); Varetto (1998); Gordini (2014)
Rough set	Dimitras et al., 1999; Ahn et al., (2000)
Fuzzy logic	Chen et al., (2009); Chou et al., (2017); Georgescu (2017)
Case-based reasoning	Park and Han (2002); Li and Sun (2009a,b); Li and Sun (2008)
DEA (data envelopment analysis)	Shetty et al., (2012); Huang et al., (2015); Yeh et al., (2010)
Adaboost	Zhou and Lai (2016); Alfaro et al., (2008); Sun et al., (2011)
K-nearest neighbors	Chen et al., (2011); Li et al., (2009)
Bayesian network	Sun and Shenoy (2007); Wang et al., (2017)

companies. Lin et al. (2011, 2013) designed a hybrid business failure prediction model using locally linear embedding, an isometric feature mapping algorithm and a support vector machine to predict financial failure of firms in different sectors. Other authors (Yeh et al., 2010; Min et al., 2006) also contributed by applying a hybrid approach combining support vector machines for business failure and bankruptcy prediction.

3.2. Top 10 most productive international journals and total citations (according to number of publications)

As shown in Table 2, the journal *Expert Systems with Applications* is ranked first due to the large number of publications (87 papers) in the corresponding area (3.78 times more than the second ranked journal, occupying 21.07 % of the total 413 papers in this study), with a total of 4484 citations. The second ranked journal is *European Journal of Operational Research* with 23 papers and 1857 citations followed by the third ranked journal *Knowledge-Based Systems* with 1068 citations. Two journals share the eighth position as they have the same number of published papers (5 papers), but it is worth mentioning that the journal *Computers & Operations Research* shows the lowest number of citations (7 citations).

Table 2. Top 10 most productive international journals and total citations.

	Name of journals	Number of publications	Total citations
1	Expert Systems with Applications	87	4484
2	European Journal of Operational Research	23	1857
3	Knowledge-Based Systems	22	1068
4	Applied Soft Computing	12	368
5	Decision Support Systems	11	638
6	Neurocomputing	10	349
7	Journal of Forecasting	9	183
8	Journal of Testing and Evaluation	5	219
8	Computers & Operations Research	5	7
10	Omega-International Journal of Management Science	4	265
10	Information Sciences	4	174
10	International Review of Financial Analysis	4	57
10	Journal of The Operational Research Society	4	39
10	Romanian Journal of Economic Forecasting	4	21

Five journals share the tenth position (4 papers) with different levels of citations. Although the journal *Omega-International Journal of Management Science* has published only 4 papers, it has gained 265 citations. To conclude, it can be observed that, although some journals (as *Omega-International Journal of Management Science* and *Journal of Testing and Evaluation*) have fewer number of publications, they have achieved great influence in the field of bankruptcy research.

3.3. Top 10 most-cited papers of intelligent techniques-based models

To identify the most influential papers in the field of bankruptcy prediction using intelligent techniques, the top 10 most-cited papers have been collected in Table 3 in terms of author's name, title, year of publication and number of citations.

Four of the most cited papers were published during 1994–2000 and six were published during 2001–2012. Among these ten papers, two of them are review studies (the number 1° and the number 9°). Four of them are about the application of a neural network (the number 2°, 5° 6° 8°) and two of them used a support vector machine (the number 3° and 4°). One (the number 7°) applied the rough set theory and the last one (the number 10°) used a hybrid model combining genetic algorithms and a support vector machine.

Ravi Kumar and Ravi (2007) wrote the first ranked paper with 388 total citations. They analyzed studies during the years 1968–2005 and grouped the statistical methods and intelligent techniques used for bankruptcy prediction into nine families. They mainly focused on comparing the source of data sets, financial ratios used, country of origin, timeline of study and accuracy. The second ranked paper used the Fruit Fly Optimization Algorithm to optimize a general regression neural network stating that it achieves good classification and prediction capability (Pan, 2012). The third ranked paper was written by Min and Lee in 2005. They proposed a new support vector machine model and compared it with some models as multiple discriminant analysis, logistic regression analysis and three-layer fully connected back-propagation neural network, concluding that the support vector machine outperforms the other methods.

With respect to the discipline collaboration of authors, the authors of the most cited paper published in *European Journal of Operational Research* are Ravi Kumar and Ravi (2007) and they are both specialized in machine learning techniques and modeling. They published another paper in 2008, entitled "Soft computing system for bank performance

Table 3. Top 10 most-cited international papers.

