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Review

Fuzzy Logic and Its Uses in Finance: A Systematic Review Exploring Its Potential to Deal with Banking Crises

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Abstract: The major success of fuzzy logic in the field of remote control opened the door to its application in many other fields, including finance. However, there has not been an updated and comprehensive literature review on the uses of fuzzy logic in the financial field. For that reason, this study attempts to critically examine fuzzy logic as an effective, useful method to be applied to financial research and, particularly, to the management of banking crises. The data sources were Web of Science and Scopus, followed by an assessment of the records according to pre-established criteria and an arrangement of the information in two main axes: financial markets and corporate finance. A major finding of this analysis is that fuzzy logic has not yet been used to address banking crises or as an alternative to ensure the resolvability of banks while minimizing the impact on the real economy. Therefore, we consider this article relevant for supervisory and regulatory bodies, as well as for banks and academic researchers, since it opens the door to several new research axes on banking crisis analyses using artificial intelligence techniques.

Keywords: fuzzy logic; finance; banking; banking crisis management

1. Introduction

Fuzzy logic has been successfully applied in the field of finance due to its ability to address imprecise, incomplete and vague data. This methodology has also been used in the field of banking, although to a lesser extent, with particular relevance to areas such as risk management and credit scoring. However, with regard to the specific field of banking crises, the footprint of fuzzy logic has been almost non-existent. This absence could be seen as a contradiction, given the properties of fuzzy logic, which seem to fit particularly well in complex and uncertain environments. Since the global financial crisis, preventing banking crises and establishing banking resolution strategies to avoid the use of public money to rescue banks have been the main priorities within the area of finance. This priority suggests the importance to both academia and practitioners of exploring this topic through different approaches. Introducing fuzzy logic to the analysis of banking crises could represent an important step towards addressing and resolving banking crises more efficiently.

Banking crises are usually associated with significant, negative impacts on growth, output levels and asset prices, tending to lead to lower tax revenues, higher public expenditures and increased public debt [1]. In accordance with this relationship, we acknowledge the urgency to develop new tools to prevent and manage banking crises. When working with banking crises, we highlight four areas on which research has focused to date and to which the use of fuzzy logic could add value, including (i) preventing banking crises; (ii) managing banking crises and assessing their impact on the economy; (iii) defining a strong institutional and regulatory framework; and (iv) banking resolution. As a pioneering study proposing the use of fuzzy logic in the field of banking crisis analysis, this work explores in detail the potential uses of fuzzy logic in these four areas.

Of the four points mentioned above, banking resolution is the area in which regulators and governments are currently exerting their strongest efforts. Banking resolution is understood as the restructuring of a bank led by a resolution authority, using one or more resolution tools while following several principles. These principles include safeguarding public interests, preserving the bank's critical services to the economy, ensuring financial stability and minimizing the impact on taxpayers [2]. The impact of the recent financial crisis on the global economy pushed the Basel Committee on Banking Supervision (BCBS) to review and strengthen the Basel accords. This decision led to the publication of Basel III [3], which was transposed into European law by the capital requirements regulation (CRR), as well as the capital requirements directive IV (CRD IV) and the bank recovery and resolution directive (BRRD). In particular, the BRRD addresses the resolution of troubled banking entities and proposes the bail-in tool as one of the key elements for resolving bank crises [4]. The bail-in tool is one of the key instruments of the new resolution framework, forcing banks to absorb any potential losses with capital and debt instruments and to recapitalize the bank if needed to avoid the use of public funds to rescue the entity. To ensure the credibility of the bail-in tool, all European banks are required to increase their loss absorption requirements through the minimum requirement of eligible liabilities (MREL), which is a concept similar to the well-known total loss absorption capacity (TLAC) with which global systemic important banks (G-SIBs) must comply. Although this paper is written from a European regulatory viewpoint, most of its conclusions are also useful from a broader international perspective.

Given the relevance of the bail-in tool to the new banking regulatory landscape, it is important to understand its potential spill-over effects on the real economy. As mentioned above, we propose the exploration of this topic later in this work. Only after the risk transmission mechanism between the banking sector and the real economy is well understood will it be possible to affirm that post-global financial crisis regulation is effectively improving the soundness of the European economy. However, this stability does not yet exist, and the new European resolution framework remains to be tested. The importance and complexity of this topic justify the need to search for new techniques to improve the knowledge on this subject. In accordance with this need, in an attempt to apply nonlinear advanced methods to assess the potential impact of the new resolution framework on the real economy, we have identified fuzzy logic as an adequate tool to perform such tasks. However, to the best of the authors' knowledge, there is no available, updated, comprehensive literature review of fuzzy logic in the field of finance.

The initial hypothesis of this work is, therefore, that fuzzy logic is a solid tool that can be applied in finance, banking crisis and banking resolution analyses due to its ability to manage imprecise, incomplete and vague data.

Several works explore the links between fuzzy logic and mathematics. Some studies are focused on this relationship from a historical perspective [5,6], other studies elaborate on the formal mathematic framework of the Fuzzy Sets Theory [7,8], while other studies take a step into the links between mathematics and fuzzy logic in practical applications [9].

In addition to the academic works devoted to exploring the generic links between mathematics and fuzzy logic, there are some works focused on analysing the fuzzy mathematics of finance. These works seek to show the relevance of fuzzy logic as a useful method to deal with financial research. In particular, one of the first studies suggesting a potential successful application of fuzzy logic techniques to finance proposes using fuzzy alternatives to classic financial data [10]. Other works focused on developing fuzzy mathematics in finance followed, including a generalization of the framework for fuzzy mathematics in finance [11]. From that point, as our analysis shows, the number of articles taking advantage of the foundations of fuzzy mathematics in finance increased exponentially.

In line with the above, the goal of this work is to critically examine fuzzy logic as an effective, useful method to be applied to financial research and, specifically, to analyse banking crises and resolution events. For these reasons, we conducted a bibliometric and literature review of a large group of articles indexed in Web of Science and Scopus, in which fuzzy logic has been applied to the financial field. Additionally, we discuss the potential applications of fuzzy logic in four specific areas, including the prevention of banking crises, assessments of the impact and management of banking crises, institutional settings and banking regulation, as well as banking crisis resolution.

This paper starts with a brief introduction, followed by a description of the methods. The main findings obtained are presented as bibliometric and systematic analyses results. Section 4 elaborates on the findings and provides related discussions, paying specific attention to the use of fuzzy logic in the field of banking crises. Section 5 concludes with the main findings of this study including the contributions of this work to the academia and to practitioners, and the limitations faced.

2. Methods

2.1. Fuzzy Logic

The Fuzzy Sets Theory was initially introduced in 1965 by L. A. Zadeh and can be described as a logic for dealing with uncertainly and imprecision [12]. The term "fuzzy" is appropriate to describe a mathematical environment where there are no well-defined boundaries between the variables under study [13]. The goal of fuzzy logic is to express the vagueness and imprecision of human thinking with the appropriate mathematical tools. The human way of thinking and reasoning is not binary, where everything is either yes (true) or no (false), and thus Boolean logic is not always the most efficient way to deal with real problems that human beings have to face [14]. Concepts like "danger–safe" or "hot–cold" cannot be sharply defined, and even human beings will use fuzzy language expressions like "very", "a little" or "a lot" to define temperature or dangerous situations.

