ANALYSIS OF THE USE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN COMMODITY MARKETS

Tereza Malátková[1], Mikuláš Gangur[2]

[1] Ing. Tereza Malátková, University of West Bohemia, Pilsen, Faculty of Economics, malatkova@fek.zcu.cz, ORCID 0009-0007-3718-982X
[2] doc. RNDr. Mikuláš Gangur Ph.D., University of West Bohemia, Pilsen, Faculty of Economics, gangur@fek.zcu.cz, ORCID 0000-0002-7731-9146

Abstract: In recent years, developments in the field of commodity markets have been marked using artificial intelligence. Global social and political disruptions, such as wars and pandemic, and the shift in the development of artificial intelligence toward users mainly contributed to this development. Compared to 2005-2019, the increased interest is evidenced by the unusually high growth in the number of scientific publications on this topic in 2020-2024. Commodities pervade many fields of interest; likewise, artificial intelligence can work with them in many ways. For this reason, studies on the subject are very diverse. In this bibliometric study, we provide a literature review analyzing using artificial intelligence (AI) and machine learning (ML) in commodity markets. Only 343 thematically focused publications from 2005-2024 provide the selection, which we process using the method of bibliometric and content analysis. We identify the development of the number of publications as a function of time and types of publications, authors and institutions, interconnectedness of citations, literature production in individual countries, and areas of research topics. Using the co-occurrence method, the study will offer an overview of the current development trends in using AI and ML to analyze commodity markets. Furthermore, the study points to possible directions for further research by defining research gaps and formulating an overview of calls for further research.

Keywords: artificial intelligence, machine learning, commodity, market, analysis

JEL Classification: G190, O330, O310

INTRODUCTION

Commodity markets are broad areas and carry important information for many different users. From those directly involved in the market, growers, processors, and large and small traders, to those subsequently affected by the market, e.g., transporters, warehouses, and politicians. At the same time, AI and ML tools have developed rapidly in recent years and are becoming more accessible to users. Integrating artificial intelligence (AI) and machine learning (ML) in commodity markets has significantly increased the accuracy of forecasts and market analysis. ML models use a support vector machine, random forests, time series, text mining, or variants of Long-Term Short-Term Memory (LSTM), a gradient type of advanced recurrent neural network that includes specialized "gates" for managing long-term and short-term memory in its structure. AI and ML technologies enable stakeholders to effectively navigate the complexities of price fluctuations and geopolitical influences.

Based on this, a wide range of studies on AI and ML use in the commodity market context is emerging. These studies show the growing importance of artificial intelligence and machine learning in analyzing and forecasting trends in commodity and financial markets, offering potential benefits for investors, traders, and policymakers.

This bibliometric study is focused on analyzing research on the use of AI and ML in the commodity market. The main goal is to specify the directions in which AI and ML are used in commodity market analysis and, above all, to identify calls and gaps for further research. The source of the analyzed research papers is the Web of Science database.

A random selection of publications in artificial intelligence from the Web of Science database provides over 1,128,282 entries. The field of commodities is also a broad topic that has been researched from the perspective of different users, and a random selection of publications in this field from the Web of Science database provides over 72,482 entries. In this bibliometric study, we provide a literature review analyzing using artificial intelligence (AI) and machine learning (ML) in commodity markets. Only 343 thematically focused publications from 2005-2024 provide the selection, which we process using the method of bibliometric and content analysis.

By implementing bibliometric methods on the given topic, in this study, we systematically evaluate and quantify the research output, publication trends, and dissemination of knowledge about artificial intelligence and machine learning in commodity markets for the period 2005 - April 2024. This analysis will bring valuable insights into the dynamics of the field, the main contributors, important publications, and especially about current development trends with identified opportunities for further research.

The dynamics of research development in the area are expressed by publication activity in individual years and the type of research papers. The study lists the main contributors from the position of authors, as well as institutions, countries, and journals. Furthermore, important publications, framework areas of research, and a network of publication citations and authors are listed. Using co-occurrence analysis, which looks for links by keywords, 7 areas are defined that can be considered the main research directions. Using qualitative content analysis, these 7 directions are processed and formulated. Furthermore, possibilities and needs for further research are identified for each direction.

Identifying trends and needs for further research is the main goal of this bibliometric analysis.

While AI and ML offer powerful tools to improve market forecasting, challenges remain in addressing global commodity markets' inherent complexity and unpredictability. To master them, it is important to fully understand the environment and the development of research in this specific area. By applying bibliometric techniques to literature research, we can develop a comprehensive understanding of the research field, facilitate informed decision-making, and guide future research efforts in the field.

1. METHODOLOGY AND DATA

To get relevant results of the research, we follow the standard procedure: defining the aims and research design, choosing the methods and techniques for analysis, data selecting and collecting, conducting the analysis, and results interpretation. This section describes methods and techniques of processing, as well as data selection and collection.

1.1 Choosing the methods and techniques for analysis

In this study, we used both, bibliometric and content analysis. We first use quantitative tools of bibliometric methodology to analyze a large amount of bibliometric information.

For an overview of the publication aimed at the use of AI and ML in commodity markets, we use bibliometric analysis techniques. Bibliometric analysis involves the systematic study of scientific literature to identify patterns, trends, and impacts within a field, using data collection, cleaning, and various bibliometric methods for meaningful information generation (Passas, 2024).

Carrying out a quantitative analysis helps to obtain an overview of the essential scientific articles, important authors, titles, and current trends. One of the advantages of quantitative analysis is the possibility of processing a large amount of data using SW. In this study, co-citation analysis, bibliographic coupling, and co-word analysis are used from the quantitative techniques.

Co-citation analysis identifies connections between documents by examining how often they are cited together. This method can reveal clusters of related research, as demonstrated in studies on investment efficiency (Phan et al., 2024). In statistics, co-citation networks have been utilized to map research interests and trends, revealing significant shifts in focus over time ("Co-citation and Co-authorship Networks of Statisticians", 2022).

Bibliometric coupling (BC) is a method used to analyze the relationships between academic publications based on shared references. BC occurs when two documents cite a common third document, indicating a thematic connection between them. This is distinct from co-citation, which focuses on documents that are cited together (Yun, 2022). This technique helps in mapping the intellectual structure of various research fields and identifying emerging trends.

Co-word analysis is a technique used to explore the relationships between keywords in various research fields, revealing the underlying knowledge structures.

After detecting the main trends in the use of AI and ML in commodity markets using quantitative methods of bibliometric analysis, we proceed to a qualitative content analysis of these trends. Initially focused on archived texts like newspapers, content analysis has adapted to include electronic and digital media, reflecting changes in communication practices (Liauw, 2022; Tunison, 2023). AI is a dynamically developing field so information for content analysis is drawn from electronic databases.

1.2 Data collection and software

The research papers data for this study were searched in the databases Web of Science (WoS), Scopus, ScienceDirect, and Google Scholar. Performance analyses were processed based on data collected from WoS. Relevant resources from other databases mostly duplicated WoS resources, so they were not included. The Web of Science is a global comprehensive research database facilitating bibliometric analysis across various fields. It serves as a critical source for understanding trends, citation patterns, and the impact of research.

Table 1 illustrates the gradual targeting of conditions for finding suitable studies. The number of publications focused on AI or ML proves the high interest in this area. The study focuses on using AI and ML for commodity market analysis. Further resource selection, therefore, focuses on commodities. By commodity, we mean raw materials, natural resources, hard assets, and other real things. In relation to commodity markets, Garner (2014) states, "We consider any substitutable product to be a commodity. Indeed, futures contracts can, according to their definition, be written on any commodity for which the underlying asset is a substitutable product." Commodities (using only the "commodity" keyword), as a permanent and broad topic, also offer a wide range of studies through the Web of Science, albeit in orders of magnitude smaller than the dynamically developing field of AI. However, when searching for publications connecting these areas, Web of Science offers 343 publications.

Table 1: Search criteria to find the final 343 publications for review.

Search Criteria	Find
Search engine: Web of Science	
Search date: 8.9.2024	
Search terms: "AI" or "artificial intelligence"	1,128,282
Search terms: "ML" or "machine learning"	2,404,134
Search terms: "commodity"	72,482
Search terms: ("AI" or "artificial intelligence" or "ML" or "machine learning") and "commodity market" Search fields: Topic (title, abstract, keywords plus and author keywords)	343

Source: Authors' own research of WoS, 2024

Data from these publications are cleaned and used as a basis for bibliometric analysis. Before co-citation analysis and co-word analysis, it was also necessary to adjust the data from the point of view of uniting terms, so that different diacritics of titles, abstracts, or keywords did not affect the results of the analysis. For example, we adjusted the plural numbers to be uniform, unified the way of using hyphens, or united different names expressing the same meaning into one.