	Author's name	Title	Year	Citation
1	Ravi Kumar, P.; Ravi, V.	Bankruptcy prediction in banks and firms via statistical and intelligent techniques - A review	2007	388
2	Pan, Wen Tsao	A new Fruit Fly Optimization Algorithm: Taking the financial distress model as an example	2012	342
3	Min, JH; Lee, YC	Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters	2005	332
4	Shin, KS; Lee, TS; Kim, HJ	An application of support vector machines in bankruptcy prediction model	2005	323
5	Wilson, Rl; Sharda, R	Bankruptcy Prediction Using Neural Networks	1994	285
6	Zhang, GQ; Hu, MY; Patuwo, BE; Indro, DC	Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis	1999	251
7	Dimitras, AI; Slowinski, R; Susmaga, R; Zopounidis, C	Business failure prediction using rough sets	1999	247
8	Atiya, AF	Bankruptcy prediction for credit risk using neural networks: A survey and new results	2001	230
9	Dimitras, AI; Zanakis, SH; Zopounidis, C	A survey of business failures with an emphasis on prediction methods and industrial applications	1996	222
10	Min, SH; Lee, J; Han, I	Hybrid genetic algorithms and support vector machines for bankruptcy prediction	2006	204

prediction" in *Applied Soft Computing Journal* (Ravi et al., 2008). Pan, the author of the second most cited paper (Pan, 2012) published in *Knowledge-Based Systems*, is specialized in both the finance and modeling fields. Besides, he has published several modeling papers in the areas of business and finance using intelligent techniques such as genetic programming, fuzzy, data mining, neural network, etc. (Chang et al., 2010; Pan, 2010; Mei and Pan, 2010; Ming-Te et al., 2012). Min and Lee (2005), the authors of the third most cited paper, published their study in *Expert Systems with Applications Journal*. Both authors are active in finance and modeling, which can be observed in their subsequent paper applying a difference approach (data envelopment analysis) to credit scoring in 2008 (Min and Lee, 2008).

4. Bibliometric and network analysis results and findings

In order to observe and assess the trends of publications in this field of research, a bibliometric study regarding intelligent techniques-based bankruptcy prediction models was conducted. VOSviewer software was applied to analyze the academic literature and examine the evolution of published papers, co-authorship, geographical area (country/territory) of authors, co-citation, co-occurrence and text mining in this area.

VOSviewer is one of the widely used computer programs that serves as "visualization techniques that can be used to map the ever-growing domain structure of scientific disciplines and to support information retrieval and classification" (Borner et al., 2005). It was chosen because it pays special attention to the graphical representation of bibliometric maps and it specializes in displaying large bibliometric maps in ways that are easy to interpret and comprehend (Waltman et al., 2010).

Figure 2 shows the evolution in number of publications of intelligent techniques-based models. Comparing with the breakthrough statistical method-based article published by Altman in 1968, the first intelligent technique model was recorded in 1991 and the number of papers initially increased very slowly in the following 17 years until the 2008 global financial crisis. It can be observed that there was a significant increase during 2008–2009, as the number of papers increased from 10 to 29. From then on, interest in the bankruptcy prediction research field grew rapidly, which aligns with the findings obtained by do Prado et al. (2016). The peaks, in terms of the number of papers published were recorded in the years 2011 and 2017 (38 papers in each year, respectively).

4.1. Individual and country co-authorship analysis

Co-authorship research is an important content of bibliometric studies and the level of collaboration is an index to access the status of research in a specific field (Reyes et al., 2016). In this section, it helps to address the collaborative strength and research groups of intelligent technique users in the field of bankruptcy prediction, from the perspectives of individuals and countries.

It is worth defining the difference between the concept of co-authorship and co-citation before moving forward with the interpretation of network of both. Co-authorship analysis aims to investigate the level of research collaborative strength in a specific field (Liao et al., 2018). The term co-author means to write a book, article, report, etc. together with another person or other people (Cambridge University Press, 2008). The co-citation occurs when a

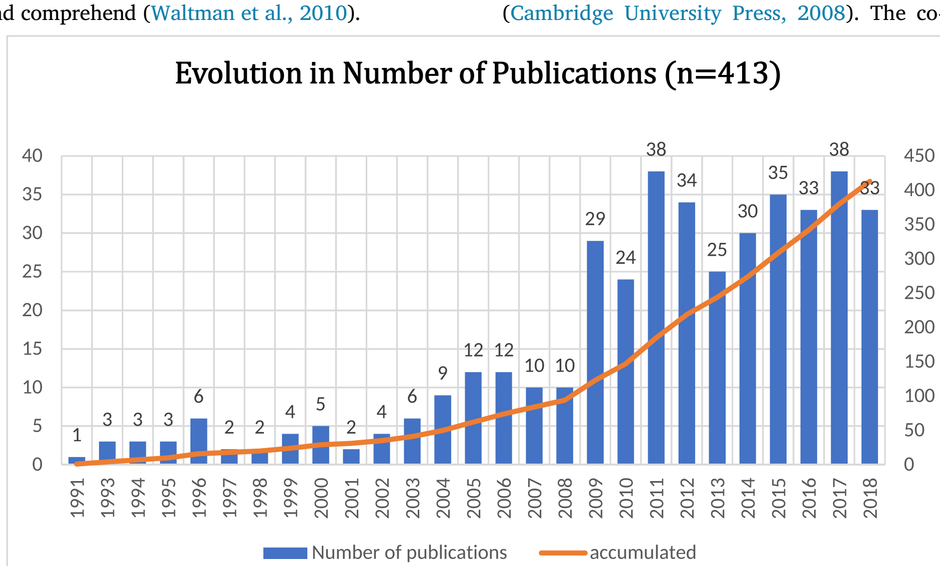

Figure 2. Evolution of publications related to intelligent techniques in bankruptcy prediction.

