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A Bibliometric Analysis of Artificial Intelligence Technique in Financial Market

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Abstract

This article aims to explore the main areas of research, development trends and provide a systematic overview of publications in the field of artificial intelligence in financial markets. The bibliometric tool VOSViewer is used in this paper. We analysed 353 articles and contributions obtained from the database of Web of Science, and summarized our findings as follows: artificial intelligence is becoming increasingly widespread in the field of finance and interdisciplinary interconnection; artificial intelligence tools such as neural networks and fuzzy logic are most often used to predict the development of financial time series, or to create decision models; the most important cited authors in this field are Markowitz and Lebaron. Expert System with Application is the cradle of a significant part of fundamental research in the field of artificial intelligence. By using effective bibliometric methods, we provide comprehensive analysis and in-depth insight into the subject area of research, which allows individuals and especially new beginners interested in this area to obtain valuable information and possible direction of future research. The study is recommended to focus on hybrid models prediction of individual sectors of the financial markets, which are present in the current research on the rise.

Keywords

Artificial Intelligence, AI, ANN, Bibliometric Analysis, Financial market, Fuzzy Logic, Neural network, Stock Market

JEL Classification

G12, G15, G17

Introduction

Financial markets play an important role in the economic and social organization of modern society. In these types of markets, information is an invaluable asset. However, with the modernization of financial transactions and information systems, the large amount of information available to the trader may make it impossible to analyze a financial asset. In recent decades, many scientists have attempted to develop computational intelligent methods and algorithms to support decision-making in various segments of the financial market, as described by Cavalcande et al. (2016). Janková and Dostál (2019a) further add that the financial industry was increasingly dependent on advanced computer technology, mainly to maintain its competitiveness in the global market. The issue of capital market decision-making using data mining techniques is one of the most important areas of financing. This attracted great scientific interest and became a key point of research to ensure a more accurate predictive and decision-making process (Cibulskiene and Brazauskas, 2017).

Although a number of techniques have been developed to improve financial market forecasts, improving the accuracy of predictions can bring investors significantly higher returns. A large number of research and scientific papers have recently been published looking for optimal forecast models for financial markets. Most forecast research uses statistical methods of time series analysis. However, these models are severely limited, especially with regard to seasonal and non-linear uncertainty issues. It is reasonable to assume that since data on the prices of financial instruments are influenced by deterministic and random factors, the financial market forecast can only be successful using tools and techniques that can overcome the problem of price uncertainty, noise and non-linearity. According to Bahrammirzaee (2010), many current real financial applications today have nonlinear and uncertain behaviours that change over time. The need to solve highly nonlinear problems of time variants therefore grew rapidly. These problems, along with other problems of traditional models, have caused a growing interest in artificial intelligent techniques. Similarly, Janková and Dostál (2019b) emphasize that linear models are widely used to forecast financial time series, however, these models are considerably limited, especially when applied to seasonal and non-linear problems associated with uncertainty. Janková (2019) draws attention to two main currents in the field of AI in financial markets. These are fuzzy logic and neural networks. Fuzzy logic makes it possible to draw final conclusions from unclear, ambiguous or inaccurate information (Borovička, 2019). The

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artificial neural network has been widely accepted mainly for its ability to learn and reveal relationships between nonlinear variables. The artificial neural network primarily outperforms statistical regression models and allows deeper analysis of large data sets. Among computational intelligence models, the artificial neural network has become the dominant modelling paradigm.

There is a large body of scientific work in the literature that examines the use of computational intelligence techniques to solve financial market problems (Sathe and Mali, 2017; Fanita and Rustam, 2018; Jiang et al., 2018; Vlasenko et al., 2018; Brzeszczyński and Ibrahima, 2019; Janková and Dostál, 2021). Most existing review articles have a limited scope, either by focusing on a specific application in the financial market (Mochkabadi and Volkmann, 2020) or by focusing on a family of machine learning algorithms (Sezer et al., 2020). This article presents an overview of the application of artificial intelligence tools in several financial applications in financial markets.

Methodology and Data Collection

Information preparation of research plays an important role in the process of research work. It not only provides a knowledge base, but also allows the researcher to learn from the work of other experts. This part focuses on the key authors and research issues they have addressed in the researched topic. With a focus on the key research methods and tools that have been used and the key results and conclusions that the authors have reached. Finally, it is necessary to reveal which issues remain open in this area and in the next part of the work to focus on these white spaces in research. Within the methodology, the collection of data and the selection of research approaches for the analysis of scientific articles and contributions in the subject area are key. In this section, we will first introduce the effective bibliometric tool VOSViewer version 1.6.15 and introduce database selection and data collection, including the setting of various parameters that will ensure the accuracy of the research.