After cleaning the data, we proceed to co-citation analysis and co-word analysis using the WOSviewer software. WOSviewer allows users to construct bibliometric maps that illustrate relationships between authors, institutions, and publications, enhancing the understanding of research trends (Nees & Waltman, 2009).

2. BIBLIOMETRIC ANALYSIS

In this chapter, we proceed to the analysis of selected 343 articles from the Web of Science on the analysis of the use of artificial intelligence and machine learning in the commodity market. The bibliometric analysis first processes the performance analysis in Chapter 2.1, based on which the content analysis in Chapter 2.2 is subsequently developed.

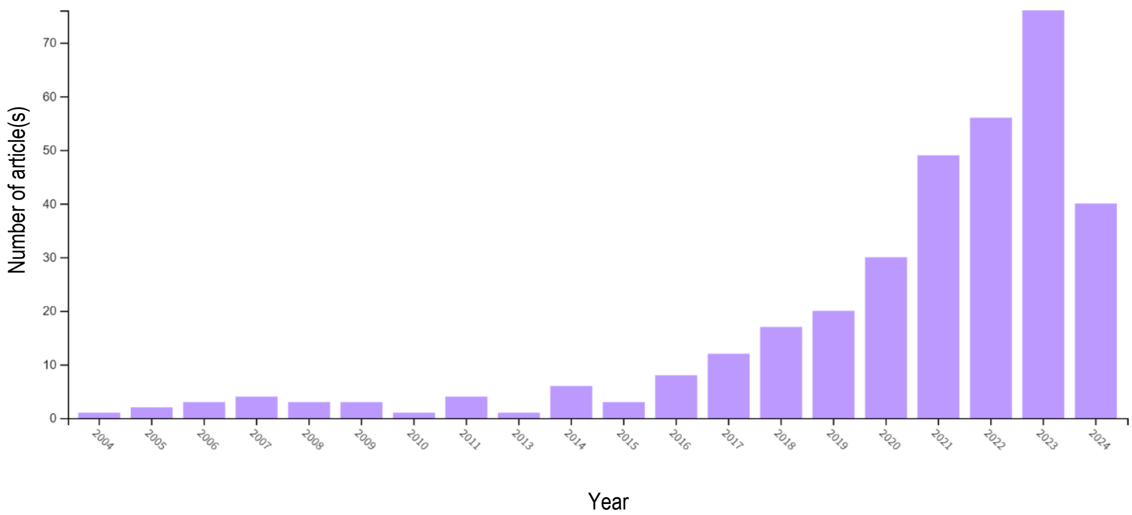
2.1 Performance analysis of the use of AI and ML in the commodity market

This part of the bibliometric analysis processes data on publication activity, types of documents, main contributors, topics, and areas. Furthermore, a citation, co-citation, and co-occurrence analysis is processed, from which the main trends are defined.

2.1.1 Publication activity and types of documents

The publication activity of the use of AI and ML in the commodity market is presented in Fig. 1, wherein the total number of research papers is recorded in the year of publication. From the mapped period 2004 – April 2024, we recognize the beginnings of the use of AI and ML in commodity markets, when usually 1-4 articles were published annually until 2015, in 2014 there were 6 articles. This is followed by a period of moderate growth in 2016-2019 and from 2020 an expansion of publications, namely in 2020 (30 articles), 2021 (49 articles), 2022 (56 articles), 2023 (76 articles), and by April 2024 40 articles have already been published. Covid-19, the war in Ukraine, and innovations in the field of IT leading to the creation of user-friendly AI contributed to the increased scientific interest in this area and, as a result, a visible growing trend in publishing.

Figure 1: Record count of research papers in publication years



Source: Web of Science, 2024

Of the 343 publications published on the Web of Science, more than 75 % are articles (the record count is 260). Furthermore, 72 proceeding papers constituting almost 21 %. Other types of documents individually occupy up to 5 % of the searched publications, as shown in Table 2. The absence of a book-type document is interesting, which we attribute to the dynamic development in this area (the book's topicality is a limiting factor).

Table 2: Document types

Document Types	Record Count	% of 343
Article	260	75.802
Proceeding Paper	72	20.991
Early Access	15	4.373
Review Article	11	3.207
Editorial Material	2	0.583
Retracted Publication	1	0.292

Source: Web of Science, 2024

2.1.2 Top authors, affiliations, and countries of research on the use of AI and ML in the commodity market

The top authors of research on the use of AI and ML in the commodity market are presented in Table 3. To be included in Table 3, there is a condition of at least 3 publications in the researched area per author.

In Table 4, the affiliations that are most dedicated to research in the monitored area were selected. To be included in Table 4, there is a condition of at least 4 publications in the researched area per institution. The most productive institutions are in India, the USA, China, Great Britain, and Canada.

The location of the most productive institutions corresponds almost exactly to the productivity of individual countries in the monitored research, presented in Figure 2. The discrepancy in publishing between institutions and countries can be found in the affiliates of China, where most of the research papers (5 articles) were published by Tsinghua University. Other Chinese institutions did not exceed 3 articles. Nevertheless, most research papers are published by researchers from China (77).

Table 3: Top authors

Authors	Record Count	% of 343
Paul RK	6	1.749
Sadorsky P	5	1.458
Xu XJ	5	1.458
Yeasin M	4	1.166
Zhang Y	4	1.166
Garai S	3	0.875
Gong LY	3	0.875
Kumar RR	3	0.875
Li ZH	3	0.875
Lin H	3	0.875
Liu YH	3	0.875
Misra S	3	0.875
Sueyoshi T	3	0.875
Tadiparthi GR	3	0.875
Vochozka M	3	0.875
Showing 15 out of 1 195 entries		

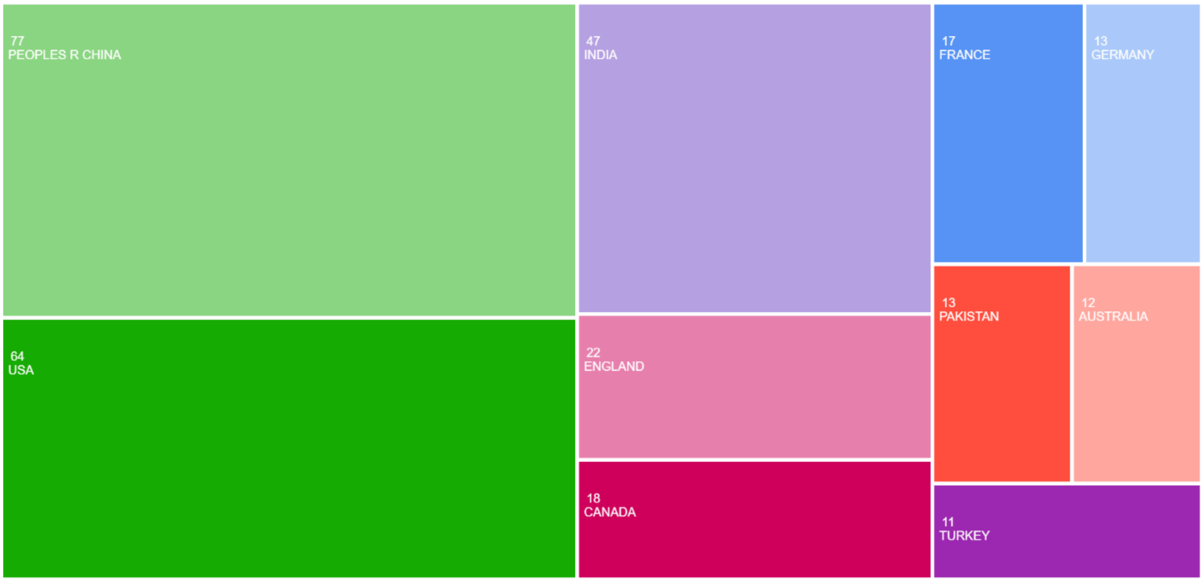
Source: Web of Science, 2024

Table 4: Top affiliations

Affiliations	Record Count	% of 343
Indian Council of Agricultural Research Icar	13	3.790
Icar Indian Agricultural Statistics Research Institute	10	2.915
North Carolina State University	7	2.041
United States Department of Agriculture Usda	7	2.041
Tsinghua University	5	1.458
University Of London	5	1.458
York University Canada	5	1.458
Edc Paris Business Sch	4	1.166
Inrae	4	1.166
Michigan State University	4	1.166
Showing 10 out of 638 entries		
1 record(s) (0.292 %) do not contain data in the field being analyzed		

Source: Web of Science, 2024

Figure 2: Number of publications by country



Source: Web of Science, 2024

When analyzing the languages of publications, English is shown to be the most used language in scientific studies internationally. When analyzing the languages of published articles, English appears to be the most used language in scientific studies at an international level. Interestingly, 98% of the research papers are written in English (339 publications), although most of the articles examined are not from English-speaking countries (mainly China 77, India 47). This can be explained by the interest in publication, cooperation, and citations at the global level. Publications in Chinese, Latvian, Portuguese, and Russian language are represented after 1 publication, summarized in Table 5.