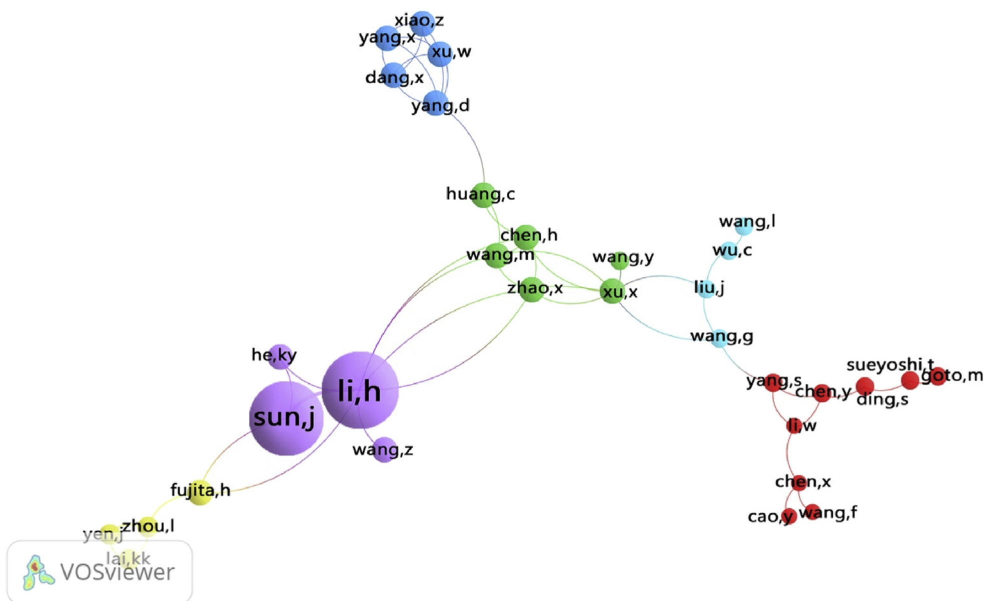

Figure 3. Individual co-authorship map.

citing paper cites any work in reference lists. It is a form of document coupling which is defined as the frequency with which two items of earlier literature are cited together by the later literature (Small, 1973).

4.1.1. Individual co-authorship analysis

An individual co-authorship network was constructed by the VOSviewer software. For the data selection and thresholds, the minimum number of documents of an author is 3, and the minimum number of citations of an author is 0. Among the 777 authors in total, 32 meet the thresholds and their co-authorship network is shown in Figure 3, where each node represents an author, and the lines and distances reflect the relation among them. The distance between two nodes indicates the intensity of the relation, which means when two nodes are closer to each other, they tend to have a strong relation. Authors who have higher weight, in terms of citations and publications, are represented as larger nodes.

A link is a connection or a relation between two items, and the stronger the link between two items, the thicker the line that is used to display the link in the visualization of the map. In Figure 3, links refer to the co-authorship links between researchers. Each link has a strength, indicating the number of publications that two researchers have co-authored (Van Eck and Waltman, 2019). The link strength can be used as a quantitative index to depict the relationship between two items and the total link of a node is the sum of link strengths of this node over all the other nodes (Pinto et al., 2014).

As shown in Figure 3, there are six clusters represented by 6 colors. It can be noticed that the largest two nodes for Li and Sun show the highest weight of citations and total link strength. The rest of the authors display significantly lower weight of citations and publications and less collaboration links, as clusters are distributed separately, and one cluster is barely connected to another. It shows the high concentration in the co-authorship network connected with Li and Sun and a huge difference in terms of the total link strength from the rest of the authors.

Comparing co-authorship analysis in different disciplines, there is no consensus achieved regarding the extent of collaboration networks of researchers. Samitas and Kampouris (2018) analyzed the co-authorship in the field of finance in general and indicated that the collaboration network of authors in the financial market area is greatly integrated. Similarly, Newman (2001) used computer science database and found intensive collaboration in this area as well. Nevertheless, Ortega (2014) analyzed the structural co-authorship network, indicating that