Research method

Bibliometric analysis is a scientific and often used statistical method for the analysis of published studies and is used to search citation relationships and influences on other disciplines and publications. We used this method to find citation networks among the most used keywords in studies examining sentimental analysis in the stock market. It is possible to use data from various databases to use this method. The database plays an important role in scientific research. Bibliographic software has been developed to examine the links between the literature to increase accuracy and convenience in obtaining relevant information. As widely used bibliometric software VOSViewer, it is able to display large bibliometric maps with interpretation of the shown clusters (van Eck and Waltman, 2009). This software is commonly used for bibliometric to present the structure of knowledge and dynamics of research. This software is freely available for researchers (see www.vosviewer.com). Other advantages include the fact that it allows to examine in detail the constructed bibliometric maps from various aspects. A great advantage is also the colour visualization that easily identifies individual clusters, and in addition, this program is user-friendly. As van Eck and Waltman (2009) further note, most computer programs used for bibliometric mapping do not display such maps satisfactorily. Other important requirements are set forth in van Eck and Waltman (2007).

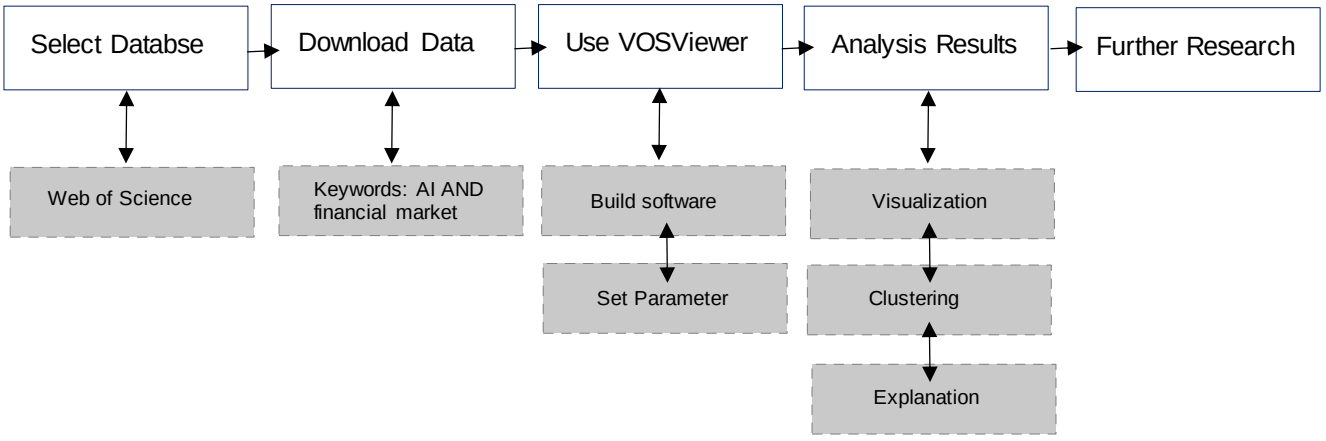

Fig. 1. Diagram of the VOSViewer usage process.

Visualization of the scientific distribution of articles can reveal potentially hidden relationships and connections, thus laying a solid foundation for scientific research. Figure 1 shows a diagram of the architecture of the data collection process and the use of VOSViewer, which represents the selection of specific parameters during the use of VOSViewer.

Based on the document data, the VOSViewer node types are set to "quoted author", "keyword", "link" and

"quoted journal". Research knowledge maps are displayed intuitively. Keyword analysis provides information on research sites and research boundaries. Citation analysis of the literature can report the importance of each document between keywords. A list of research results can be found by analysing the journal citation. In addition, influential authors may be known based on the analysis of the cited authors.

Data Collection

To ensure the relevance and validity of research, it is essential to select and select high-quality international scientific articles that publish original and reliable sources of information and knowledge. Regarding artificial intelligence in the financial markets, articles are searched from the Web of Science (WoS). The Institution of Scientific Information is the largest and most comprehensive academic resource in the world, covering more than 8,700 key academic journals in the most influential areas of natural sciences, engineering and biomedical sciences, etc., according to Zhou et al. (2020). As a trusted and comprehensive bibliographic database, WoS is the most commonly used database in bibliographic research. Choosing a WoS as source as a source of knowledge can widely obtain high-quality journal articles. In this article, data is retrieved from WoScore journals. The data were searched on March 4, 2020. The time range is all years. A comprehensive list of keywords has been compiled, which the authors regularly use to describe the application of artificial intelligence in the financial markets. This list includes terms that relate to various alternative notations of the methodological area of artificial intelligence (e.g. "AI"; "fuzzy logic"; "neural networks") and a specific area of research (e.g. "financial market"). Only keyword-based articles or part of an abstract were considered. A total of 353 articles and contributions were found, which are further analysed from a bibliometric point of view. By updating the version, the results of this post can be more representative and coherent.