Table 5: Used languages of the publications

Languages	Record Count	% of 343
English	339	98.834
Chinese	1	0.292
Latvian	1	0.292
Portuguese	1	0.292
Russian	1	0.292

Source: Web of Science, 2024

2.1.3 Top publishers of the use of AI and ML in the commodity market

Specific authors, institutions, or countries do not limit publishers. The publishers focus on the selected topic and the quality of the research content. When analyzing published research on the use of AI and ML in the commodity market, we mapped which publishers publish the most articles in the researched area. The results are presented in Table 6. The publishing house Elsevier represents 21,57 % of the research, and the publishing houses IEEE (12,828 %) and Springer Nature (11,828 %) can also be listed as important representatives.

Table 6: Top publishers

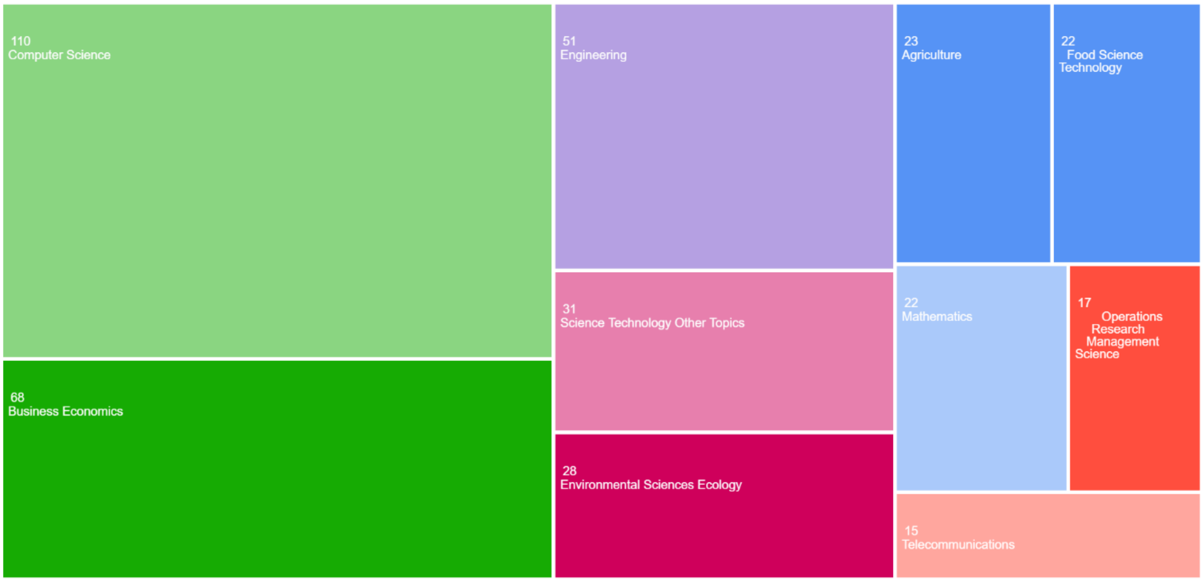
Publishers	Record Count	% of 343
Elsevier	74	21.574
IEEE	44	12.828
Springer Nature	44	12.828
Mdpi	33	9.621
Wiley	20	5.831
Taylor & Francis	10	2.915
Assoc Computing Machinery	7	2.041
Sage	6	1.749
Emerald Group Publishing	5	1.458
Frontiers Media Sa	5	1.458
Showing 10 out of 74 entries		

Source: Web of Science, 2024

2.1.4 Topics and areas of research on the use of AI and ML in the commodity market

The use of AI and ML in the commodity market can be explored, focusing on various specific areas. This section maps out 10 main areas within which the topic is researched. Research areas show the perspective and focus from which the article is approached. The research area of Computer science is devoted to 110 publications, which makes up 32.070 %. 68 publications (19.825 %) focus on the area of Business economics, followed by Engineering 51 (14.869 %), Science Technology other topics 31 (9.038 %), Environmental sciences ecology 28 (8.163 %), Agriculture 23 (6.706 %), Food science technology 22 (6.414 %), Mathematics 22 (6.414 %), Operations research management science 17 (4.956 %), and Telecommunications 15 (4.373 %). The results of this analysis demonstrate the predominance of interests in AI and ML research falling mainly in Computer science. The distribution of research areas is shown in Figure 3.

Figure 3: Top 10 research areas



Source: Web of Science, 2024

The focus of works on topics, which include the titles of publications, the content of their abstracts, and keywords, is also closely related to the areas of research. The found similarities in topics illustrate important research directions. 10 main directions are mapped in Figure 4. Interesting is the significant preponderance of articles with the topic of Computer science over Business, Economics, and Food topics. Researchers are focusing mainly on Computer science, to which a total of 155 publications are devoted. Computer science is further broken down into main directions: Artificial intelligence (52), Information systems (39), Theory methods (37), and Interdisciplinary applications (27). Other important research directions are Engineering – electrical, electronic (34), Business Finance (27), Management (22), Food science technology (22), Multidisciplinary sciences (21), and Economics (20).

The analysis of directions on the use of AI and ML in the commodity market again reflects researchers' predominant interest in AI and ML, which was already evident during data collection.

Figure 4: Topics of publications

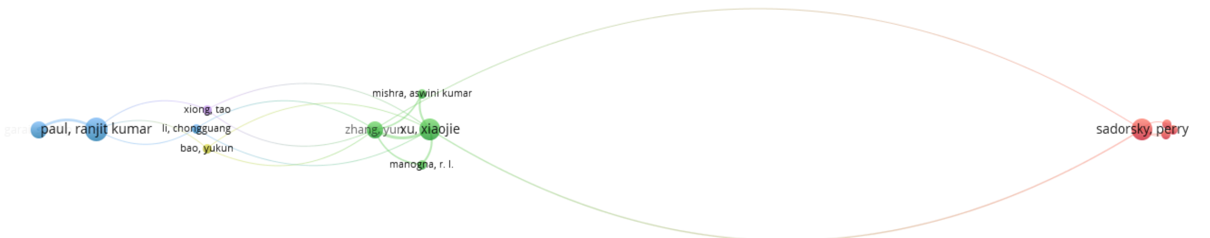
Source: Web of Science, 2024

2.1.5 Analysis of the citations and analysis of content

This chapter analyzes the citations, their intensity, and the connections between the items. We use the WOSviewer program for this. The analysis outputs are visualized using lines and nodes, which together form maps. The lines represent the frequency with which the article was cited. Citation sources are defined using nodes and their size indicates their importance. Publications, journals, authors, organizations, countries, or keywords for co-occurrence analysis can be chosen as the source to which we are looking for links. A link can be created based on citations, co-citations, bibliographic coupling, co-authorship, and co-occurrence. The WOSviewer software offers many views of the links between individual elements. This analysis presents a selection of visualizations that carry interesting or important information.

We identify important authors in the field by visualizing the network of citations between authors. The map in Figure 5 is constructed under at least 30 citations per author, which selected 140 out of 1220 authors for display. Of these, a citation network was detected in only 13 of them. These 13 authors can, therefore, be considered the most important in the field.

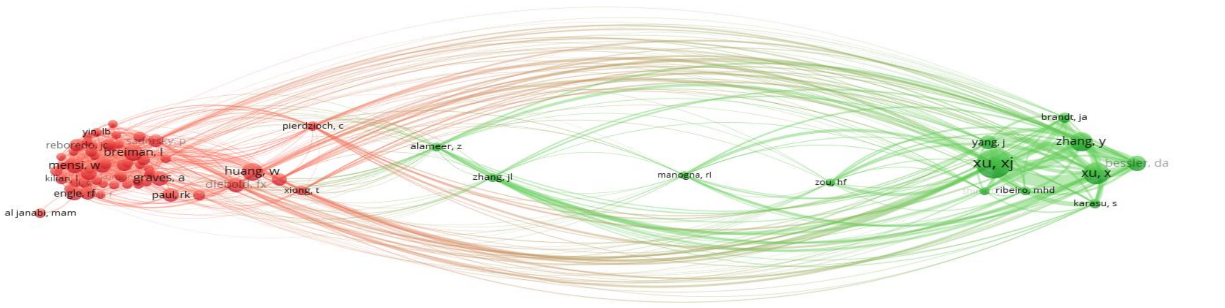
Figure 5: Citation analysis of authors



Source: WOSviewer, 2024

For the visualization co-citation of authors, we set a minimum of 10 citations of an author, which gave us a result of 71 authors out of the 11,488. The map in Figure 6 shows the co-citation of authors. The length of the lines expressing the frequency of citations here visibly divides the authors into 2 main groups. Within the group, authors are cited intensively, co-citations also exist between groups, but they are not so frequent.