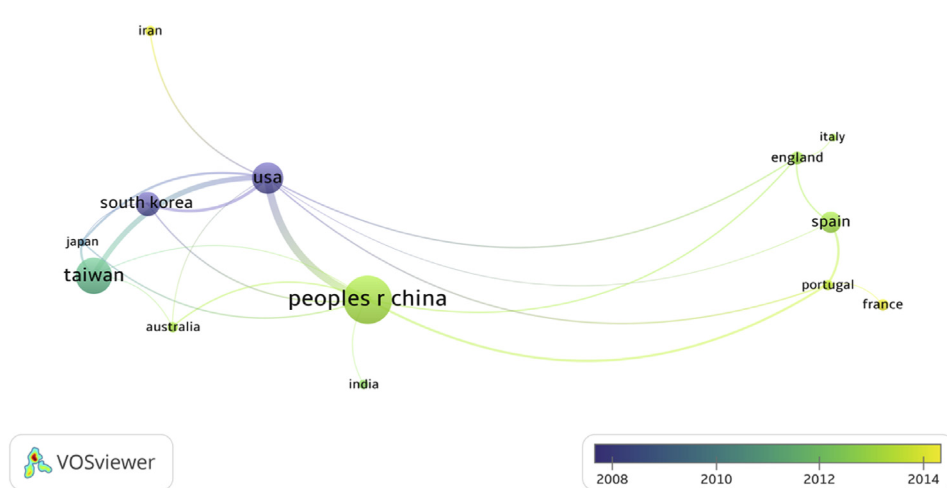

Figure 4. Country co-authorship overlap visualization map.

Mathematics, Social Sciences and Economics & Business present a disperse and little collaborative network, while Physics, Engineering and Geosciences show intense and concentrated networks. In the context of bankruptcy prediction, Shi and Li (2019) carried out the co-authorship analysis without specifying the use of techniques and found low density in a collaboration network among the main researchers, which aligns with the obtained results of this paper. Thus, the authors observed that the collaboration in this interdisciplinary study (business, finance and modelling) is weak among authors, which displays a pattern that is not similar, as suggested by the literature in either finance or modelling disciplines (Samitas and Kampouris, 2018; Newman, 2001).

4.1.2. Country co-authorship analysis

Country co-authorship analysis is an important form of co-authorship analysis, as it can reflect the degree of communication among countries and the most influential countries in a research field (Liao et al., 2018). A country co-authorship network overlay visualization map has been elaborated and shown in Figure 4. For the data selection and thresholds, the minimum number of documents from a country is 10 and the minimum number of citations from a country is 0. Among the 52 countries, there are 13 that meet the thresholds. It is worth mentioning that the overlay visualization is according to the average publication year, where the colors of items are determined by the score ranging from blue (lowest score) to yellow (highest score).

As we can see in Figure 4, there are several big nodes on the map that indicate countries and regions with the largest number of publications: China, the USA, Taiwan area, South Korea and Spain. Research centers with the highest number of total links in this field are the USA and China. It should be stated that on this map, the size of a node depends on the number of publications. That is to say, although the USA is not presented as the largest node on the map, it has the highest total link strength for the widest connection and collaboration with various countries and regions of different continents. Spain has the largest node in Europe and is linked closely with other European countries, such as England, France and Portugal. This observation displays that being geographically close tends to enhance the authors' cooperative and collaboration relationship in this area of study.

Regarding the average publication year as displayed in Figure 4, both Iran and France (colored yellow) present a high volume of publications after 2014, which may indicate scholars in these two countries show an increasing interest in this research topic in the most recent years. Both the USA and South Korea (colored blue) exhibit a peaking publication trend before year 2008, which may reveal their historical contribution and importance to this field. China, Australia, India and other European countries (colored green) show a notable increasing number of publications between 2010-2012, which confirmed the discovery of an immediate growing trend in the number of publications after the 2008 financial crisis in this field (Yu et al., 2010; do Prado et al., 2016).

4.2. Reference Co-citation analysis

Co-citation is a form of document coupling which is defined as the frequency with which two documents are cited together by other documents (Small, 1973). A co-citation map consists of a set of nodes representing journal articles and a set of edges representing the co-occurrence of nodes and/or articles in the reference list of papers of that map (Fahimnia et al., 2015). Therefore, the authors conducted the co-citation analysis accordingly regarding the literature on intelligent techniques for bankruptcy prediction.

A reference co-citation map based on bibliographic data was created in VOSviewer (see Figure 5) and the minimum threshold setting for number of citations of an author has been set at 65, a threshold that only 14 of the 9496 authors meet.

In Figure 5, the authors find that the largest node is Altman (1968), whose paper entitled ˙Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcÿ firstly introduced the multivariate analysis known as Z-score. It has 286 co-citations, which means that among the total literature regarding bankruptcy prediction using intelligent-based techniques (413 papers), 70% of them have cited this article. As a result, it has the strongest total link strength. The second largest node is Ohlson (1980). He created an O-score for bankruptcy prediction as an alternative to the Altman Z-score. The third ranked study is the article published by Beaver in 1966, in which he used univariate analysis to study the ratios in order to test their predictive ability for classifying failed and non-failed firms. The second and third ranked paper (Ohlson, 1980; Beaver, 1966) have fewer citations and total link strength compared with the first one, but the impact in terms of co-citation is still influential. It can be noticed that among the top 14 studies in the ranking list, all had been published before 2008, which indicates that most papers published during the last ten years (after 2008) have not generated great impact in this research field.