The fuzzy logic theory is based on the concept of "fuzzy sets", which is a generalization of the classical set theory [14]. A crispy set can be defined by a mathematical function that only accepts binary values, meaning that it can only represent elements that fully belong to the set (represented by the value 1) and elements that do not belong to that set (represented by 0). A fuzzy set is defined by a membership function that allows every element to be represented by a different "grade of membership" specifying to which extent the element belong to the set. It is important to observe that the grades of membership are subjective and rely on the context. To illustrate this, consider a cow, which could be labelled as a "big animal" if the universe of disclosure is "farm animals", but probably will be considered a "medium-size animal" if elephants and hippopotamuses are added to the universe of disclosure.

A fuzzy set is defined from the universe of discourse, which constitutes the reference set and it cannot be fuzzy. Being $U = \{x1, x2, ..., xn\}$ the universe of disclosure, a fuzzy set F ($F \subset U$) is always defined as a set of ordered pairs, the second part of the pair being the degree of membership $\{(xi, \mu F(xi))\}$ and μA will always take a value between 0 (non-belonging to the set) and 1 (fully belonging to the set).

Various fuzzy sets tend to be defined on the same universe of disclosure forming a partition of the universe. At this point, a linguistic expression will need to be used to label the different fuzzy sets. This is known as the linguistic variable and can be defined as a variable whose values are words instead of numbers. L.A. Zadeh defines a linguistic variable by a quintuple (X,T,U,G,M) where X is the name of the variable, T are the linguistic values of the variable, U is the universe of disclosure, G is the rule to give a name to the terms in T, and M a semantic rule which associates with each linguistic value X its meaning [15].

The mathematic foundations of fuzzy logic include basic concepts previously described, such as fuzzy sets, membership functions and the basic fuzzy operations (intersection, union and complement). There is a large number of academic papers using fuzzy logic in theoretical fields of traditional mathematics, such as topology, differential equations, probability theory, mathematics and statistics, or measure and integral theory, which shows the strong link between mathematics and fuzzy logic [8].

2.2. Systematic Review Methodology: ProKnow-C

Several authors have conducted literature reviews on fuzzy logic applied to different knowledge fields, such as decision making [16], social policy [17] and medical sciences [18], showing a wide range of applications in which fuzzy logic can be used. However, literature reviews of the use of fuzzy logic in finance published so far are not complete nor comprehensive enough, with some examples focusing on the application of neuro-fuzzy systems in business [19] or the uses of fuzzy logic in insurance [20]. It is noted that some interesting books on the subject exist, although they focus on particular applications rather than providing a general overview of fuzzy logic applied to finance [21–23].

There are several ways to approach a literature review, with theoretical background literature reviews being the most common, and hence the approach followed in this study. In particular, two essential forms of analysing the literature regarding a given topic are found: within-study literature analyses and between-study literature studies [24]. The former refers to analysing a specific work while the latter involves contrasting the content of several sources. Some of the benefits of a theoretical background literature review include highlighting what has been explored in a given area and what is still pending to be explored, identifying links between key concepts and listing the main analysis and methodologies that have been successfully used [25].

Rigorous literature reviews must be systematic in following a methodological approach [26]. The method used was based on the knowledge development process-constructivist (ProKnow-C) [27], a technique that describes a process analogous to a protocol. Hence, this study included an extensive search across different databases to conduct a systemic analysis to obtain information on the content of the different papers that comprise our final portfolio. A bibliometric analysis was conducted to obtain relevant data on publication trends, the most relevant authors and journals on the topic. This method has been widely applied in the literature reviews on different topics in recent years [28–30]. One of the main advantages of the methodology chosen is that it is particularly effective to deal with descriptive and exploratory tasks. Therefore, ProKnow-C is especially useful for theoretical background literature reviews such as the one developed in this analysis.

The eligibility criteria focused on identifying all relevant academic articles that somehow apply fuzzy logic to solve problems linked to the field of finance. Thus, it is important to define exactly what is meant by “finance” in this work, given that this subject is broad and therefore difficult to precisely define. Among the many definitions of finance, Drake and Fabozzi [31] defined finance as the application of economic principles to decision making that involves the allocation of money under conditions of uncertainty. The study of finance is usually divided into four main categories: corporate finance, financial markets, public finance, and personal finance. In this study, we especially focus on the fields of corporate finance and financial markets because these fields are those in which fuzzy logic has been the most frequently applied to date.

The information sources considered were the Web of Science and Scopus databases. The choice of Web of Science and Scopus was motivated by the academic acknowledgement of these databases as being two of the main academic literature collections [32,33].

The search was defined as a Boolean combination of key words grouped on two main axes, namely “fuzzy logic” and “finance”. The selected key words were deliberately vague to increase the number of results in the searches.

The study selection was carefully conducted as follows. We introduced our queries of the database already defined and filtered the output by type of source, excluding all documents except academic journals and books. Then, we identified the duplicated records and excluded them from our portfolio. The records remaining were then assessed manually based on the title, abstract and full text, in that order. A full-text review at this point was also a method to reduce the risk of bias in individual studies, as it allowed better direct scanning of the articles. Another way to control risk of bias, but across studies, was the inclusion of studies from the list of references as an attempt to not exclude all grey literature without lowing the quality by considering records from the main databases. Additionally, articles with no citations in the Google Scholar database were removed. Given the small number of citations, they cannot be considered relevant from an academic viewpoint. Finally, all the references included in the final group of records were analysed with the same criteria mentioned above.

This work focused on the following data items: the number of publications per year, the most prominent journals on the topic, and the most active authors. Finally, the synthesis of the results is depicted in five main proposed areas: financial markets (forecasting, valuation financial assets, portfolio management, and trading and decision making), corporate finance (fundamental analysis, banking, insurance, investments and decision making, and others), public finance, personal finance and others.

One of the disadvantages of the methodology is that given the large number of articles on fuzzy logic applied to economics and the social sciences, settling boundaries between each and defining the eligibility criteria was a manual and complex task. As a result, some articles could have been involuntary omitted. However, our final portfolio is large enough to represent a comprehensive list of articles applying fuzzy logic in finance. It is also a large sample that helps to identify areas in which more research has been accomplished and to understand why and which methods seem to be more effective in the field of finance.

We deliberately excluded conference proceedings from our bibliographic portfolio, seeking to increase the scientific relevance of the sample under study, rather than the quantity of all the documents analysed. Both approaches are generally accepted; however, it is frequently perceived that conference proceedings are less mature than academic papers [34,35].

3. Results

The purpose of this section is to present the results of the analysis of the study characteristics (included in the bibliometric characteristics) and the content of the 795 final articles included, corresponding to the results of individual studies in the portfolio. We first present an analysis of the bibliometrics of the portfolio, with special attention paid to the recent trends in numbers of publications per year, as well as the most prominent journals and authors on the subject. Then, a section focused on the content of the articles follows.