Figure 6: Co-citations of authors



Source: WOSviewer, 2024

The citation network of sources in Figure 7a maps 35 sources out of 272 that meet the condition of at least 2 citations. Here, the citation connection of only part of the sources is visible. Figure 7b provides a closer look at the connected sources. The most cited journals are listed in Table 7.

Figure 7a: Citation network of sources

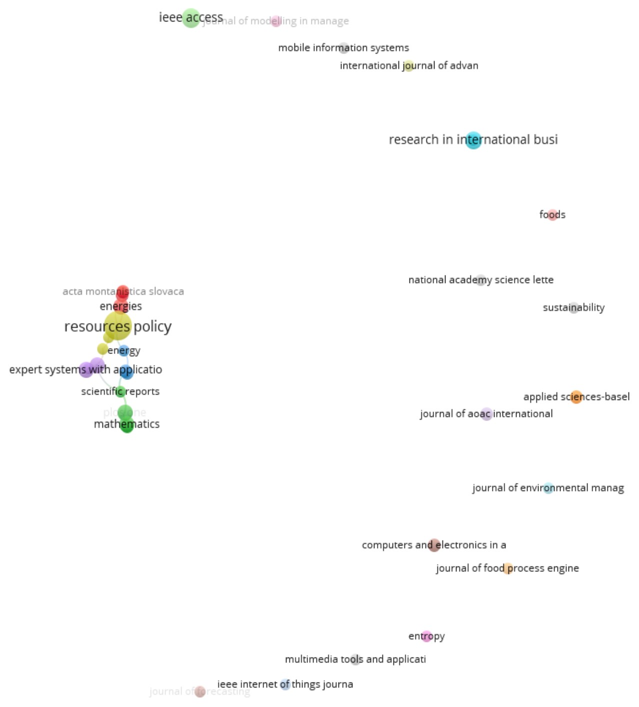
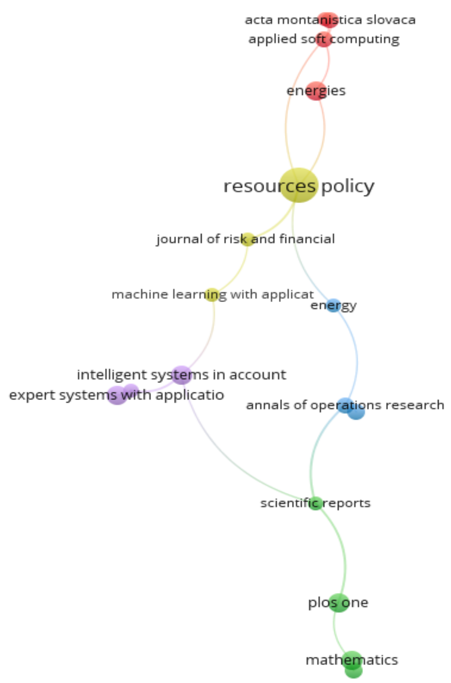


Figure 7b: Cooperating network of sources



Source: WOSviewer, 2024

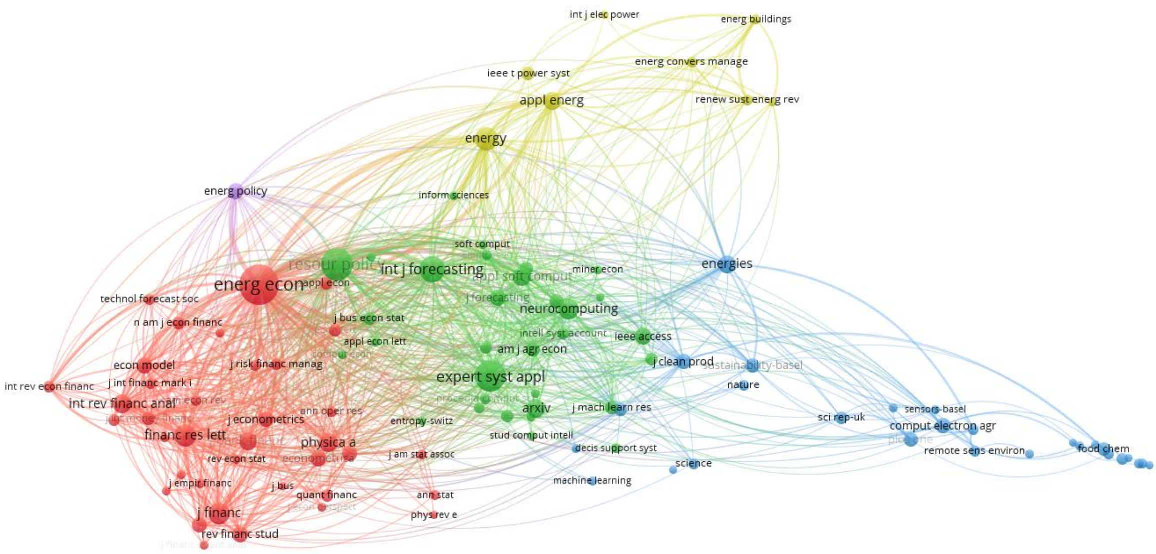
Table 7: Top cited journals

Source Title	Times Cited, All Databases
Applied Soft Computing	485
Harvard Business Review	210
Plant Disease	186
Expert Systems with Applications	118
Annals Of Operations Research	98
Neurocomputing	97
Computer Physics Communications	89
IEEE Internet Of Things Journal	80
Crop Protection	80
Energy	79

Source: Web of Science, 2024

The co-citation mapping of sources is illustrated in Figure 8. Under the condition of at least 20 citations per source, the map shows the network of connections of 105 sources out of a total of 7,042. The most co-cited journals are Energy Economic Journal with 464 citations, Resource Policy Journal (285), International Journal of Forecasting (193), Expert Systems with Applications (273), and Finance Research Letters (148).

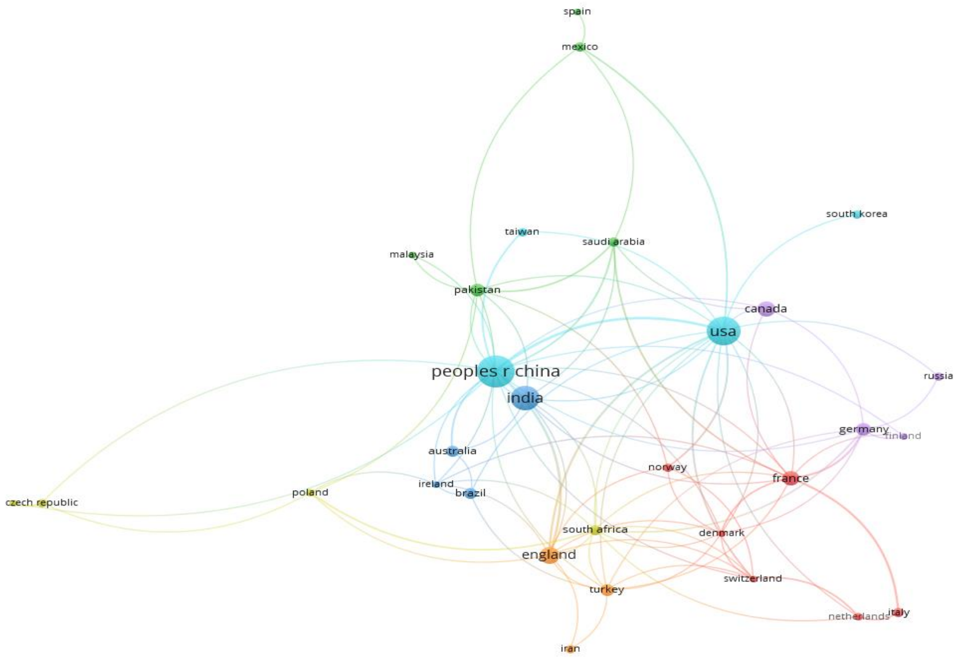
Figure 8: Co-citations of sources



Source: WOSviewer, 2024

Analysis of co-authorship by countries is presented in Figure 9. The distribution corresponds to the initial finding of publication production in individual countries.