Bibliometric analysis

The ever-increasing number of publications and citations in recent years explains in detail the growing challenges and uses of artificial intelligence in financial markets. The number of publications and citations per year in the subject area of research for each year is shown in Figure 2. The vertical bars represent the number of publications per year and the horizontal columns show the trend of citations of the examined publications. This is a remarkable increase in witnesses in almost 30 years. The number of publications has grown significantly in recent years. The number of citations for the year until 2020 is rising. It is clear that the research of fuzzy portfolio has made great progress over the last 30 years, and this research is certainly not definitive, as evidenced by the significant increase in publications over the last three years.

Current state of AI research in financial markets

According to the growth curve of the research shown in Fig. 2, four phases can be identified as follows: (1) Early phase (1991–1998): in this phase, the number of documents published each year is very limited and is around 2 articles per year. During this period, there are also influential authors, such as Kim and Chun (1998), who evaluated several backpropagation models, including the recurrent neural network (RNN) model. These concepts are examined against the background of practical applications involving stock market index prediction. Abramson and Finizza (1991) use artificial intelligence knowledge bases to model all variables that are thought to have an impact on the oil market. Malliaris and Salchenberger (1993) use a neural network model that processes financial input data to estimate the market price of options. The network's ability to estimate closing prices is compared with the Black-Scholes model, the most widely used option pricing model. The authors' research laid a solid foundation for AI research in various areas of financial markets and made a significant contribution to the development of research. (2) Development phase (1999-2008): is characterized by a gradually increasing pace of published outputs in the subject area. The number of works published annually has increased from 6 publications per year. There is a gradually increasing interest and awareness of the scientific community about AI environments and their potential wide application to financial markets. Quah and Srinivasan (1999) state that, thanks to its proven generalizing ability, ANN is able to derive the characteristics of executive stocks from historical patterns. The article Oj and Kim (2007) shows that case-based reasoning (CBR), an artificial intelligence technique, is a fairly effective tool for monitoring the financial market before it can collapse. Nastac et al. (2007) improve the original mechanism based on artificial intelligence for specific economic forecasts. The aim is to forecast the exchange rate using a large set of financial data. The number of publications has increased since 2009, which means that the occurrence of the mortgage crisis may increase the attention of researchers in AI research. (3) Development phase (2009-2015): at this stage, the number of published articles reached 11 per year and is still growing. The subprime mortgage crisis that erupted in 2008 has raised the awareness of investors, regulators and scientists about financial risk management, according to Zhou et al. 2020). The most cited authors are Hadavandi et al. (2010). The authors integrate an approach based on genetic fuzzy systems (GFS) and artificial neural networks (ANN) for the construction of an expert system for forecasting stock prices. The results show that the proposed approach overcomes all previous methods, so it can be considered a suitable tool for solving problems of stock price forecasting. Bahrammirzaee (2010) conducted a comparative survey of three famous artificial intelligence techniques, i.e., artificial neural networks, expert systems and hybrid

intelligence systems, in the financial market. The financial market was also categorized into three domains: credit rating, portfolio management and financial forecasting and planning. The results show that the accuracy of these artificial intelligent methods is better than the accuracy of traditional statistical methods in solving financial problems, especially regarding nonlinear formulas. (4) The expansionary phase (2016-202x) contains the last years when the outputs of the applicability of artificial intelligence tools in the financial markets have really expanded and published, and this is far from the final word of AI in this area. This phase is characterized mainly by the improvement of functions and input parameters to the models. The combination of various artificial intelligence techniques and the creation of hybrid models are also quite obvious. For example, the empirical results of Qui et al. (2016) found that the selected input variables were effective in predicting stock market returns. The hybrid approach based on GA and SA significantly improves the accuracy of the prediction and surpasses the traditional BP training algorithm. To improve the performance of time series model prediction, Wei (2016) proposes a hybrid time series model of the adaptive network fuzzy inference system (ANFIS), which focuses on the empirical decomposition model (EMD) for stock price forecasting. Lee (2020) discusses a proposal for a legal and regulatory framework for the use of artificial intelligence (AI) in financial services markets to improve access to finance (financial inclusion). The author makes policy recommendations and proposes some guidelines for governance in the use of artificial intelligence in financial services in order to improve access to finance.