Prior to presenting these results, we describe the process followed to define our final portfolio. After performing the search in both databases, filtering by type of source and excluding all documents but academic journals and books, we obtained a total of 10,941 records (5289 from Web of Science and 5652 from Scopus). Before starting the manual filtering process by the title and then by the abstract, the next step was to remove duplicates. A total of 2952 documents were found in both databases; therefore, we ended up with an initial gross bibliographic portfolio of 7985 records. The 7985 articles were then manually filtered first by title adequacy, and then followed by abstract and full-text alignment with the subject of interest. After conducting these steps, we obtained 931 papers in our final portfolio. However, all articles with no citations in the Google Scholar database were removed because, given the small number of citations, they cannot be considered relevant from an academic viewpoint. Following this approach, the number of articles decreased to 768. For the final bibliographic portfolio, all of the references included in each of the 768 papers were analysed to assess whether they could be included in the final portfolio. This increased the number of eligible papers by 27, resulting in a final portfolio of 795 articles. A flow diagram showing this study selection process at each stage is presented in Figure 1.

This section elaborates on key aspects, including the particular topics within the field of finance in which fuzzy logic has been more commonly applied to date and the combination of methods seen with greater frequency.

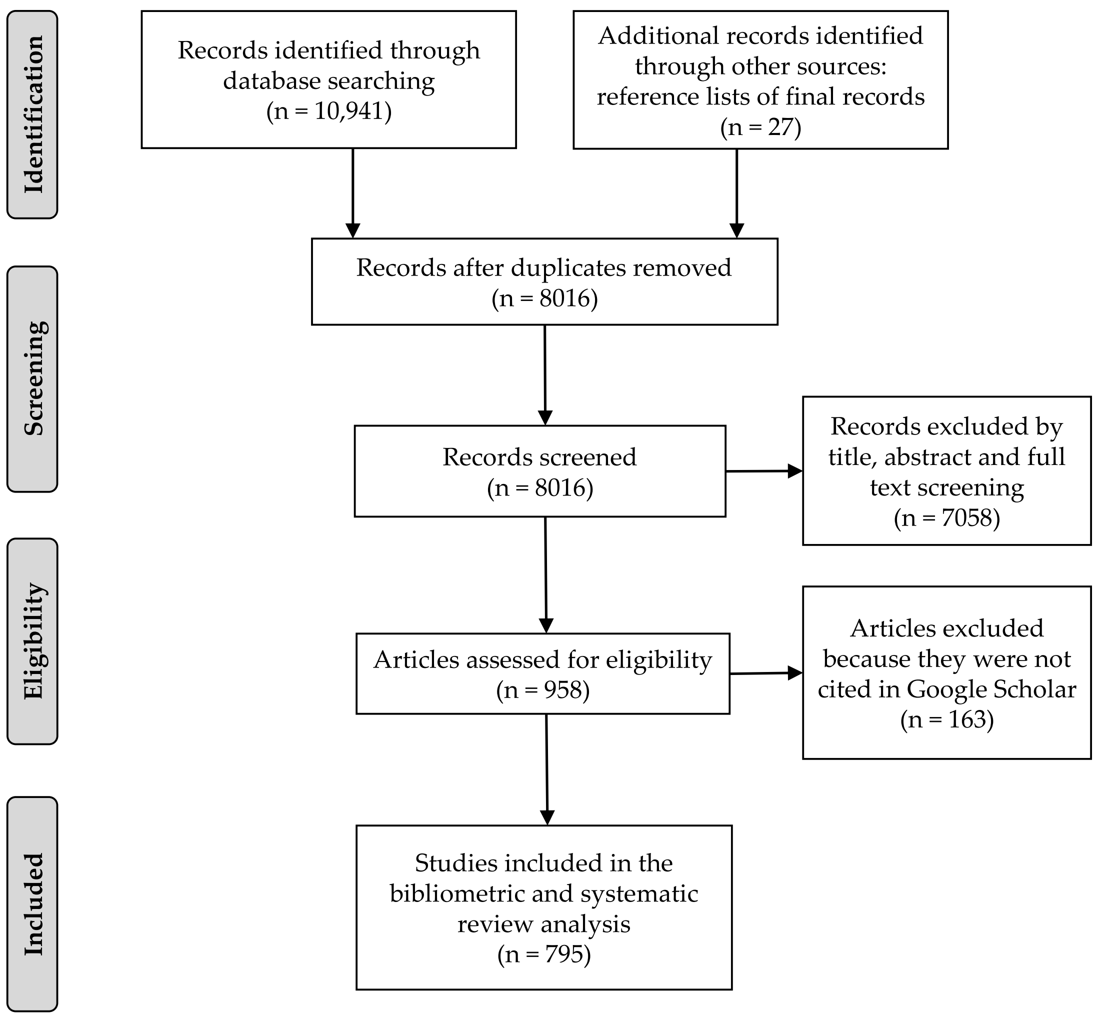

Figure 1. Flow diagram of the study selection process. Source: PRISMA Model [34].

3.1. Bibliometric Analysis

Fuzzy logic was introduced to the financial field by Buckley, who explored the mathematics of fuzzy logic in finance, applying them to the study of the time value of money [10]. Following the success of Buckley's work, Calzi [11] continued exploring the topic, widening the scope of applications to which fuzzy logic can be applied in the financial field. Several studies followed, investigating the net present value of investments [35,36]. More recently, other authors have also contributed to increasing the literature with studies related to bankruptcy forecasting, stock market prediction or portfolio management optimization, among others [37–39]. However, as shown in Figure 2, it was not until recently that the research on finance using fuzzy logic truly became sizeable. In accordance with this development, the analysis of the publications per year reveals that, from the mid-2000s, the number of articles exploring the use of fuzzy logic in finance increased significantly.

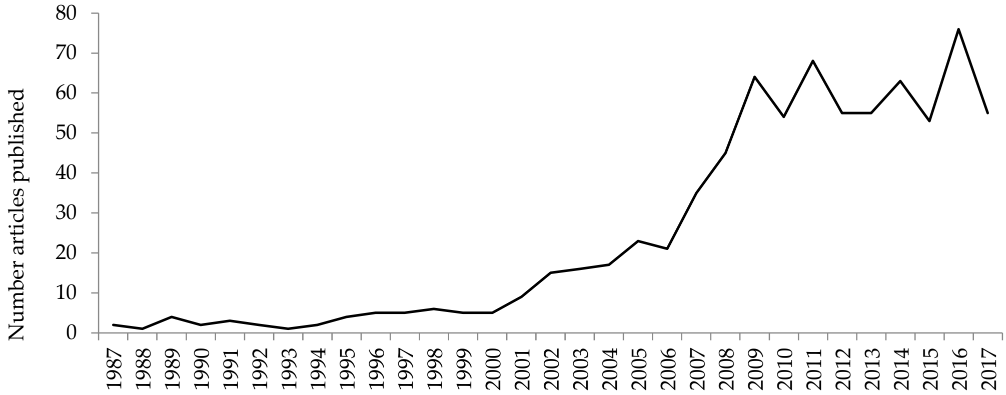

Figure 2. The number of articles published by year (1987–2017) exploring the use of fuzzy logic in finance has increased significantly since the mid-2000s.