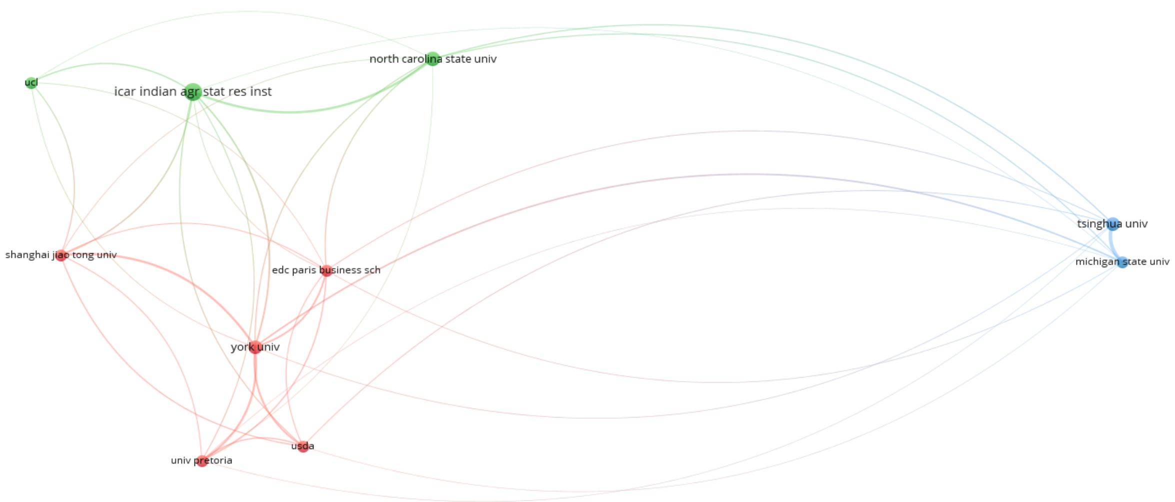
Figure 9: Co-authorship by countries



Source: WOSviewer, 2024

The bibliographic coupling of institutions maps the interconnectedness of the works of individual institutions based on reference analysis in Figure 10.

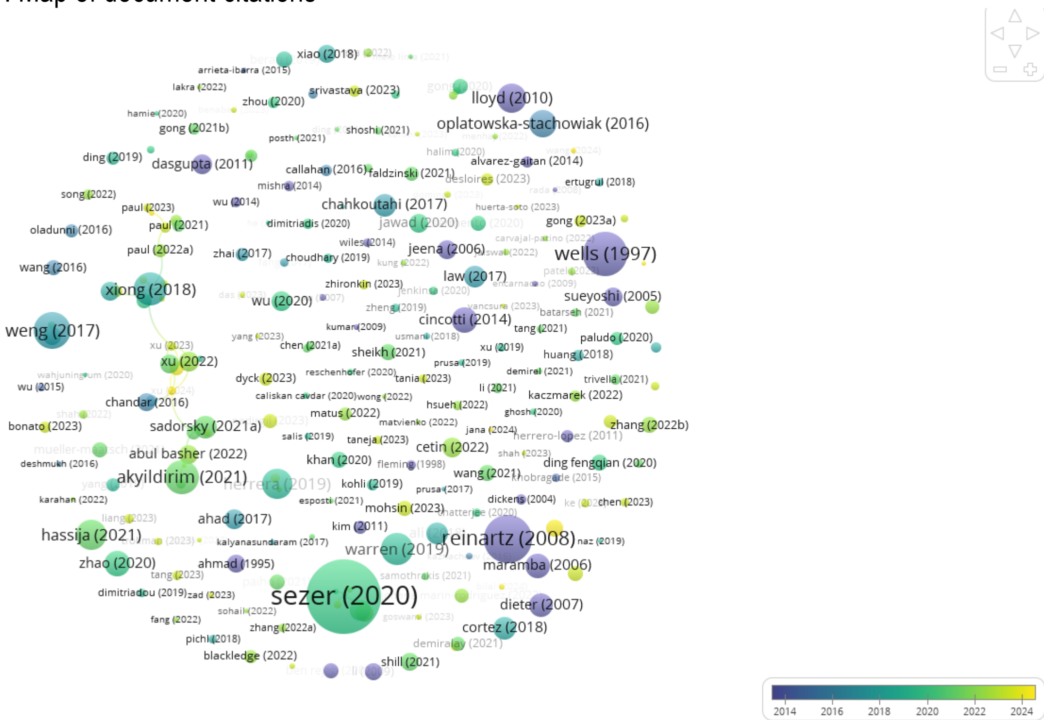
Figure 10: Bibliographic coupling by institutions



Source: WOSviewer, 2024

Network mapping can also be used for content analysis. We identify the main research directions by identifying matches in Topics. From Topics, we primarily find publication citations and analyze keywords. When analyzing the linkage of documents using citations, we find out which documents are cited the most. Visualization of the map in Figure 11 highlights the title: "Financial time series forecasting with deep learning: a systematic literature review: 2005-2019" written by Sezer et al. (2020) with 452 citations. Next is a title: „Stock market one-day ahead movement prediction using disparate data sources“ written by Weng et al. (2017) with 113 citations. Title: „How to sell services more profitably“ source Harvard Business Review, written by Reinartz et al. (2008) with 189 citations. Title: „Prediction of cryptocurrency returns using machine learning“ written by Akyildirim et al. (2021) with 95 citations, or title: „Seasonal forecasting of agricultural commodity price using a hybrid stl and elm method: evidence from the vegetable market in China“ written by Xiong et al. (2018) with 89 citations.

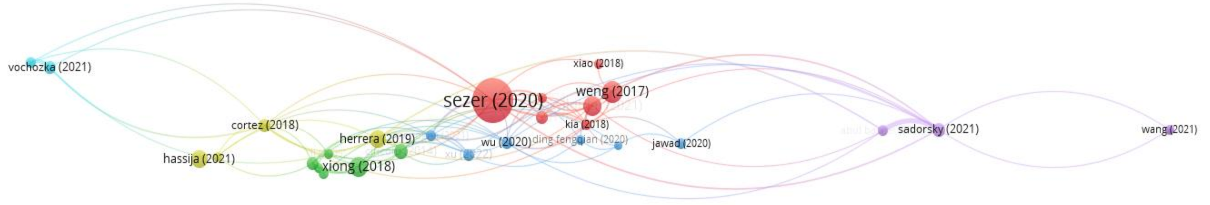
Figure 11: Map of document citations



Source: WOSviewer, 2024

The most cited documents also show their importance from the point of view of the bibliographic coupling of documents, as shown in Figure 12. The condition of at least 20 citations per document is met by 50 of the total 343 documents, and only 29 of them are linked. The map is built of nodes and means keywords. The size of nodes presents the frequency of use, and the link connects the keywords if they appear in the same document. The 29 connected documents are color-coded into 6 clusters and are suitable for qualitative content analysis to describe current research directions in detail. We identify clusters focused on the use of AI and ML for 1) Forecasting stock market, cryptocurrency, commodity, and time series, 2) Commodity prices forecasting, 3) Production and price development, 4) Security threats, 5) Forecasting models, 6) Random forests and energy. This method has been effectively utilized to visualize research landscapes, such as in the study of data literacy, where key documents and their interconnections were mapped (Nwagwu, 2024). In this case, we do not recommend taking clusters of the bibliometric analysis as research directions due to insufficient connection (29 out of 343). A research landscape created on such a basis could lead to the omission of important directions.