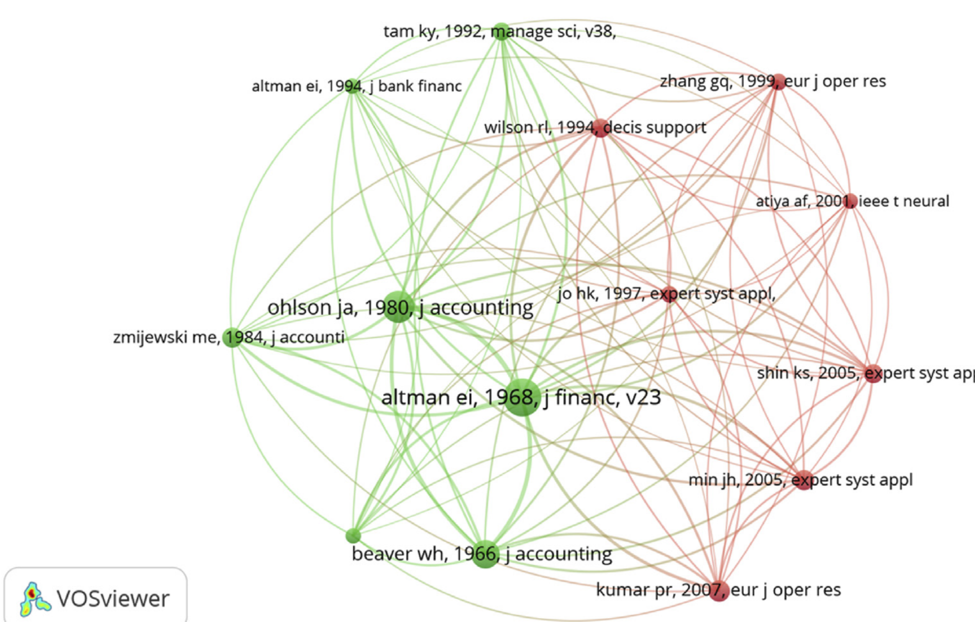

Figure 5. Reference co-citation map.

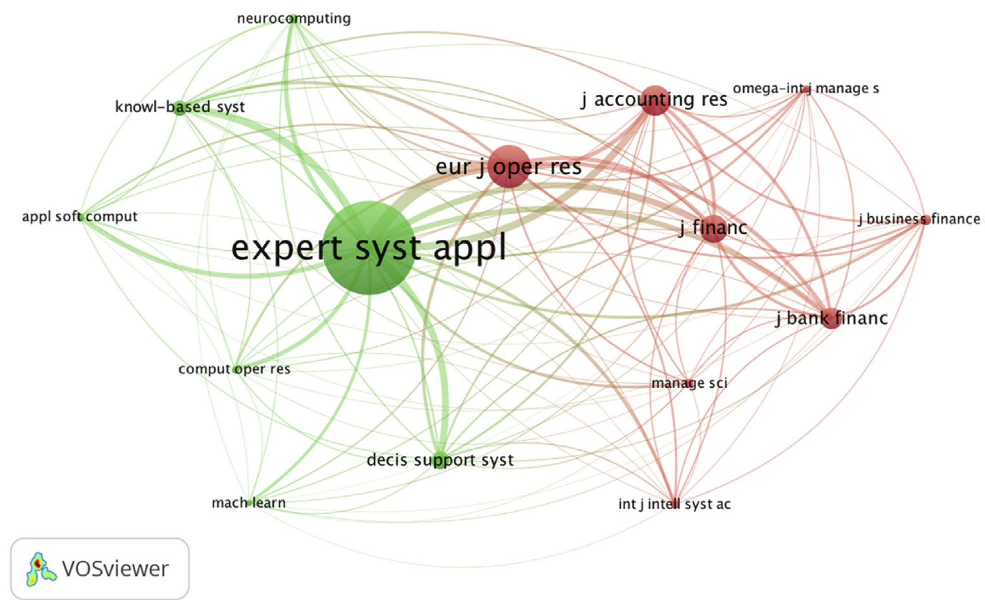

Figure 6. Journal co-citation map.

4.3. Journal co-citation analysis

The journal co-citation analysis can reveal the overall structure of the subject and the characteristics of a journal (Liao et al., 2018). The distance between two journals in the visualization approximately indicates the relatedness of the journals in terms of co-citation links. In general, the closer two journals are located to each other, the stronger their relatedness. The strongest co-citation links between journals are also represented by lines (Van Eck and Waltman, 2019). Figure 6 shows the journal co-citation network with minimum number of citations of a journal set at 150. Among the 4218 sources, 15 journals meet the threshold. The size of the nodes represents the activeness of the journal and a smaller distance between two nodes represents a higher co-citation frequency.

A ranking according to co-citation frequency of these fifteen journals with total link strength is presented in Table 4. The number of co-citation frequency is calculated according to the reference list of papers within the same dataset. More specifically, journal co-citation analyzes how many times one journal is cited together with another journal by the same document (Van Eck and Waltman, 2019). For instance, the first ranked journal *Expert Systems with Application* was co-cited (be cited together with another journal by one paper) 2040 times. There are two colors distinguishing the two assigned clusters. It can be noticed that the green cluster contains seven nodes, which are mainly within the computer science area. On the other side, the red cluster contains eight nodes. These journals are principally in the areas of business, management and accounting/economics, econometrics and finance/decision sciences. According to the ranking by total link strength and citations, the first journal *Expert Systems with Applications*, which is a computer science and engineering journal, is far ahead of the rest of the journals in terms of both citations and total link strength. Among these fifteen most co-cited journals, the computer science discipline and management and finance discipline have almost equal distribution in terms of number of journals (seven journals and eight journals respectively).