In Figure 3, the academic journals that appear with greater frequency in our portfolio are shown. In addition, we included the 2017 impact factor for each article. When focusing on the most relevant journals, we found that Expert Systems with Applications is the journal with the greatest number of articles within our portfolio, with more than 90 articles and an impact factor of 3.76. Information Sciences and Fuzzy Sets and Systems followed, with 28 and 27 articles, respectively, and impact factors of 4.31 and 2.68. These findings place Expert Systems with Applications as the leading journal associated with financial research conducted using fuzzy logic methods. Overall, in our final portfolio, we found 300 different journals. However, approximately 50% of all articles are concentrated in only 25 journals, with an average impact factor of 2.7.

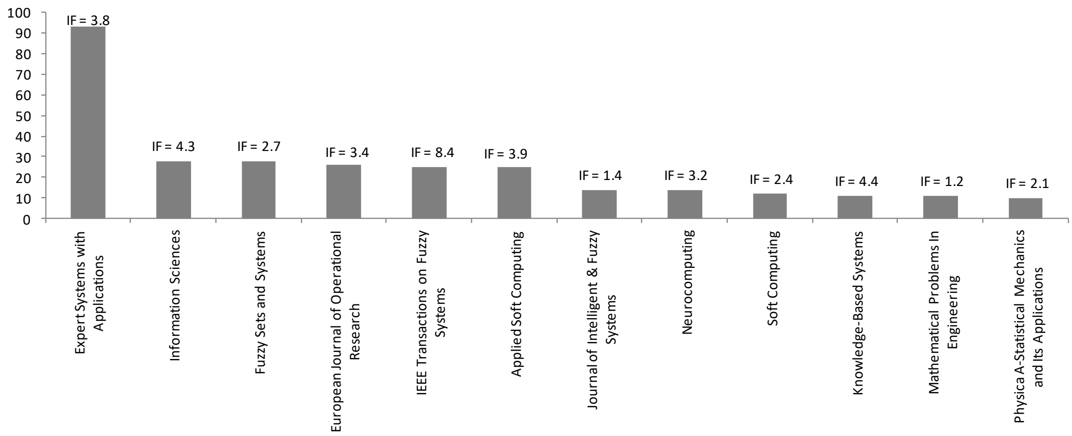

Figure 3. Academic journals that appear with greater frequency in our portfolio and their 2017 impact factors.

The most cited paper within our portfolio is entitled "Bankruptcy prediction in banks and firms via statistical and intelligent techniques—a review", with 849 citations. The article focuses on different approaches to address bankruptcy prediction, with fuzzy logic as one of the techniques explored. Other articles with more than 450 citations include "Effective lengths of intervals to improve forecasting in fuzzy time series", "Surveying stock market forecasting techniques—Part II: Soft-computing methods", and "The fuzzy mathematics of finance".

Table A1 summarizes the authors with the largest numbers of publications in our final portfolio. We show the aggregated number of citations per author considering only the articles included in the portfolio. Cheng, from National Yunlin University of Science and Technology (Taiwan), with 21 articles published and a total of 925 citations, is the most prominent author in the field. Other authors, with 12 articles published, are Quek and Zhang from the Nanyang Technological University (Singapore) and South China University of Technology (Guangzhou, China), respectively. Finally, we also consider the journals in which the authors have published their work, sorted first by number of articles published and second in alphabetical order.

Bibliometric analysis enables the investigation of numerous, diverse questions on the subject under study from a bibliographic viewpoint. The results presented above clearly indicate that the use of fuzzy logic in financial research has increased significantly over the last two decades, and the trend seems to indicate that the number of publications on the subject could continue rising in the near future. In addition, we obtained information regarding the most prominent journals and authors. However, no analysis of the content of the papers included in our final portfolio has yet been performed; hence, developing a systematic analysis at this point is crucial to completing the task of reviewing the literature on the topic under study. The next section focuses precisely on that topic by providing relevant insights into the most common financial topics in which fuzzy logic has been traditionally used in finance while briefly describing the main findings in each field.

3.2. Systematic Analysis

After a comprehensive review of the articles in which fuzzy logic has been used in the financial field and to develop the systematic analysis, we propose a classification of the articles by topic. The most frequent topic in which fuzzy logic has been applied in the field of finance is financial markets, with approximately 60% of the total articles classified in this category, followed by corporate finance, with approximately 35%. The remaining articles focused on public finance (3%), personal finance (1%) and other topics (2.52%). This fact clearly underscores the focus of the academic research on financial markets and corporate finance, and it can be explained by the greater volume of publicly available data in these fields compared with other areas, such as personal finance.

Figure 4 shows the breakdown of the main topics usually analysed when applying fuzzy logic in finance in the categories of financial markets and corporate finance. Regarding financial market research, Bahrammirzaee [40] emphasizes that the study of financial markets has been traditionally conducted following three different methodologies, namely (i) parametric statistical methods, such as discriminant analysis and regression; (ii) non-parametric statistical methods, such as nearest neighbour and decision trees; and (iii) soft-computing and artificial intelligence (AI) methods, including fuzzy logic, neural networks and genetic algorithms. The existing literature tends to agree that most of the research conducted using artificial intelligence methods, such as fuzzy logic or neural networks, generally tend to outperform parametric and non-parametric statistical methods [41,42].

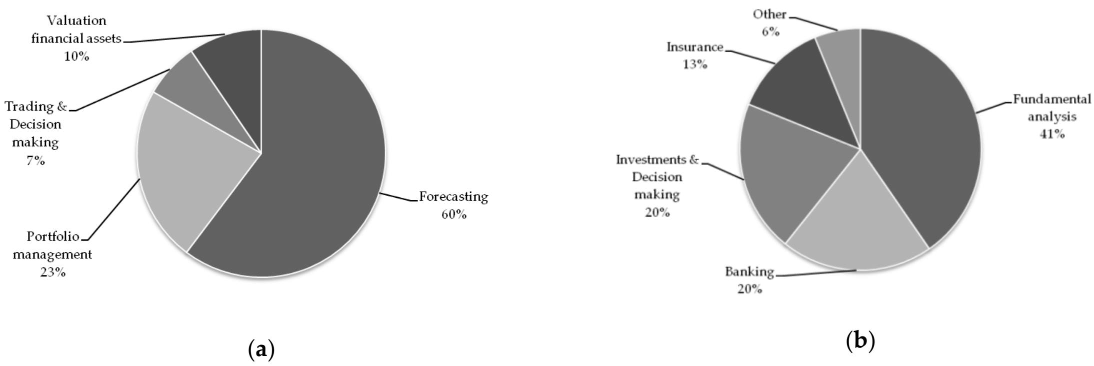

Figure 4. Categorization of the main topics usually analysed when applying fuzzy logic in finance: (**a**) Category of financial markets, and (**b**) category of corporate finance.

In particular, approximately 60% of papers analysing financial markets focused on forecasting. As noted by Atsalakis and Valavanis [41], the non-conventional forecasting methods, such as fuzzy logic, neural networks and genetic algorithms, outperform conventional forecasting techniques in almost all circumstances. Most of the papers reached the conclusion that optimal results are obtained when combining fuzzy logic with neural networks.