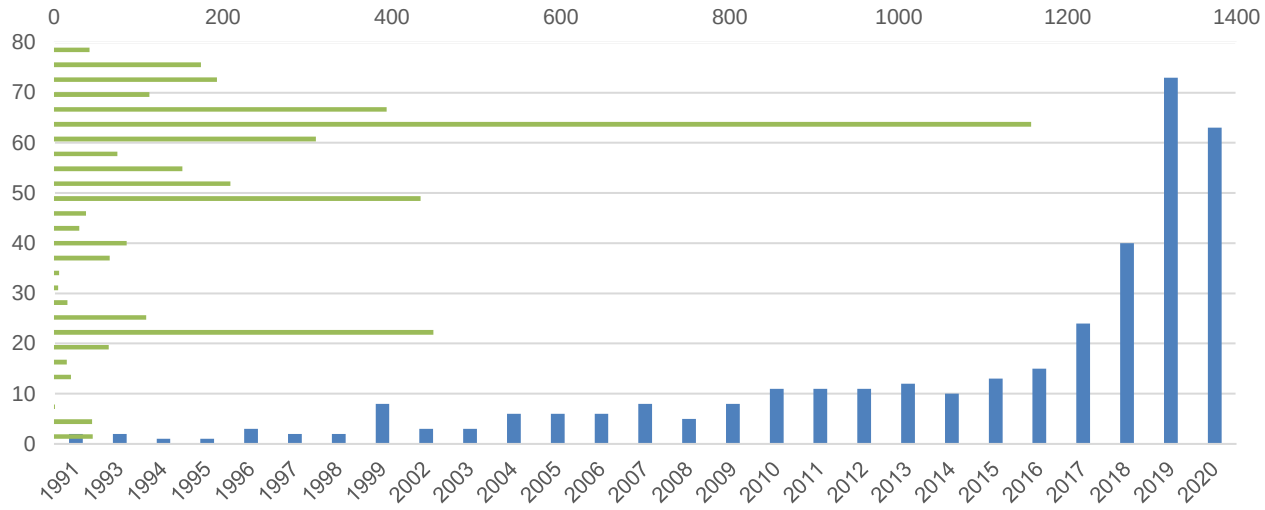

Fig. 2. Development of the number of publications and citations for individual years.

All research documents consist of 4 different file types, such as article, proceeding paper, review and editorial material. Details of each type are shown in Figure 3. It is clear that the obtained database of articles consists of two dominant types, namely 54 % are scientific articles in journals, and 40 % of the analysed materials are conference papers. Minority type documents are review (5 %) and editorial material (1 %).

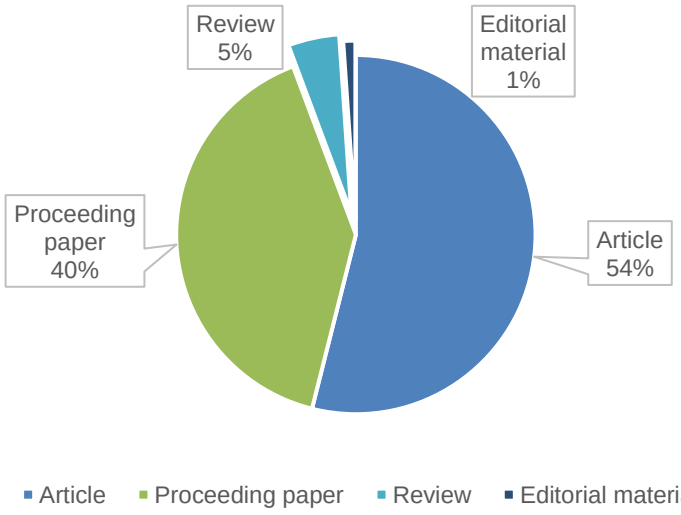

Fig. 3. Type of documents analyzed.

Each of the analysed articles and contributions included in the WoScore collection belongs to at least one category of subjects. Each record in the main WoS collection therefore has a "WoS Category" field, which

contains the subject category to which its source publication belongs. According to the distribution of categories, it can be clearly concluded that AI research in financial markets has become multidisciplinary. A summary of the top 10 categories in the field of AI in financial market search is given in Table 1. It is clear that "Computer Science Artificial Intelligence" is the most popular category with 100 publications, representing 14.9% of total publications, which means that the idea of AI in financial markets is widely used in computer science and artificial intelligence. "Engineering Electrical Electronic" is the second most popular category with 68 publications, which represents 10.13% of total publications. Other categories ranging from 40 to 50 publications are "Computer Science Information Systems", "Economics", "Computer Science Theory Methods" and "Management". It is also a "Computer Science Interdisciplinary Applications" with 31 publications; "Operations Research Management Science" contains 29 publications and "Business", respectively. "Business Finance" includes 26, respectively 24 articles and contributions for the monitored period.

Table 1. Top 10 subject categories of WoS in AI in financial market.

Subject categories of WoS	Number	Percentage of total
Computer Science Artificial Intelligence	100	14.90 %
Engineering Electrical Electronic	68	10.13 %
Computer Science Information Systems	53	7.90 %
Economics	46	6.86 %
Computer Science Theory Methods	44	6.56 %
Management	39	5.81 %
Computer Science Interdisciplinary Applications	31	4.62 %
Operations Research Management Science	29	4.32 %
Business	26	3.87 %
Business Finance	24	3.58 %

Table 2 lists the 10 most cited WoS documents in the study. These articles were published between 1991 and 2016 and the articles come from various types of magazines.

Table 2. Top 10 cited documents of WoS in AI in financial market.