Table 4. Top 15 journals with total link strength (according to co-citation frequency).

Name of Journal	Subjects	Co-citation frequency	Total link strength
1 Expert Systems with Applications	Computer science/Engineering	2040	33518
2 European Journal of Operational Research	Decision sciences/Mathematics	946	19447
3 The Journal of Accounting Research	Business, Management and Accounting/Economics, Econometrics and Finance	676	12625
4 The Journal of Finance	Business, Management and Accounting/Economics, Econometrics and Finance	603	10756
5 The Journal of Banking and Finance	Economics, Econometrics and Finance	478	9975
6 Decision Support Systems	Arts and Humanities/Business, Management and Accounting/Computer Science/Decision Science/Psychology	386	9083
7 Knowledge-Based Systems	Business, Management and Accounting/Computer Science/Decision Sciences	352	8707
8 Journal of Business Finance and Accounting	Business, Management and Accounting/Economics, Econometrics and Finance	244	5654
9 Management Science	Business, Management and Accounting/Decision Sciences	199	4206
10 International Journal of intelligent systems in accounting finance and management	Business, Management and Accounting/Economics, Econometrics and Finance	198	4822
11 Neurocomputing	Computer Science/Neuroscience	197	4894
12 Applied Soft Computing Journal	Computer Science	186	4825
13 Computers and Operations Research	Computer Science/Decision Science/Mathematics	178	4770
14 Omega-International Journal of Management Science	Business, Management and Accounting/Decision Sciences	167	4233
15 Machine Learning	Computer Science	151	3201

4.4. Co-occurrence analysis

The authors construct a map based on a co-occurrence matrix, dividing keywords into three clusters (see Figure 7) with the minimum number of occurrences of a keyword set at 30. Among 1288 keywords, 15 meet the threshold; they are presented as 15 nodes. It should be mentioned that, due to the difference in ways that authors describe a term (like plural or single, with or without hyphen), one item that was expressed in distinct ways may be counted separately. In order to obtain more precise results, the authors used the thesaurus function of VOSviewer and successfully combined the different formats of keywords. The keyword "bankruptcy prediction" has the highest occurrence and total link strength. Other keywords with a high occurrence include "neural networks", "discriminant-analysis", "financial distress prediction" and "classification". The node, bankruptcy prediction, displays thick lines connecting with discriminant analysis, financial distress, classification, and neural network.

4.5. Text mining analysis

In order to better understand the over-explored and under-explored research areas, the authors use the text mining functionality of VOSviewer as it can provide support for creating term maps based on a corpus of documents. A term map is a two-dimensional map in which terms are located in such a way that the distance between two terms can be interpreted as an indication of the relatedness of the terms (Van Eck and Waltman, 2019). In this case, an overlay visualization term map has been created, based on terms extracted from a title and abstract of a corpus of academic publications in the field of intelligent techniques applied for bankruptcy prediction (see Figure 8). A full counting method has been chosen and the minimum number of occurrences of a term is configured to 50. Of the 7464 terms, 35 meet the threshold. After a relevance score calculation, which enables the authors to select the most relevant terms, 10 terms have remained.

In Figure 8, the smaller the distance between two terms, the stronger the terms are related to each other. The relatedness of terms is determined based on co-occurrence in documents. "The higher the occurrence of an item, the larger the node of the item" (Van Eck and Waltman, 2019). It can be observed that prominent terms in this area include "bankruptcy prediction", "financial distress prediction", "support vector machine", "neural network", and "case-based reasoning". The authors also noticed papers that used a neural network and multivariate discriminant analysis were published intensively before 2008. These two widely applied methods have been studied and explored over a long period of time. Since 2010, case-based reasoning has been applied much more frequently by researchers in this field, followed by a support vector machine and data envelopment analysis models, which were mainly developed after 2012. The decision tree presented in yellow reveals that scholars paid more attention to this technique since 2014.

Among the twelve artificial intelligent metrics discussed in this present study, only six of them are shown on the term map: support vector machine, neural network, case-based reasoning, data envelopment analysis, genetic algorithm, and decision tree. It should be noted that three of them display relatively low occurrence: data envelopment analysis, genetic algorithm and decision tree. That is to say, in the field of intelligent techniques applied to bankruptcy prediction, support vector machine, neural network and case-based reasoning are explored more than other methods. The rest of the methods, such as fuzzy, rough set, data mining, Adaboost, K-nearest neighbors, and Bayesian network may be under-explored and expected to be adopted more in the future.

5. Conclusions, limitations and future research

5.1. Conclusions and implications

A bibliometric study is carried out regarding the intelligent techniques used for bankruptcy prediction, with the objectives of identifying and assessing the trends of research in the area and presenting the evolution of published papers, co-authorship, geographical area (country/territory) of authors, co-citation, co-occurrence analysis and text mining. Some conclusions can be drawn.