One of the areas with more practical implementations is the field of technical analysis. In this vein, one of the most cited papers proposed the use of a neuro-fuzzy system composed of an adaptive neuro-fuzzy inference system (ANFIS) to predict short-term stock market trends with encouraging results [43]. Another similar example using an ANFIS model is applied to the Istanbul Stock Exchange, and once again, the results show significant improvement in financial market predictions when the ANFIS model is used [37]. Fuzzy expert systems have also been used for financial market forecasting purposes, with Ijegwa et al. [44] proposing a pure fuzzy system to perform financial market forecasting. The authors justified the relevance of using a fuzzy system given that, in many cases, responses of technical indicators to market movements are not a definite yes or no. Hence, fuzzy reasoning is very effective in this type of environment. Van den Berg et al. proposed a probabilistic fuzzy system based on the Takagi–Sugeno method that combines the properties of probabilistic systems with the interpretability of fuzzy systems. In particular, Chang and Liu [45] developed a Takagi–Sugeno–Kang fuzzy system that predicted stock price movements across different sectors, claiming to achieve an accuracy of approximately 97.6% in the Taiwan Stock Exchange.

Portfolio management, which represents approximately 25% of all papers in financial markets research, relies heavily on Markowitz portfolio optimization theory. However, implementation of the Markowitz model requires future mean returns and correlations between assets. In real life, predicting these metrics accurately could represent a problem, making uncertainty and lack of accuracy two characteristics that all portfolio management models must address. To overcome this issue, fuzzy logic has been applied in the area of portfolio management, obtaining successful results [46–49].

Moving to the field of financial asset valuation, one of the areas in which fuzzy logic has been widely used is in options pricing. Muzzioli and De Baets [50], in a comprehensive literature review on the topic, identified that the majority of papers using fuzzy logic for option pricing have addressed the direct problem of pricing in both discrete and continuous time settings. Several articles have shown that fuzzy logic is suitable for identifying the market value of complex instruments, such as derivatives [51–53].

Trading and decision making represent approximately 7% of the articles focused on financial markets analysis. Many research papers in this area seek to find trends and identify patterns, to define complex trading strategies or to simply make, buy or sell decisions based on a set of rules. Several papers have proven the success of fuzzy logic in trading algorithms and financial decision-making processes [54–56]. In particular, Kuo et al. [57] combined genetic algorithms, fuzzy logic and neural networks to present a “buy–sell” system using both quantitative and qualitative factors. This study proved once again the advantages of combining multiple AI techniques.

The papers analysed thus far point towards the increasing use of fuzzy logic in financial market analysis in the coming years. Some of the areas in which we see the scope for further expansion include not only credit trading, particularly when managing illiquid products, but also in areas such as market analysis through human behaviour reactions (behavioural finance) and social media and trading decisions (social trading).

Once we reviewed the literature linked to financial markets, we focused on corporate finance research. However, the field of corporate finance is vast and includes a wide range of subjects. One of its predominant fields, accounting for approximately 40% of the articles, is fundamental analysis. In contrast to technical analysis, fundamental analysis relies on macroeconomic data, including interest rates, inflation rates and GDP growth, as well as on microeconomic data, which can be obtained from the annual accounts and more specifically from the profit and loss (P&L), cash flow statement and balance sheet. Therefore, fundamental analysis requires uncertain information, such as macroeconomic forecasts, and vague and imprecise data, such as management guidance and press releases, as input data. The nature of this information makes fuzzy logic one of the most suitable AI tools for managing fundamental analysis. An example can be found in the work by W. Berlin and N.F. Tseng, in which macroeconomic and company-specific data were used as linguistic variables in a fuzzy regression model to analyse the business cycle [58]. Other works include the use of fuzzy methods to address cash flow forecast analyses [59], corporate acquisition analysis [60], company evaluations [61] and credit rating analysis [62].

Another area in which fuzzy logic has been traditionally applied within corporate finance is the choice of investment opportunities, representing approximately 20% of the articles. Fuzzy logic was applied to a wide range of specific topics to evaluate the different investment options from the oil sector [63] to the real estate market [64]. These decision-making processes have been traditionally conducted in relation to multiple criteria decision aiding (MCDA) techniques. Basically, MCDA enables the inherent uncertainty linked to financial decisions to be assessed through a multidimensional process. The combination of MCDA with fuzzy logic, allowing for the treatment of variables as fuzzy, opens a wider range of possibilities to successfully use MCDA techniques [65]. Among the MCDA techniques, we highlight the frequent use of the technique for order of preference by similarity to ideal solution (TOPSIS).

Fuzzy logic has been introduced into the insurance sector by De Wit [66]. In their original work, De Wit [66] sought to identify fuzziness in underwriting. From this area, several papers studying different insurance areas in which fuzzy logic could be applied emerged. Approximately 13% of the papers in the category of corporate finance address insurance-related problems. In particular, Lemaire [67] contributed to the expansion of fuzzy logic theory applied to the insurance field by presenting some of the concepts of fuzzy logic in an insurance framework. A study published by Ostaszewski and Karwowski [68] included an in-depth analysis of the uses of fuzzy logic in actuarial sciences. Derrig and Cummins [69] explored further uses of fuzzy logic in the insurance business, with relevant contributions to the fields of property–casualty insurance forecasting and price modelling. Fuzzy logic has proven to be useful in determining insurance pricing decisions, which consider additional data on an ongoing basis [70] and the opinions of experts [71]. As observed in other knowledge areas, in its early stages, fuzzy logic was applied on a stand-alone basis in the insurance field. However, more recently, with the expansion of neural network methods, both tools have been combined, delivering in most cases even better results [72]. Shapiro also elaborated on the subject of fuzzy logic being used in the insurance sector from a broader perspective, pointing out a wide range of areas in which fuzzy theory can be successfully applied in insurance, including classification, underwriting, present value and pricing calculations, as well as asset allocation [20].

The use of fuzzy logic in public and personal finance is much more limited compared with financial markets and corporate finance. Regarding public finance, we witnessed increasing interest from scholars in the use of AI techniques applied to the public sector. Some examples of studies applying fuzzy logic to public finance address import and export forecasts [73], financing of public schools [74], forecasting countries' domestic debt using a combination of fuzzy logic and neural network techniques [75] and the analysis of the degree of effectiveness of European public policies in meeting sustainable development goals [76]. In particular, studies using AI methods in the public finance sector are particularly relevant from a regulatory and government perspective, and we should expect an increase in these types of studies in areas such as the potential impacts of quantitative easing programmes, central banks' decisions about interest rates and the impact of national regulations on the funding profiles of corporations.

Finally, focusing on the analyses of banks, the existing literature shows that the introduction of AI techniques represents a breakthrough in the analysis of several areas, such as risk management. Using big data to increase banks' knowledge of their customers, to provide loans according to certain credit scores, to measure their efficiency, to use advanced computational systems to balance their ALCO portfolios and to optimize the capital structure and liquidity and funding needs, banks have come to rely heavily on these advanced methodologies [77–82]. The growing importance of fuzzy logic in this type of analysis is demonstrated by the finding that approximately 20% of the portfolios focused on corporate finance are concerned with bank analysis.