Title	Authors	Citations	Source	Year
Time series properties of an artificial stock market	LeBaron et al.	345	Journal of economic dynamics & control	1999
Integration of genetic fuzzy systems and artificial neural networks for stock price forecasting	Hadavandi et al.	188	Knowledge-based systems	2010
A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems	Bahrammirzaee	166	Neural computing & applications	2010
Computational Intelligence and Financial Markets: A Survey and Future Directions	Cavalcante et al.	160	Expert systems with applications	2016
Fuzzy Support Vector Machine for bankruptcy prediction	Chaudhuri and De	87	Applied soft computing	2011
Hybridization of evolutionary Levenberg-Marquardt neural networks and data pre-processing for stock market prediction	Asadi et al.	83	Knowledge-based systems	2012
Improving returns on stock investment through neural network selection	Quah and Srinivasan	76	Expert systems with applications	1999
A hybrid ANFIS model based on empirical mode decomposition for stock time series forecasting	Wei	74	Applied soft computing	2016
Graded forecasting using an array of bipolar predictions: application of probabilistic neural networks to a stock market index	Kim and Chun	65	International journal of forecasting	1998
Application of artificial neural network for the prediction of stock market returns: The case of the Japanese stock market	Qiu et al.	57	Chaos solitons & fractals	2016
Using belief networks to forecast oil prices	Abramson and Finizza	46	International journal of forecasting	1991

Visualization of keyword analysis, co-citations of journals, authors and references

First, attention is focused on keyword analysis using the full-count method, which means that each occurrence of a keyword term in a document is counted. Out of a total of 2711 keywords, only networks were selected where the keywords appeared at least 5 times, resulting in 200 keywords displayed on the final map. The final map shows a number of colored and differently sized bubble fields, which are connected at a shorter or longer distance. Color is part of a group - a cluster. This group mapping identifies topics with highly interconnected aspects. The size of the bubble fields represents the frequency of use - the more often a keyword is used in a sample, the larger its bubble. Distances between keywords represent connections, shorter distances mean stronger associations between keywords, and finally the connection of terms in studies is symbolized by lines.

Figure 4 shows the common occurrence of keywords using the full count method. There are a total of 200 items arranged in 4 clusters. The core of the first cluster, which is colored green, was the term "artificial intelligence" with references to "data mining", "decision", "support", "investment" and "economics". The most common keywords of the second cluster, which is highlighted in red, were "neural networks", then "deep learning", "big data" and "financial data", i.e., terms related to a particular means of artificial intelligence, specifically this cluster refers to artificial neural networks in connection with financial data. The third group - yellow includes links between the words "forecasting", "time series forecasting" and "stock forecasting". This indicates the purpose of using AI, which are used in financial time series primarily for predictions of future development, market direction or prediction of corporate bankruptcy, etc. Finally, a somewhat smaller cluster is shown in blue. This cluster again contains a special type of AI tool, this time it is fuzzy logic, which is widely used in financial markets right after neural networks. There are links to keywords such as "fuzzy inference", "fuzzy logic" and "anfis". The size of the bubbles is the largest in the area of interest, which is AI, forecasting and investment. The relationship between the expression bubbles is not too far apart. All clusters overlap considerably, which indicates a significant interconnectedness of these clusters, and therefore the keywords used in the analyzed scientific and research articles and contributions.