First, since the first intelligent technique bankruptcy prediction paper was collected in Web of Science in 1991, the number of publications increased very slowly until 2008 when a significant increase can be observed during 2008–2009. Since then, the interest in the bankruptcy prediction research field has grown rapidly. This booming trend in terms of number of studies coincides with the collapse of the major economies due to the financial crisis from 2007-2008 and it marked great demand for applications in business failure prediction applying artificial intelligent or machine learning techniques so as to process large amounts of data (do Prado et al., 2016).

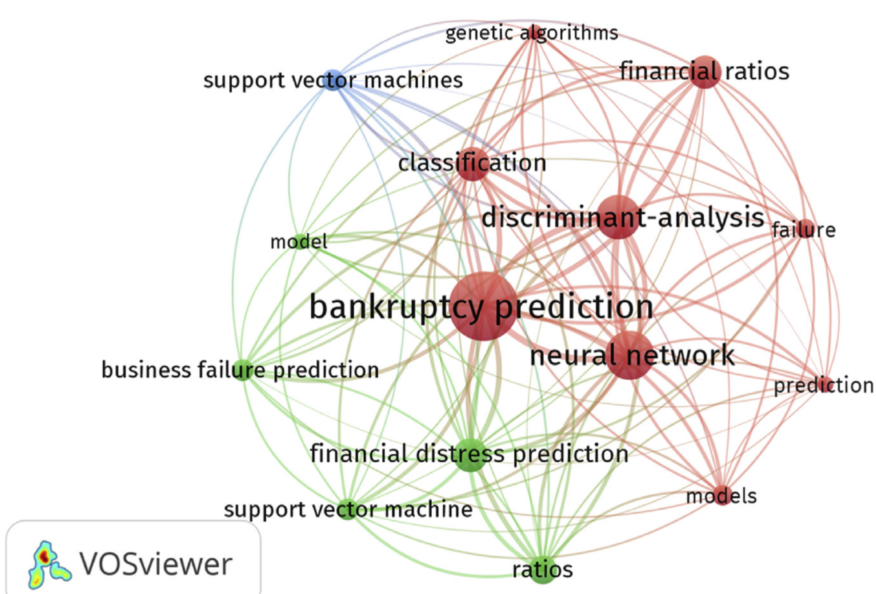

Figure 7. Keyword co-occurrence map.

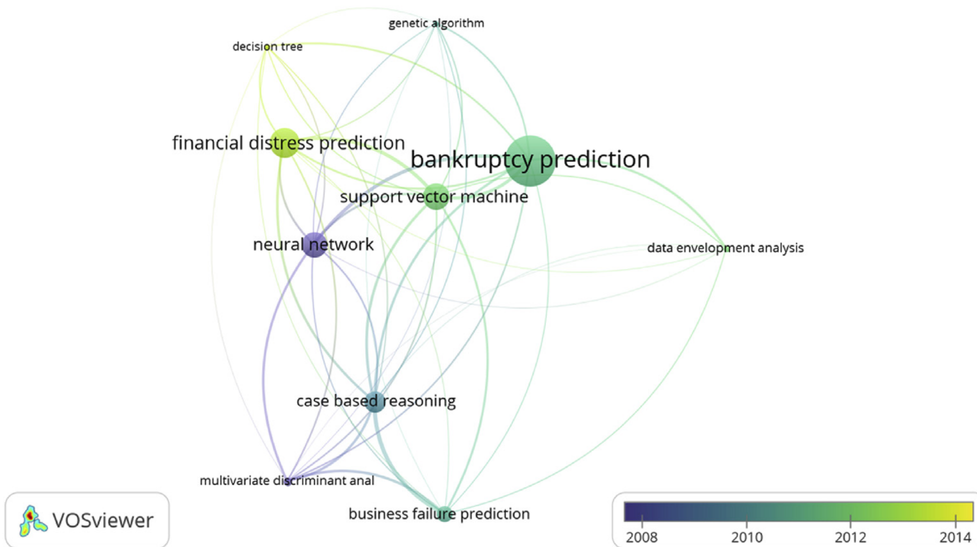

Figure 8. Term map based on publications.

Second, the collaboration among authors is weak, especially at the international level. Among the most important authors of this research topic, Li and Sun (first and second most important authors with highest weight of citations, number of publications and total link strength) are closely linked to each other for collaborating together in publishing a great number of articles regarding bankruptcy prediction. However, main authors in this area barely collaborate with other groups, which reveals a high concentration in the co-authorship network connected between Li and Sun and dramatic difference in the total link strength from the rest of the authors. As for the country co-authorship, the most influential countries and regions, in terms of amount of publication, are China, USA, Taiwan, South Korea and Spain. The results indicate that geographically nearby countries tend to have a relatively higher level of collaborative and cooperative relationships in this area of study. Besides, the authors observe a diverse publication timeline among different countries. Researchers from the USA and South Korea published intensively before 2008, while scholars from Iran and France showed publication peak after 2014. China, Australia, India and other European countries demonstrate a growing tendency in publications from 2010, which aligns with the findings in the literature (Yu et al., 2010; do Prado et al., 2016) that more attention had been placed in bankruptcy prediction after the 2008 crisis.