4. Discussion

The analysis of the literature on fuzzy logic in the field of finance opens the door to a wide range of new and promising applications. A particular field in which the impact of fuzzy logic could be especially greater is in banking crisis and banking resolution analyses. Next, we discuss the applications of fuzzy logic in the following areas linked to banking crises and resolutions: (i) applications in banking crisis analysis and banking resolution; (ii) impact and magnitude of banking crises; (iii) institutional setting and financial regulation; and (iv) banking crises resolution.

4.1. Fuzzy Logic and Its Potential Applications in Banking Crisis Analyses and Banking Resolution

The existing academic literature has identified the three main factors associated with the probability and magnitude of banking crises [83]. These factors are classified as (i) pre-crisis macroeconomic conditions, since banking crises are usually preceded by credit and asset price booms, suggesting the importance of developing early warning systems to identify the build-up of imbalances at the macroeconomic level; (ii) pre-crisis characteristics of the banking sector, highlighting the importance of maintaining a sound banking sector through the entire economic cycle; and (iii) institutional settings, which should be responsible for enforcing an efficient regulatory and supervisory framework to ensure that the banking sector is solid and serves its main purposes with regard to the real economy. Of these three factors, the pre-crisis characteristics at the macroeconomic level and at the banking sector level can be grouped into one category, directly linked to the prevention of banking crises through early warning systems. The institutional setting is particularly relevant with regard to the key role that the regulatory framework and the supervisory and resolution institutions play to ensure a sound and safe banking sector; therefore, in this work, we classify it as a different topic.

In addition to the two topics mentioned above, understanding the impact of banking crises on the real economy is another key area to be addressed. Finally, since the global financial crisis, governments, regulators and banking supervisors have focused their efforts on developing a solid resolution framework to minimize the impacts of banking crises on the real economy. Therefore, the study of banking resolution is the fourth main area that we develop further in this section.

The results obtained in the previous section demonstrate that fuzzy logic could be a particularly relevant tool for addressing the four aforementioned topics. Accordingly, we next elaborate on the main topics within these four areas to which fuzzy logic could potentially add more value.

Systematic analysis reveals a reduced number of articles in which fuzzy logic has been used for banking crisis and banking resolution analysis to date. Additional analysis includes papers sorted by number of citations, author names, the journals in which the articles have been published, the year of publication, the main purpose of the articles, and the methodologies used. Most of these articles focused on early warning systems to predict banks' defaults, as shown in Table A2. However, there was also one article on systemic risk, one on contagion risk analysis and one on the analysis of bank supervisory criteria.

4.1.1. Preventing Banking Crises by Monitoring Pre-Crisis Macroeconomic and Banking Sector Conditions

Banking crises are considered a recurrent systemic phenomenon, often triggering deep and long recessions. They are not random events, and they tend to occur following periods of very strong credit growth (credit booms), significant increases in asset prices and other financial imbalances, such as strong correlations in risk exposures among banks [84]. Banking crises are also associated with the concept of systemic risk, which can be defined as the risk that can damage financial stability, impairing the correct functioning of the main activities of the financial system with major negative effects on the real economy. Systemic risk also builds up over a long period of time, and it is not a random event triggered suddenly. In particular, authors have emphasized that approximately one-third of banking crises are preceded by a credit boom, generally stemming from correlated risk exposures and increases in asset prices, leading to bubbles. In accordance with this observation, we suggest that early warning systems powered by fuzzy logic could be an extremely useful tool. We acknowledge the large number of variables that must be considered when attempting to prevent financial crises, ranging from macroeconomics to aggregated banking sector data or individual bank dynamics. This extremely large number of factors led us to conclude that fuzzy logic could be a useful tool for addressing this subject.

Most of the articles included in the table above elaborated on early warning systems to prevent banking crises or predict bank failure. Bankruptcy prediction is one of the areas in which fuzzy logic and other AI techniques clearly outperform classic analysis methods. The prominent work developed by Ravi-Kumar and Ravi [85] presented a list of bankruptcy prediction methods, including statistical techniques, neural networks, decision trees, evolutionary algorithms and fuzzy logic techniques. In particular, focusing on the use of fuzzy logic for bankruptcy prediction tasks, the authors highlighted that this method successfully manages imprecision and ambiguity, combining it with human expert knowledge. Interestingly, bankruptcy prediction has been traditionally studied as a classification problem. Different techniques have been applied to predict firms' defaults, including regressions, linear discriminant analysis (LDA), multiple discriminant analysis (MDA), neural networks, support vector machines and decision trees. In one of the pioneering studies on bankruptcy prediction, Altman [86] proposed a multivariate discriminant analysis technique to classify firms as solvent or bankrupt. Focusing exclusively on bank default prediction, Sinkey [87] also used MDA to detect failing banks, while Altman [88] later published a study focused on banks' insolvency prediction. The use of a fuzzy-clustering algorithm to forecast bank failure is another example [89]. Overall, the academic literature on bankruptcy prediction has tended to agree that neural networks commonly outperform other methods [90]. However, when samples are smaller, or more transparency is sought, support vector machines obtain better results [91]. Ravi-Kumar and Ravi [85] used an ensemble of classifiers to predict failures of Spanish and US banks, emphasizing that ANFIS is among the top performers. From a decision support systems viewpoint, an optimal system to predict the failure of a bank should not be a classifier on a stand-alone basis but a combination of them [92]. Therefore, a combination of two or more classifiers seems to be the most appropriate technique for predicting which banks could fail in the short or medium term. A combination of fuzzy-SVM and ANFIS could be a useful tool for determining whether a bank should be considered "failing or likely to fail" and subsequently entered into a liquidation or resolution procedure.

A particularly interesting study conducted by W.L. Tung et al. [93] elaborated on early warning systems to predict banking failures using a neuro-fuzzy system. This paper showed how the use of fuzzy logic and its combination with other AI techniques could be seen as a powerful tool for addressing banking supervision and regulatory issues. In particular, after the analysis of the literature, we propose the use of neuro-fuzzy models, particularly ANFIS, to address bankruptcy prediction.

4.1.2. Impact and Magnitude of Banking Crises

One of the key topics when studying banking crises is understanding their impact on the economy. Only with accurate methodologies to account for the holistic impact of such events will regulators and supervisors be able to design regulatory frameworks that could offset the existing trade-off between the benefits and costs of tight banking regulations. Currently, the academic literature is not aligned with regard to the variables that determine the impacts of banking crises [94]. As authors have pointed out, this lack of consensus could be partly explained by the proxy used as a measure of the impact on the real economy of a banking crisis. However, the large number of factors to be considered when performing such calculations is a limitation of any methodology based on traditional analysis. Following the results obtained in Section 4, we consider that fuzzy logic methods, combined with other artificial intelligence tools, such as neural networks or machine learning, could significantly increase the accuracy of such estimates.

Financial contagion is another important topic to focus on when addressing the study of banking crises. The links between banks through interbank lending and the interconnection between banks and other economic sectors must be monitored even more closely in the new resolution framework. The literature using fuzzy logic to analyse this point has been scarce; however, in a recent study, De Marco et al. [95] modelled a financial network with fuzzy numbers, which could be a good starting point for a deeper analysis of the contagion risks using fuzzy logic techniques.