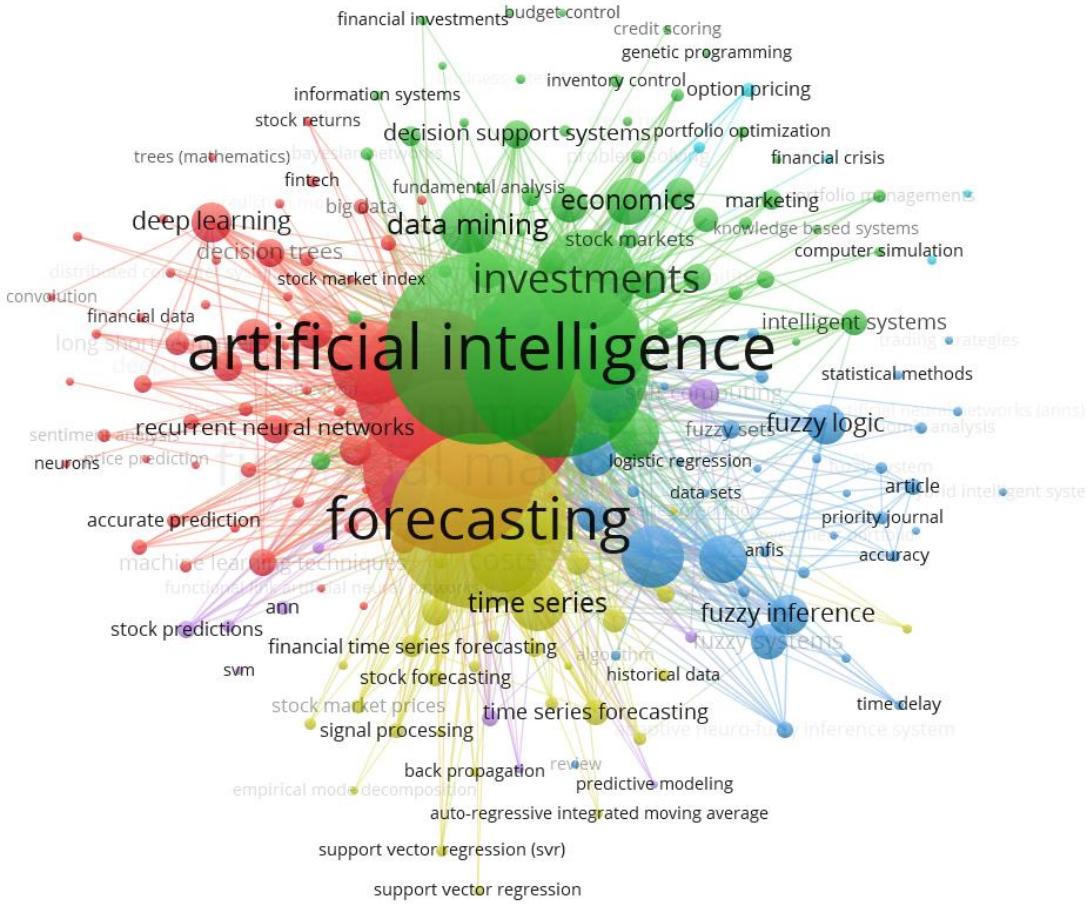

Fig. 4. Keyword occurrence analysis.

Analysis of journal co-citations

This section analyzes the co-citations network of magazines about AI resources in the financial markets. McCain (1990) proposed a citation analysis of the journal to contribute to the study of the organization of scientific disciplines. The frequency of citation of two sources indicates similarities between the scope of the journal and its research topics. Figure 5 shows sources that have been cited at least 25 times. Out of the total number of 5887 journals that were cited in the analyzed journals, a total of 53 of them complied with the requirement for the number of citations. Each node represented the source and the size of each node represented the number of

received citations. The connection between the two items indicated a citation relationship. The nodes were grouped by similarity; that is, the sources in the same cluster (color) and those that are closer were more similar to each other.

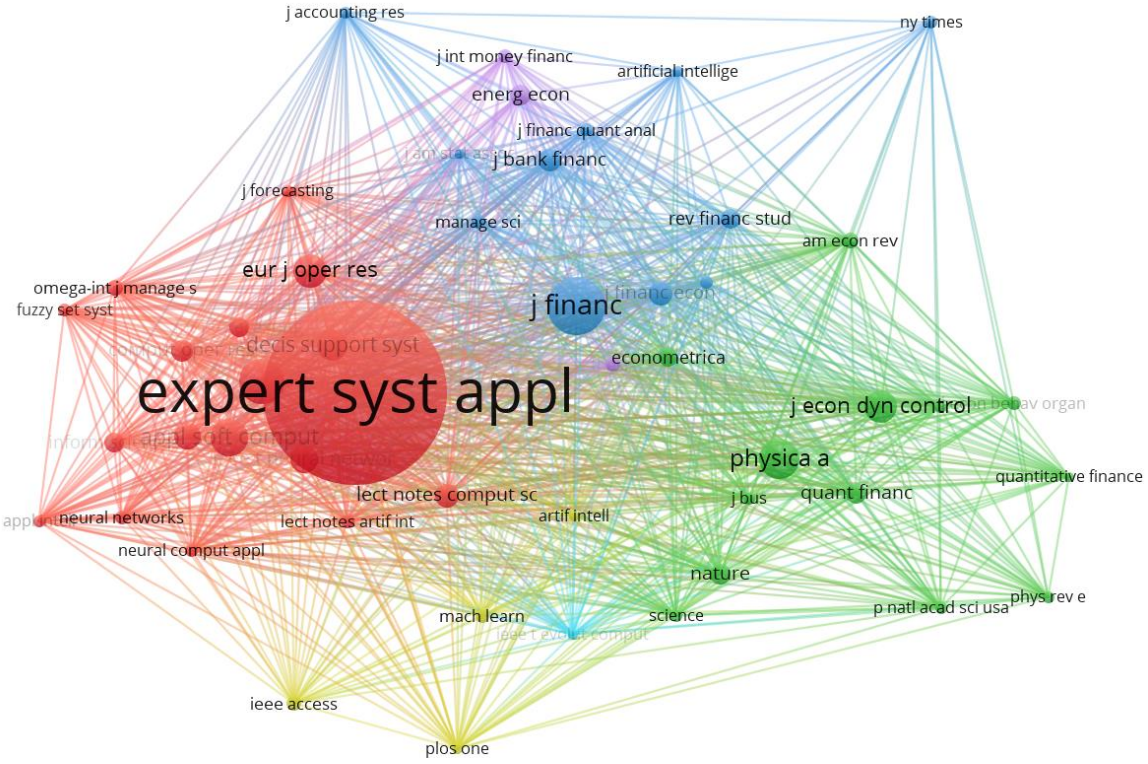

Fig. 5. Analysis of journal co-citations.