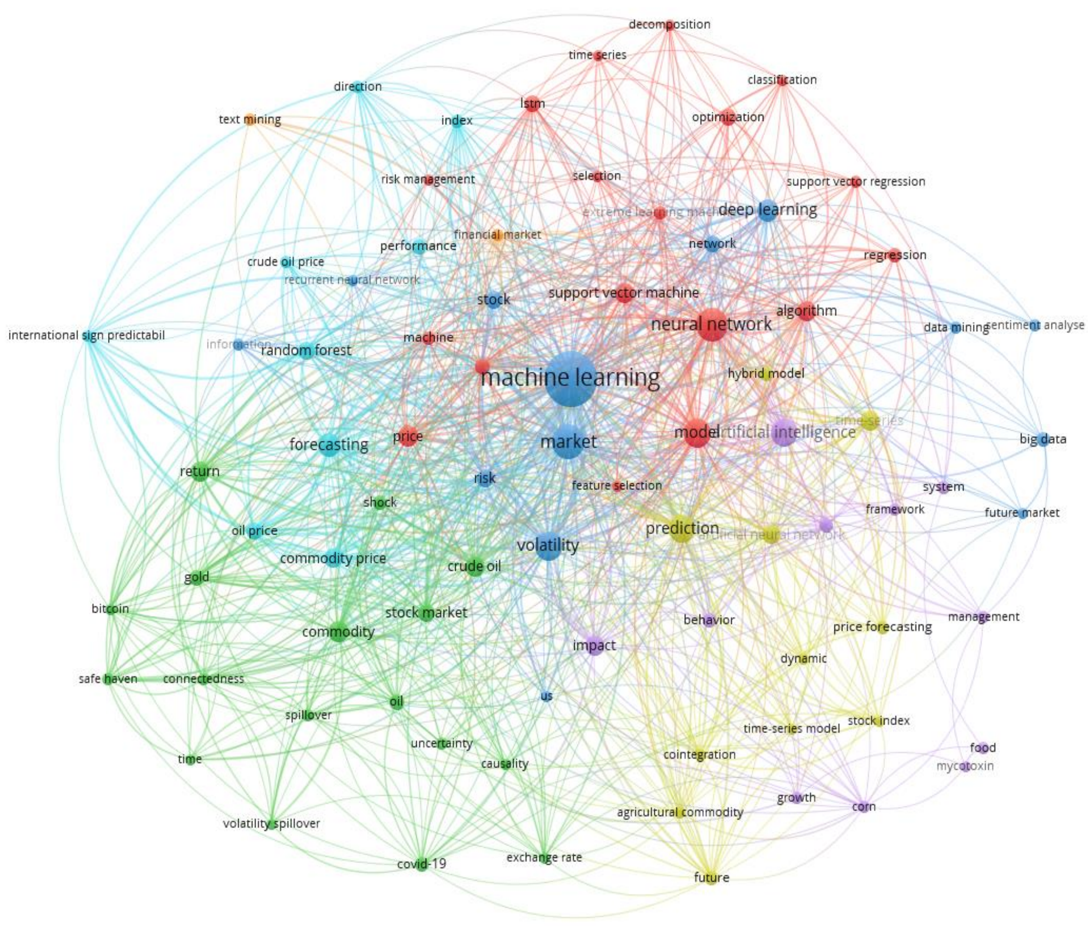
Figure 12: Bibliographic coupling of documents



Source: WOSviewer, 2024

Co-occurrence analysis looks for links by keywords. When entering the condition of a minimum of 5 occurrences of a keyword, we get 82 related keywords out of 1837. The resulting map in Figure 13 identifies machine learning, neural networks, and artificial intelligence as essential keywords of the researched publications. The network is made up of 7 color-differentiated clusters with keywords 1) commodity and stock market, shock, and return, 2) ML, market, and volatility, 3) neural network, models, price, and optimization, 4) artificial intelligence, management, food, and impact, 5) forecasting, commodity price, and random forests, 6) prediction, futures, time-series models, 7). text mining

Figure 13: Co-occurrence analysis



Source: WOSviewer, 2024

2.2 Qualitative content analysis and Suggestions for future research

Qualitative content analysis systematically evaluates the qualitative data contained in the text. It mainly focuses on the information hidden in the text. In this work, we approach a qualitative content analysis focused on research directions defined using quantitative bibliometric analysis. For this purpose, we can use the results from the previous co-occurrence analysis. By this method we defined a network, Figure 13, made up of 7 clusters 1) commodity and stock market, shock, and return, volatility, and spillover 2) ML, market, and volatility, 3) neural network, models, price, and optimization, 4) text mining, 5) forecasting, commodity price, and random forests, 6) prediction, futures, time-series models, 7) artificial intelligence, management, food, and impact. All directions are connected by the essential keyword machine learning (and neural network, and artificial intelligence).

In the next sections, the research directions are described and for each, a significant publication is listed, and further research steps are recommended.

2.2.1 Research direction: Commodity and stock, shock and return, volatility and spillover

Machine learning (ML) is a powerful tool for predicting prices on commodity and stock markets, especially in predicting price shocks and returns. Vardar et al. (2018) indicate in research significant bidirectional shock transmission and volatility spillover between stock and commodity markets, especially during crisis periods. Authors identify a gap in the research to get more significant effects during crisis and post-crisis compared to pre-crisis. For future research, they recommend exploring the impact of central bank policies on shock transmission and volatility spillover (STVS) effects and investigating the long-term implications of STVS effects on the global economy.

Wang and Zhang (2023) explore using machine learning to predict commodity futures returns, not stock shocks. It identifies dominant predictors and outperforms traditional models in predicting commodity futures returns. It is recommended for future research to explore additional predictors for improved future returns predictability and to investigate the impact of different ML models on predictions.

This trend is also explored from a resource policy perspective. Chen et al. (2021), in their study, employ unsupervised machine learning to cluster commodity markets in space and time, clarifying returns, volatility, and trading regimes and showcasing its applicability to stock shocks and returns. A shortcoming in this research is the limited discussion of the impact of clustering on market efficiency. Furthermore, there is a lack of research on the relationships between trade regimes and market clustering. It is recommended for future research to include more advanced ML techniques or to investigate the impact of external factors on commodity markets.

2.2.2 Research direction: Market and volatility

AI and ML are highly used to identify volatility in the markets. Machine learning approaches, when combined with GARCH models, have demonstrated improved out-of-sample forecasting performance for energy commodities, highlighting the importance of hybrid models in volatility analysis (Chung, 2024). For further forecasting in the energy sector, a hybrid modeling framework that combines the strengths of both methodologies is proposed. Further exploration of volatility transmission in the natural gas market is needed. Next interesting research is the transfer of volatility between commodities. The study of volatility transmission among commodities, such as from crude oil to gasoline, underscores the interconnectedness of these markets and the need for sophisticated modeling techniques (Chung, 2024). Here, the author recommends expanding the research, incorporating more variables for better predictability and beyond using complex models to predict energy market volatility.

2.2.3 Research direction: Models, price, and optimization

There are a lot of advanced ML and AI techniques in commodity price forecasting. Various machine learning models, including Support Vector Machines (SVM), Long Short-Term Memory (LSTM) networks, and ensemble methods like Random Forests, have been employed to forecast commodity prices effectively

(Gupta et al., 2024; Tami & Owda, 2024). The research Forecasting Commodity Prices using Machine Learning (Gupta et al., 2024) employs ML for forecasting commodity prices and volatility using technical analysis and economic indicators across 14 diverse commodities, enhancing decision-making in commodity trading. For future research is recommended to use advanced ML models and explore the impact of external factors on commodity market trends. Future research is also called to incorporate sentiment analysis for price prediction and to explore ensemble methods, or to explore the LSTM model for other commodity types.

In the research of Massahi and Mahootchi (2023), A Deep Q-Learning algorithm is proposed for commodity futures markets, leveraging machine learning to optimize trading decisions in volatile environments and enhancing profit potential through sophisticated decision-making tools. Subsequent research should improve the performance of the algorithm in different market conditions. Furthermore, the applications of the proposed system in other financial markets could be investigated. ML techniques continue to increase predictive accuracy, but challenges remain in their application, particularly regarding the interpretability of complex models and the need for robust data. Current advanced feature engineering increases prediction accuracy and model simplicity. Despite this progress, challenges such as model interpretability and computational complexity persist, especially in sensitive areas such as finance. The development of eXplainable AI (XAI) methods aims to address these issues and ensure that AI systems remain transparent and user-friendly (Hadji-Misheva & Osterrieder, 2023).

Future research opportunities can incorporate external factors for better forecasting accuracy and more variables for better predictability. It is also necessary to improve models' interpretability and applicability in different fields.

A comparison of the effectiveness of individual models is also important in this area. Vancsura et al. (2023), in a study Evaluating the Effectiveness of Modern Forecasting Models in Predicting Commodity Futures Prices in Volatile Economic Times, compare the decision tree method and the use of AI. This study is limited insofar as the models were only used individually and not combined. Hybrid models may have several advantages over the traditional approach. The study Deep Learning Based Prediction of Commodity Prices Using LSTM (Deepa & Daisy, 2023) explores using deep learning, specifically LSTM models, for commodity price prediction and compares the performance of different models. The study Deep Learning Based Models: Basic LSTM, Bi LSTM, Stacked LSTM, CNN LSTM and Conv LSTM to Forecast Agricultural Commodities Prices (Mishra & Krishnan, 2021) evaluates five LSTM-based deep learning models for forecasting agricultural commodity prices. For future research, it is recommended to expand the analysis to more agricultural commodities beyond the 5 studied in this paper and compare the performance of the LSTM models to popular machine learning techniques to provide more insights into agricultural price forecasting.