Third, through the analysis of reference co-citation, the most frequently cited papers are Altman (1968), Ohlson (1980) and Beaver (1966). Although none of their work is based on an artificial intelligent-based approach, due to the fact that all aforementioned work are pioneer studies in the bankruptcy prediction field, the posterior authors tend to cite them in their papers with high frequency. In respect to the journal co-citation network, *Expert Systems with Applications* as a computer science and engineering journal, stood out among the rest of the journals in terms of both citations and total link strength. Relating discipline and journals, it is shown that computer science journals and management and finance journals have almost equal discipline distribution.

Fourth, the co-occurrence analysis reveals that the most frequently used keywords are: “bankruptcy prediction”, “neural networks”, “discriminant-analysis”, “financial distress prediction” and “classification”. The majority are related to the subject, except that discriminant analysis and neural network are methods, indicating the importance of these two techniques (statistical and artificial) in this field (Gissel et al., 2007).

Fifth, text mining is conducted by creating an overlay visualization term map based on publications regarding intelligent techniques applied in bankruptcy prediction. Observing the terms on the map, neural network and multivariate discriminant analysis have been studied and explored over a long period of time. Since 2010, case-based reasoning had been applied much more frequently than the support vector machine and data envelopment analysis models, which were mainly developed after 2012. The most recent studied metric is decision tree (after 2014). The rest of the methods, such as Fuzzy, Rough set, data mining, Adaboost, K-nearest neighbors, and Bayesian network, display a low occurrence, which reflects that the aforementioned metrics may be currently under-explored, and researchers can capture this niche for future studies.

The major contribution of this study is to bring new knowledge and key insights into the bibliometric trends of intelligent techniques applied in bankruptcy prediction study. Artificial intelligent techniques are now serving as important alternatives to statistical methods and demonstrate very promising results. Therefore, it is necessary to understand the trend in bankruptcy prediction studies and identify the intellectual structure aiming to discover new niches in this area for future research. Secondly, the results of this paper provide a comprehensive view of interdisciplinary research on bankruptcy modelling in finance, business management and computer science fields that have addressed this subject since 1968. This approach broadened the current understanding of bankruptcy prediction modelling, providing further insights in applying some under-explored alternative machine learning techniques. Thirdly, the study contributes to the theoretical development in this field as it can help graduate students and junior scholars to identify main research topics and discover possible opportunities within this field (Koseoglu, 2016). Also, senior researchers from this area or other disciplines can have an overview of the evolution in this research area and dedicate future research efforts in under-explored niches.

The implications of this paper shed light on identifying under-explored areas of study and provide new insights into the existing gaps on which future studies should focus (Saggese et al., 2015). It suggests that some intelligent techniques in bankruptcy prediction studies are not sufficiently explored. However, such techniques may outperform when dealing with large data, which is crucial nowadays in management and decision making for corporate firms. In fact, artificial intelligence, as a research tool, is becoming more and more popular in many disciplines, and this gap encourages scholars and practitioners to consider the use of intelligent-based techniques as alternatives in their investigations and analysis for decision-making. Meanwhile, policy makers can also benefit from the accuracy and validity of applying machine learning methods to detect financial distressed firms in their reporting so as to proactively design regional or national policies for different industries accordingly.

5.2. Limitations and future research

Although the findings of this study can be helpful for researchers in this area, some limitations should be addressed. One limitation of bibliometric methods is that the corresponding quantitative approach does not reflect the context and the intention of why authors refer to other studies, so that bibliometric analysis cannot capture the complex nature of citing behavior thoroughly (Vogel and Guttel, 2012). The second limitation lies on the restriction to one scientific database (the Web of Science). Therefore, a bibliometric review based on other databases can be carried out in future research.

The third limitation is related to keywords collection, where objective quantitative co-occurrence measures can be adopted. In concrete, future study can include an automatic process where articles are crawled based on meta keywords and a co-occurrence/LDA-topic definition list, so as to collect topic keywords from literature databases in a forward-backward search manner.

Additionally, it is also recommended that future studies can focus on the suitability of different artificial intelligence or machine learning algorithms for bankruptcy prediction and further evaluating their performance.

Moreover, greater dedication can address the observation of weak collaboration among authors, especially at the international dimension, in this research field. The issues raised are that weak authorships are due to some geographic limitations or there might be other important factors involved. In addition, the future authorship or co-authorship research in the bankruptcy prediction field may consider authors' affiliations and/or gender (Koseoglu, 2016), which are not explored so far.

Notwithstanding these caveats, this bibliometric analysis provides new insights in identifying the under-explored niches within the bankruptcy prediction field and display the evolutionary pattern of the existing studies in the literature.

Declarations

Author contribution statement

Y. Shin, X. Li, F. Campa-Planas: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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