Expert System with Application was cited a total of 740 with the greatest overall strength of reference 455. It should be noted that the scope of this journal publishes high-quality articles in the field of expert systems, such as AI, NN, FL and the like in various fields and spheres not only in financial markets. It is obvious that the authors draw from this journal mainly the technical detail of the AI device with subsequent application in the subject area. Another journal from the field of red, i.e. the "technical" cluster with a total number of citations of 146, respectively 188, is *Neurocomputing*, resp. *Applied Soft Computing*. Technical necessities and drawn in detail from the first disassembled cluster are then applied to the financial markets and published, for example, in magazines depicted by the blue cluster. These are, in particular, the Journal of Finance with 195 citations and total reference strength of 166.42, and the *Journal of Financial Economics* with 69 citations and a total reach strength of 62. *Journal of Banking & Finance* with 66 citations and a total reference strength of 62.12. This is followed by a green cluster with journal citations focusing on applications of used systems such as *Physica A: Statistical Mechanics and its Applications* (128), *Journal of Economic Dynamics and Control* (100) or *Quantitative Finance* (60). The smallest cluster is yellow and contains a small number of magazines. This cluster includes a journal and a conference deviating from the analyzed thematic area of *PLOS ONE, IEEE Access* (especially due to the higher number of conference papers) or the Machine Learning magazine. However, these journals are only marginally cited and are drawn in the graph, as they meet the set condition of the number of citations on the edge 25.

Analysis of co-citations of authors

In this part, we perform an analysis of the cited authors. Within the co-citation of authors, attention is focused on the number of cited publications of each author and on their close cooperation. Based on the research of the cited authors, VOSViewer shows us authors with high citations, which can help us find the most important authors in the field of AI in finance area research. Figure 6 shows the visualization of a network for co-citing authors. The threshold value was set at 7, which means that out of the total number of co-citations of 8715 authors; only those authors who are cited at least 7 times in the analyzed publications will appear on the map. A total of 174 authors meet the set value. Each node represents the number of articles published by one author, and the links represent the collaboration between authors. From Figure 6, it can be concluded that in the field of application of artificial intelligence in the field of finance, the research directions of the authors are relatively scattered due to the fact that the presented images are relatively discrete. Although there are overlaps, there is little connection and cooperation between them. Lebaron et al. (53) and Fama (41) have the largest number of cited publications. Lebaron et al. is a green cluster of publications containing 39 other widely cited authors, including Lux (31), Raberto (24) and Farmer (29). While Fama (1970) belongs to the largest - red cluster and there are 58 other authors related to it, such as Chang (32) and Kim (24). Smaller clusters like yellow are

represented by Altman (18), the purple cluster by Markowitz (21) and the blue cluster by Murphy (10). It is evident that the green cluster deviates them considerably from the rest, as the connection is considerably distant between it and the other clusters.

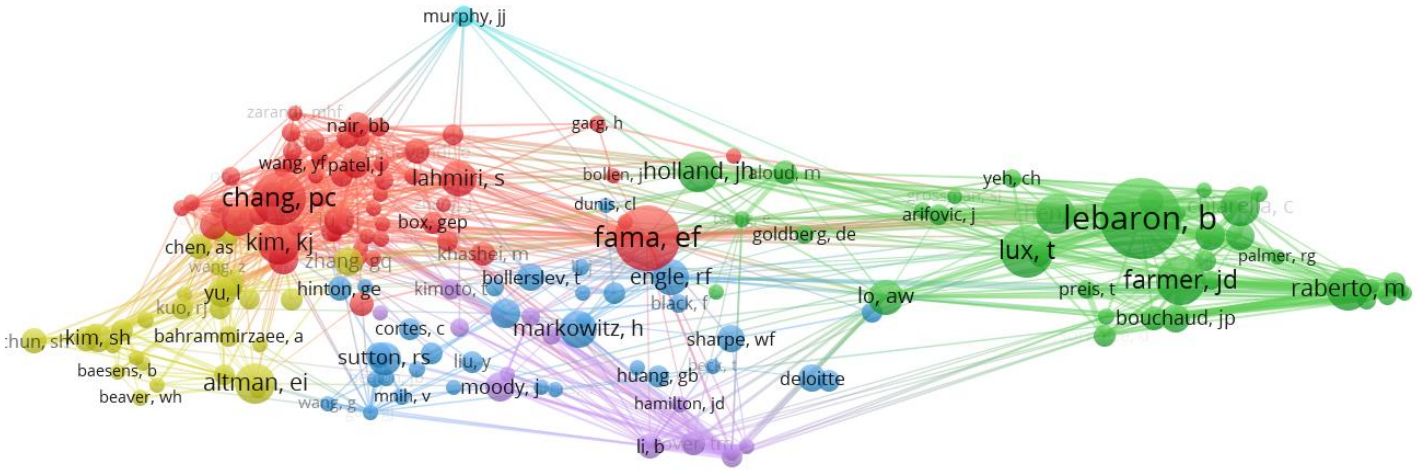

Fig. 6. Analysis of co-citations of the authors.