The bail-in tool seems to be a promising technique with which to address banking failures. However, loss absorption requirements force banks to issue bail-in-able debt and capital instruments that are mainly acquired by non-banking entities. This process could spread financial risk across other sectors instead of achieving the goal of reducing systemic risk. Understanding the potential risk transfer from the financial sector to other sectors of the real economy and from banks to citizens is a topic that must be analysed. We propose fuzzy numbers and ANFIS as candidate methods to address contagion risk issues.

4.1.3. Institutional Setting and Financial Regulation

We also consider it relevant to analyse banking regulators' and supervisors' performance. In the current environment, entities such as the SRB or the ECB in Europe have significant power to address banking crises. Despite the fact that it seems necessary to have institutions in charge of the stability of banking and the financial system, the complexities of the current regulation and the power of such institutions make it necessary to monitor their tasks and decisions. Understanding whether and how banks are reaching the capital, leverage and liquidity targets imposed by regulators could be a method of assessing the banking regulators' performance. Using fuzzy MCDM and neuro-fuzzy approaches to evaluate regulators' and supervisors' performance could open a door to a new wave of studies analysing whether regulators are making the right decisions, whether the methods used are effective and whether any significant mistakes have been made thus far.

In addition, regulators should enhance banks' transparency and the accuracy of the information reported by financial entities. Fraudulent reporting is, at the time of writing, another major concern for regulators, investors and other economic agents. Proof of this concern is the interest shown by academia in studying financial reporting fraud and how to detect and prevent it [96]. Well-known examples of fraudulent reporting, such as the case of Bankia in Spain or Banco Espirito Santo in Portugal, emphasize the importance of detecting such fraudulent techniques. In the case of the Spanish entity, a potential manipulation of the financial information disclosed by the bank before the initial public offer (IPO) is currently under investigation by the Spanish High Court [97], while in the case of the Portuguese bank, the management decisions and reporting techniques are considered borderline fraud [98]. The work published in 1986 by Albrecht and Romney [99] is considered to be the first study analysing empirically the prediction of fraud in financial reports, and from this point, several articles have been published on the subject [100,101]. Fuzzy logic has proven to be useful in this field as well, with several papers published on the subject [102,103]. In particular, Lin et al. [104] proposed a neuro-fuzzy technique to detect fraudulent reports. The authors showed how neuro-fuzzy methods outperform traditional methods, such as logit models, in the detection of fraudulent reporting. The literature on this topic suggests that the application of fuzzy logic top fraud reporting will contribute to enhancing transparency in the banking sector. In particular, in accordance with other research axes, neuro-fuzzy systems seem once again to be the most efficient method for developing solid banking fraud reporting research analysis.

4.1.4. Banking Crisis Resolution

The triggering of a banking resolution and its effects on the real economy are very sensitive and complex processes that involve managing financial information, macroeconomic data and legal aspects. The decision to trigger the resolution of a banking entity represents a decision-making process that combines different expertise areas, in which a significant degree of uncertainty and subjectivity arises. Therefore, we suggest that the use of fuzzy logic in the banking resolution field could be a disruptive technique to model and better understand several of its implications for the real economy. However, banking resolution analysis must be extended further, with the triggering of the bank resolution representing only the first step. Setting the right loss absorption requirements, choosing the optimal resolution tool in each case and limiting the contagion from the financial sector to other sectors are some of the points that should be explored further. In accordance with these issues, due to the complexities linked to this type of analysis, in which information is uncertain, and the fact that several factors, such as politics, macroeconomic variables and regulation, participate, the impacts on the real economy of preventing a banking crisis with tools such as bail-in or deposits guarantee that schemes are difficult to analyse with traditional econometric models. We therefore suggest that the application of fuzzy logic, combined with other innovative tools, such as neural networks, could yield solid results.

To address the decision-making process of determining a financial institution "failing or likely to fail", this work considers that multicriteria decision aid (MCDA) could potentially be a key methodology for addressing such a complex decision. MCDA is a method that enables analysis of different criteria at the same time, and, according to the recent literature, it is the best method for choosing optimal solutions in probability option exercises [105]. Following this literature review, we consider that using fuzzy MCDM (and fuzzy AHP in particular) to decide whether to trigger the resolution of a bank could be a more objective and unbiased method than that currently used in Europe based on the judgement of ECB and SRB experts.

In accordance with the above discussion, it is also important to design efficient loss absorption instruments; hence, these instruments should also be a focus of study. It is also important to bear in mind that regulatory requirements, such as total loss absorption capacity (TLAC) or minimum requirement of eligible liabilities (MREL), could potentially result in higher funding costs for banks. They could also lead to a transfer of these higher funding costs to the real economy through a worsening of credit conditions. Analysing the impact of such requirements on the real economy is a complex task; however, in accordance with the existing literature on fuzzy logic, it seems that neuro-fuzzy methodologies could contribute significantly to the development of such analyses. In addition, it is essential to design instruments that are sufficiently attractive to investors to maintain a relatively low cost of funding for banks, while simultaneously, the banks' resolvability should be increased due to the loss absorption features provided by these instruments. In this regard, both fuzzy valuation methods and ANFIS seem to be good methodologies for managing this task.

5. Conclusions

The existing literature shows that fuzzy logic has already been applied to a wide range of areas within the field of finance. However, it is far from reaching its full potential compared with its use in other fields, such as control systems, engineering and environmental sciences, in which the number of articles using fuzzy logic is much greater. After analysing the results published in studies in which fuzzy logic has been used, one of our main conclusions is that fuzzy logic has shown to be especially efficient when addressing uncertainty and vagueness, which are two of the most common characteristics linked to financial analysis. Therefore, given the particularities of this tool in managing complex and uncertain scenarios, the first conclusion of this analysis is that we should expect a significant increase in the number of papers within the finance field using fuzzy logic in the coming years. In particular, areas such as financial market forecasting, credit market analysis, public finance and personal finance could be some of the areas benefiting the most from standardization of the use of fuzzy logic and other AI techniques in the field of business and finance.

This work also emphasizes that a combination of AI techniques, including fuzzy logic, neural networks and evolutionary programming, outperforms traditional techniques according to the results presented in Section 4. In particular, the use of fuzzy logic and neural networks as a hybrid approach tends to be the most common technique and demonstrates the best performance. We acknowledge the efficiency of this method; therefore, we expect a significant increase in the number of scholars applying such hybrid techniques in their work in the near future.

This study is, to the authors' best knowledge, pioneering in terms of the introduction of fuzzy logic to the field of banking crisis analysis and banking resolution. Consequently, this work is intended to represent only a first step in this research area, suggesting key topics in which further research would be particularly welcomed. In particular, this work proposes four research axes in which we strongly believe fuzzy logic would improve the results obtained to date when using traditional analysis methods. These topics include the (i) prevention of banking crises through fuzzy logic-powered early warning systems; (ii) management of banking crises and measurement of their impacts on the real economy; (iii) institution setting and financial regulations to address, prevent and resolve banking crises; and (iv) overcoming banking crises through efficient resolution methods.