2.2.4 Research direction: Commodity price and random forests

Random forest is an algorithm used by AI to predict movements in commodity markets. It leverages historical data to identify patterns and make informed predictions.

The study Unraveling the crystal ball: Machine learning models for crude oil and natural gas volatility forecasting by Tiwari et al. (2024) employs machine learning models to forecast crude oil and natural gas volatility, recommending Random Forest Regression and XGBoost for natural gas volatility forecasting in commodity markets. A shortcoming of the work is the variation in model performance across forecast horizons and the lack of comparison with traditional statistical models. The author recommends exploring other machine learning models for volatility forecasting and investigating the impact of external factors on volatility prediction as an extension of the research.

2.2.5 Research direction: Prediction, futures, and time-series models

Simple and effective time series forecasting models ARIMA and Prophet have been replaced by advanced Deep Learning Approaches like Long-short term models. Vuppalapati (2021) introduces machine learning for commodity analysis, including stock-to-use ratio impact on pricing models and time series techniques for predicting worldwide commodity prices and fertilizer prices. Long Short-Term Memory (LSTM) networks excel in capturing complex temporal patterns, as demonstrated in stock market predictions and environmental data forecasting (Jarrah, 2024; Mustakim et al., 2024). Researchers can continue by exploring different sets of financial data for broader analysis. For an overview, Tian (2023) proceeds with the article A Review of Time series prediction methods based on Deep Learning.

Currently, the latest method uses artificial intelligence. AI excels in time series prediction, classification, and sequence-to-sequence problems, showcasing accuracy in forecasting the Air Pollutant Index, vibration classification, and remaining shelf-life estimation (Mustakim et al., 2024). Now, improving AI models for more complex time series patterns is important. And further exploring the applications of AI in various industrial fields. The TimesFM model, a recent innovation, utilizes transformer layers for efficient time series forecasting, outperforming traditional methods in various benchmarks (Pertsev & Korotka, 2024). Another challenge for researchers is to improve the performance of TimesFM on specialized time series data and to investigate the scalability of TimesFM for large-scale forecasting tasks.

2.2.6 Research direction: Management, food, and impact

Integrating AI in the food industry enhances efficiency, quality, and sustainability by transforming management practices, enhancing food safety, and optimizing commodity production. AI enhances supply chain efficiency by predicting demand and managing inventory, reducing waste and costs (Agrawal & Kumar, 2023; Bendre et al., 2022). A shortcoming of AI applications is the absence of human intuition. Its integration into AI systems is another challenge for research. Further, AI in the agri-food sector enhances management, food quality, and sustainability. It impacts commodity production through precision agriculture, supply chain optimization, and personalized nutrition, revolutionizing the industry (Taneja et al., 2023).

AI is being used to improve quality assessment by detecting defects, ensuring compliance with safety standards, monitoring microbial contamination, and improving cleanliness protocols. AI innovations are revolutionizing this sector, as described by Barthwal et al. (2024) in the study: New Trends in the Development and Application of Artificial Intelligence in Food Processing. The challenge in this area is to ensure sustainable food production while increasing quality, safety, and waste management during food processing.

Hedgers use AI to analyze commodity markets to achieve greater efficiency in their primary activity. AI tools assist farmers in maximizing crop yields and minimizing resource use through data analytics (Henrietta, 2024). Another focus may be precision agricultural technology and the application of AI to new products.

Artificial intelligence is also impacting the agricultural and food industries closely linked to commodities from the perspective of personalized nutrition and consumer engagement. AI facilitates personalized nutritional recommendations and targeted marketing, improving customer experience and satisfaction (Agrawal & Kumar, 2023). Here, the impact of artificial intelligence on food processing efficiency needs to be explored and consumer behavior analysis done using AI in the food industry.

Although artificial intelligence offers significant progress, problems such as high implementation costs and data dependency remain and challenge further research in all the mentioned areas. Nonetheless, the potential for AI to revolutionize the food industry is substantial, paving the way for a more efficient and sustainable future.

2.2.7 Research direction: Text mining

With the development of natural language processing (NLP) and machine learning techniques, artificial intelligence continues to be used for text mining from the vast number of reports, overviews, reviews, and other text data in the field of commodity markets. This information is valuable for hedgers, investors, information, and trading platforms to streamline their work and make better-informed decisions.

The classification of commodity text data using fastText allows for effective category and attribute mining across different e-commerce platforms, improving user experience and category architecture (Zhang et al., 2020). An improved model for web page text representation by Wei and Zhang (2021) achieves high accuracy in classifications using a support vector machine for web page text presentation. A challenge for future research is to use the knowledge to improve natural language understanding and feature selection for web text classification. And an effective and accurate combination of topic characteristics for text segmentation to improve the classification of web texts.

SUN (2017) uses ML and distributed word representation for word-level text classification to extract attributes from online reviews. Shen et al. (2012) introduce a hierarchical approach for large-scale item categorization, automatically discovering groups of similar classes using a graph algorithm. These studies demonstrate the importance of advanced text classification techniques, attribute mining, and hierarchical approaches.

Advanced research in this direction is made by Chou and Cho (2023) in Utilizing Text Mining for Labeling Training Models from Futures Corpus in Generative AI. The study utilizes text mining and generative AI to analyze financial news for bull-bear sentiment, to help investors make informed decisions in real-time in commodity markets. Future research should explore the use of the proposed method in areas other than financial futures. Further work can be done to improve the predictive power and practicality of the approach.

Table 8 provides a brief overview of calls for future research arranged according to the identified directions of research development.

Table 8: Calls structured by research trends

Commodity & stock, shock & return, volatility & spillover	**Market and volatility**	**Models, price, and optimization**	**Commodity price and random forests**	**Prediction, futures, and time-series models**	**Management, food, and impact**	**Text mining**
-get more significant effects during crisis and post-crisis compared to pre-crisis -explore the impact of central bank policies on STVS effects -investigating the long-term implications of STVS effects on the global economy -explore additional predictors for improved future returns predictability	- exploration of volatility transmission in the natural gas market - incorporating more variables for better predictability of volatility between commodities -beyond using complex models to predict energy market volatility	- improve the performance of the deep Q-Learning algorithm in different market conditions than volatile environments -explore the impact of external factors on commodity market trends - investigate the applications of deep Q-Learning algorithm in other financial markets than futures markets - explore ensemble methods or the LSTM model for more commodity types - incorporate sentiment analysis for price prediction	-explore variation in ML model, recommending Random Forest Regression and XG Boost, performance across forecast horizons -compare ML models of random forest regression and XG Boost for natural gas volatility forecasting with traditional statistical models - explore other ML models for volatility forecasting	- by LSTM networks explore financial data differences of stock market predictions and environmental data forecasting - improve AI models for more complex time series patterns - explore the applications of AI in various industrial fields -improve the performance of Times FM on specialized time series data - investigate the scalability of Times FM for large-scale forecasting tasks	-integration of human intuition into AI systems - use AI in this area to ensure sustainable food production while increasing quality, safety, and waste management during food processing - use AI for precision agricultural technology - application of AI to new products - explore the impact of AI on food processing efficiency needs	- improve natural language understanding and feature selection for web text classification -improve the classification of web texts by an effective and accurate combination of topic characteristics for text segmentation - explore the use of the Text mining method for labelling training models in areas other than financial future -improve the predictive power and practicality

Commodity & stock, shock & return, volatility & spillover	Market and volatility	Models, price, and optimization	Commodity price and random forests	Prediction, futures, and time-series models	Management, food, and impact	Text mining
- investigate the impact of different ML models on predictions - make a deep discussion of the impact of clustering on market efficiency - explore the relationships between trade regimes and market clustering - include more advanced ML techniques - investigate the impact of external factors on commodity markets		- compare the performance of the LSTM models to ML techniques to provide more insights into agricultural price forecasting - incorporate more variables for better predictability- use advanced ML models - incorporate external factors for better forecasting accuracy - improve models' interpretability and applicability in different fields - use hybrid forecasting models for predicting commodity futures prices - expand the analysis of five LSTM-based deep learning models to more agricultural commodities	- investigate the impact of external factors on volatility prediction as an extension of the ML model of random forest regression and XG Boost		- analyse consumer behavior using AI in the food industry - solve the problem of high implementation costs and data dependency	

Source: Authors' own research, 2024

3. DISCUSSION

Based on the bibliometric and content analysis, we draw theoretical and practical implications for existing research and offer a summary of proposals for future research on the use of AI and ML in commodity markets.