Analysis of co-citations references

Another citation study analyzed a citation network of artificial intelligence documents with applications to financial markets. Small (1973) assumes that frequently cited works represent key concepts, methods, or experiments in the field. This analysis of co-citations references will therefore make it possible to determine which documents define the intellectual structure of AI issues. Of the analyzed articles, 200 met the threshold of at least 4 citations per article (Figure 7). Each node represented one link, and its size indicated the number of citations to the document. The legacy represented companionship. The number of identical citations was defined as the strength of the quotations between the two cited articles. The citation was thus the frequency with which two articles from earlier literature were cited, together with later literature.

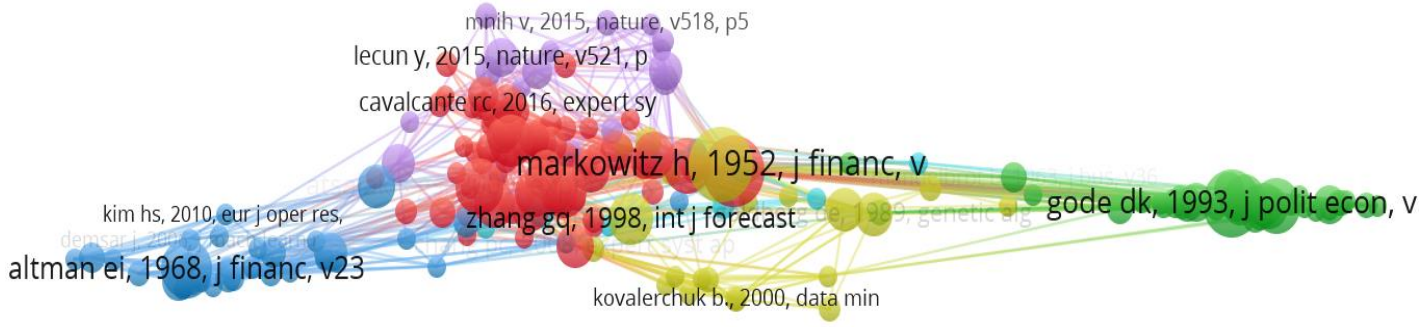

Fig. 7. Analysis of co-citations references.

Nodes of the same color belong to the same cluster. The association strength normalization method used by VOS Viewer identified 5 groups. The Red (80) and Blue (40) clusters contain mainly influential articles on financial theory by Markowitz (1952) with 17 citations and total reference strength of 92 or Fama (1970) with 16 citations and reference strength of 163 articles. These articles in the Red Cluster publish the starting points that are necessary for any analysis in the financial markets. The blue cluster contains, for example, the citation of the publication of Altman (1968). The last three clusters are relatively small compared to the previous two. Although they are relatively closely linked to the red cluster, especially by quoting cells from the purple and yellow clusters, the green cluster is the furthest from other clusters. The yellow cluster contains 14 documents, the purple cluster contains 21 and the green cluster contains 47 cited documents.

Conclusion

This article presented a bibliometric analysis of research and scientific articles obtained from the World of Science database. This analysis was based on the field of artificial intelligence and its application in financial markets using VOS Viewer software. It thus provided a unique and interesting look at the currently thriving AI domain in the field of finance. A rough visual analysis of the common occurrence of keywords, co-citations of literature, journals and authors provided an important reference for future research in this area. According to a systematic overview of visual knowledge maps and research results, a number of conclusions are drawn. As can be seen from the analysis, the number of publications in the field of research has increased significantly in the

last five years and is dispersing. Recent years of research have been a significant fusion of neural networks, fuzzy logic and genetic algorithms. This leads to the creation of hybrid systems, which are focused primarily on predicting the development of stock markets, commodity markets and the foreign exchange market. We found that in terms of categories, there is an intertwining of technical, information and economic areas. This is a multidisciplinary field of research. In terms of the highest frequency of keywords, terms such as "artificial intelligence", "forecasting", "time series", "economics" were clearly identified in the articles in question. The cradle of the most important research is the Expert System with Application, where the authors benefit mainly from the technical requirements of AI resources.

In short, this article sought to identify potential relationships between world research publications through bibliometric analysis, clarifying the development of artificial intelligence in finance over the past 30 years. The purpose of this research was to raise current awareness of the subject while helping scientists steer future research and provide an information base for beginners with strong interest linking the AI trend to anticipate or build a model to support financial market decision-making. However, it is necessary to point out certain limitations and shortcomings of the study performed. The number of analyzed articles is limited by the selected database. There is room to expand with other world databases such as Scopus and to obtain other relevant publications that fully reflect the available data sources. Another problem concerns the choice of thresholds, which are the default value for debugging the network visualization structure. This requires further research. In addition, it would be useful to focus on other software that is available for bibliometric analysis such as CiteSpace and to compare results from different software.

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