The complexities linked to the ambitious task of proposing the use of an alternative methodology to address a well-known subject, leads to several limitations in our work. First, a limitation shared by many other literature reviews is that some articles could have been involuntary omitted; hence, our work draws conclusions from an extensive, but not exhaustive, list of papers. Another limitation is associated with the lack of papers using fuzzy logic in the field of banking crisis analysis, which means that the models that we propose have not yet been tested in a banking crisis framework. Finally, identifying the key areas within the field of banking crises to which fuzzy logic can be applied opens the door to potential overlaps between areas.

This study has relevant implications not only for researchers but also for practitioners. From an academic viewpoint, the main contributions of this paper are linked to identifying in which fields of financial research fuzzy logic has been utilized and extrapolating the results to suggest other areas where the use of fuzzy logic could bring positive advances, such as in trading and behavioural finance. It also adds value regarding the management of banking crises, since a group of articles are analysed to identify the most adequate fuzzy logic techniques to deal with specific problems linked to banking crises research. From a practitioner's standpoint, this work discussed several studies where fuzzy logic has been applied in the financial field with successful results, including financial forecasting, stock markets and public finance. It could also be useful for banking regulatory and supervisory bodies, since this work briefly explores the potential use of fuzzy logic in the field of banking regulation.

In conclusion, since banking crises are among the most devastating events from an economic viewpoint, we acknowledge the relevant efforts undertaken by the academic community to better understand the existing mechanisms to prevent and manage banking crisis. Due to the nature of the data involved in such studies, we consider fuzzy logic and its combination with neural networks particularly appropriate for the analysis of banking crises and banking resolution mechanisms. This work contributes to easing the integration of fuzzy logic into the analysis of banking crises through a comprehensive literature review and identification of the key areas for development.

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Appendix A

Table A1. Main authors with the largest numbers of publications in our final portfolio.

Author	Num. Articles	Tot. Citations	Journal 1	Journal 2	Journal 3	Journal 4	Journal 5	Journal 6	Journal 7	Journal 8	Journal 9	Journal 10	
Cheng, CH	21	925	Expert Systems with Applications	International Journal of Innovative Computing Information and Control	Applied Intelligence	Applied Soft Computing	Neurocomputing	Physica A-Statistical Mechanics and Its Applications	African Journal of Business Management	Computers & Mathematics with Applications	Data & knowledge Engineering	Economic Modelling	Intelligent Automation and Soft Computing
Quek, C	12	538	Expert Systems with Applications	Computational Intelligence	AI Communications	Applied Intelligence	Contemporary Theory and Pragmatic Approaches In fuzzy Computing Utilization	IEEE Transactions on Evolutionary Computation	IEEE Transactions on neural networks	Neural Networks			
Zhang, WG	12	298	Economic Modelling	Soft Computing	Applied Soft Computing	Automatica	European Journal of Operational Research	Fuzzy Optimization and Decision Making	Information Sciences	International Journal of Intelligent Systems	Mathematical and Computer Modelling		
Chen, TL	11	787	Expert Systems with Applications	Physica A-Statistical Mechanics and Its Applications	African Journal of Business Management	Computers & Mathematics with Applications	Data & knowledge Engineering	Economic Modelling					
Wei, LY	11	383	Applied Soft Computing	Economic Modelling	International Journal of Innovative Comp. Info. and Control	African Journal of Business Management	Applied Soft Computing	Expert Systems with Applications	Neuro-computing				
Huang, XX	10	871	Journal of Computational and Applied Mathematics	Applied Mathematics and Computation	Computers & Mathematics with Applications	Expert Systems with Applications	IEEE Transactions on Fuzzy Systems	Information Sciences	International Journal of General Systems	Journal of Intelligent & Fuzzy Systems	Soft Computing		

Appendix B

Table A2. Fuzzy logic in banking resolution.

Article	Authors	Journal	Publication Year	Purpose	Method
The use of fuzzy-clustering algorithm and self-organizing neural networks for identifying potentially failing banks: An experimental study	Alam, P; Booth, D; Lee, K; Thordarson, T	Expert Systems with Applications	2000	Early warning system for bank default	Fuzzy-clustering and neural networks
GenSo-EWS: a novel neural-fuzzy-based early warning system for predicting bank failures	Tung, WL; Quek, C; Cheng, P	Neural Networks	2004	Early warning system for bank default	Generic self-organizing fuzzy neural network (GenSoFNN)
A novel bankruptcy prediction model based on an adaptive fuzzy k-nearest neighbour method	Chen, HL; Yang, B; Wang, G; Liu, J; Xu, X; Wang, SJ; Liu, DY	Knowledge-Based Systems	2011	Predict bank failure	fuzzy k-nearest neighbour
Financial distress prediction in banks using Group Method of Data Handling neural network, counter propagation neural network and fuzzy ARTMAP	Ravisankar, P; Ravi, V	Knowledge-Based Systems	2010	Predict bank failure	Neural network and fuzzy ARTMAP
FCMAC-EWS: A bank failure early warning system based on a novel localized pattern learning and semantically associative fuzzy neural network	Ng, GS; Quek, C; Jiang, H	Expert Systems with Applications	2008	Early warning system for bank default	Fuzzy CMAC (cerebellar model articulation controller) model based on compositional rule of inference. (An integration of neural networks and fuzzy systems to create a hybrid structure known as a fuzzy neural network (FNN))
Fuzzy Refinement Domain Adaptation for Long Term Prediction in Banking Ecosystem	Behbood, V; Lu, J; Zhang, GQ	IEEE Transactions on Industrial Informatics	2014	Predict bank failure	Fuzzy refinement domain adaptation algorithm
Multistep fuzzy Bridged Refinement Domain Adaptation Algorithm and Its Application to Bank Failure Prediction	Behbood, V; Lu, J.; Zhang, G; Pedrycz, W	IEEE Transactions on Fuzzy Systems	2015	Predict bank failure	Multistep fuzzy Bridged Refinement Domain Adaptation Algorithm
Using a Mixed Model to Explore Evaluation Criteria for Bank Supervision: A Banking Supervision Law Perspective	Tsai, SB; Chen, KY; Zhao, HR; Wei, YM; Wang, CK; Zheng, YX; Chang, LC; Wang, JT	Plos One	2016	Analyse bank supervision criteria	Fuzzy-DEMATEL
Aggregating expert knowledge for the measurement of systemic risk	Mezei, J; Sarlin, P	Decision Support Systems	2016	Provide a framework for measuring systemic risk by aggregating the knowledge of financial supervisors	Fuzzy cognitive maps (FCMs) and aggregation based on Choquet integrals
Financial institution failure prediction using adaptive neuro-fuzzy inference systems: Evidence from the east Asian economic crisis	Choensawat, W, Polsiri, P	Journal of Advanced Computational Intelligence and Intelligent Informatics	2013	Predict bank failure	ANFIS
On the measure of contagion in fuzzy financial networks	De Marco, G; Donnini, C; Gioia, F; Perla, F	Expert Systems with Applications	2018	Financial contagion risk	Fuzzy model using fuzzy numbers to represent the balance sheet

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