3.1 Theoretical implications

We see the consequences from a theoretical point of view mainly in the improvement of the clarity of the literature through the international definition of terms and a multi-platform data processing system. Differently entered terms and keywords can influence the very selection of publications to process the publication search, and possibly influence the results of the analysis. Even an important publication can be inadvertently neglected for this reason.

Furthermore, the current trend of information systems is multi-platform. Similarly, the normalization of output data from scientific data would greatly facilitate the overview of scientific work in a certain field. We assume that after using the above, duplication of research would be reduced, the work of scientific teams would be processed, and development would be accelerated.

While preparing an overview of increasingly advanced ML models and ways of using AI in commodity markets, no book was found in the bibliometric analysis of the selection. 90% of the development is interpreted using expert scientific articles. With the current global expansion of digital finance, trading platforms, the use of AI by the lay public, and the constant search for investment opportunities, we propose to create a defining and explanatory publication to help non-scientists assess risk and make informed decisions. At the same time, this step would help to prevent the increasing number of frauds in this area.

3.2 Practical implications

The study has practical implications for commodity market decision-makers, practitioners, and politicians.

Both investors and hedgers need to predict prices and examine market volatility. The energy market, agricultural, and food markets are changing due to the use of AI and ML for their priority goals. Artificial intelligence offers significant progress, especially in the agricultural and food industry. The problem is high implementation costs and data dependency. However, the potential for artificial intelligence to revolutionize the food industry is considerable. It paves the way for a more efficient and sustainable future. For this, it needs the support of politicians, scientific development, and the availability, simplicity, and comprehensibility of IT solutions even for small and medium-sized enterprises.

Artificial intelligence in the agri-food sector improves management, food quality, and sustainability. It impacts commodity production through precision agriculture, supply chain optimization, and personalized nutrition, revolutionizing the industry (Taneja et al., 2023).

Practitioners can draw from the study knowledge and information about the application of various models to specific areas of the commodity market, their success, and their shortcomings so that they can subsequently apply the latest knowledge in practice. Concerning the main weight of development in the IT area, it is necessary to have workers educated in this direction available. Applying the latest models along with security gaps can provide a competitive edge. Conversely, hesitating and not following trends could cause economic problems for small and large investors. However, implementing new solutions is costly and requires specialists, who must be educated in IT systems and AI and ML models; at the same time, they should be well-versed in the commodity market and the areas that affect it. Therefore, we recommend a thorough consideration of all circumstances and risks. There are many suggestions in the work that will help practitioners find the way.

Current developments in the field of AI and ML can bring dynamic changes not only in the financial sector but also in the entire economy via commodity markets. From this point of view, politicians should also be interested in the latest findings from the field. The number of publications from individual countries indicates which countries support research in this area and in these countries, it is also possible to expect support for putting the results into practice. Through a bibliometric analysis, we found that the developments in the use of AI and ML in commodity markets are mostly published by China, the USA, and India, as we have shown in Figure 2.

CONCLUSION

Artificial intelligence has made its way into most areas in recent years, and we already consider it indispensable in many activities and decisions. Likewise, commodities and everything related to them are indispensable also. Information systems, especially artificial intelligence, have been developing rapidly in the last 5 years. It is even more necessary for effective research and development in this area to know the latest procedures, models, and their applications. Subsequently, the gaps and challenges of the authors, and how it is possible to move the research further.

This work evaluates information using bibliometrics and content analysis for the period 2005-April 2024, analyzing 343 documents published in leading international journals. It offers an overview of the use of AI and ML in commodity markets from the most cited authors and papers, the most prestigious journals and institutional involvement, to the detection of the latest trends by co-occurrence analysis. In connecting with AI, ML, and neural network we identify the trends 1) commodity and stock market, shock, and return, volatility, and spillover 2) ML, market, and volatility, 3) neural network, models, price, and optimization, 4) text mining,

5) forecasting, commodity price, and random forests, 6) prediction, futures, time-series models, 7) artificial intelligence, management, food, and impact.
Using qualitative content analysis, we emphasize the trends and research directions of the use of AI and ML in the commodity market, and at the same time, we present gaps and calls for further research.
The results provide researchers with an overview of the articles on this topic and inspiration for further research.

ACKNOWLEDGEMENT
This contribution was made within the project SGS-2024-030 "Research on quantitative approaches for economic problems solving" of the Faculty of Economics, University of West Bohemia in Pilsen.

REFERENCES

Akyildirim, E., Goncu, A., & Sensoy, A. (2021). Prediction of cryptocurrency returns using machine learning. *Annals of Operations Research*, *297*, 3-36. https://doi.org/10.1007/s10479-020-03712-6

Agrawal, K., & Kumar, N. (2023). Artificial intelligence innovations: Inception of new horizons in food processing sector. *SILCON 2023*. https://doi.org/10.1109/silcon59133.2023.10404183

Ameur, H. B., Boubaker, S., Ftiti, Z., Louhichi, W., & Tissaoui, K. (2023). Forecasting commodity prices: Empirical evidence using deep learning tools. *Annals of Operations Research*, 1–19.

Barthwal, R., Kathuria, D., Joshi, S., Kaler, R. S. S., & Singh, N. (2024). New trends in the development and application of artificial intelligence in food processing. *Innovative Food Science and Emerging Technologies*. https://doi.org/10.1016/j.ifset.2024.103600

Bendre, S., Shinde, K., Kale, N., & Gilda, S. (2022). Artificial intelligence in food industry: A current panorama. *Asian Journal of Pharmacy and Technology*. https://doi.org/10.52711/2231-5713.2022.00040

Boakye, E. O., Heimonen, K., & Junttila, J. (2024). Commodity markets and the global macroeconomy: Evidence from machine learning and GVAR. *Empirical Economics*. https://doi.org/10.1007/s00181-024-02612-0

Chakraborty, M., Mahmoud, T. M. H., Sinha, R., Goel, S., & Rehman, M. U. (2021). Clustering commodity markets in space and time: Clarifying returns, volatility, and trading regimes through unsupervised machine learning. *Resources Policy*. https://doi.org/10.1016/J.RESOURPOL.2021.102162

Chakraborty, M., Hussein, T. M., Ray, I. S., Kler, R., Goel, S., & Mishra, S. (2023). Forecasting the geopolitical impact among Russia and Ukraine on commodity export prices: An AI-based analysis. In *2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS)* (pp. 1049-1054)

Chen, J. M., Rehman, M. U., & Vo, X. V. (2021). Clustering commodity markets in space and time: Clarifying returns, volatility, and trading regimes through unsupervised machine learning. *Mutual Funds*.

Chou, H. M., & Cho, T. L. (2023). Utilizing text mining for labeling training models from futures corpus in generative AI. *Applied Sciences*. https://doi.org/10.3390/app13179622

Chung, S. (2024). Modelling and forecasting energy market volatility using GARCH and machine learning approach. *arXiv*. https://doi.org/10.48550/arxiv.2405.19849

Co-citation and co-authorship networks of statisticians. (2022). *arXiv*. https://doi.org/10.48550/arxiv.2204.11194

Deepa, P. B., & Daisy, J. (2023). Deep learning based prediction of commodity prices using LSTM. *Proceedings of the International Conference on Sustainable Energy & Computing*. https://doi.org/10.1109/icosec58147.2023.10276011

Foroutan, P., & Lahmiri, S. (2024). Deep learning systems for forecasting the prices of crude oil and precious metals. *Financial Innovation*. https://doi.org/10.1186/s40854-024-00637-z

Francisco, J., Barba, J. M., Castagnini, N., Leksawasdi, N., & Phimolsiripol, Y. (2023). Artificial intelligence: Implications for the agri-food sector. *Agronomy*. https://doi.org/10.3390/agronomy13051397

Garner, C. (2014). *Komodity: úvod do investování na nejrychleji rostoucím trhu* (R. Čížek, Překl.). BizBooks. ISBN 978-80-265-0019-3.

Gupta, H., Aafrein, R., Kumari, R., Rajput, S., & Puri, N. (2024). Forecasting commodity prices using machine learning. *International Journal of Scientific Research in Science and Technology*. https://doi.org/10.32628/ijsrst52411110

Hadji-Misheva, B., & Osterrieder, J. (2023). A hypothesis on good practices for AI-based systems for financial time series forecasting: Towards domain-driven XAI methods. *arXiv*. https://doi.org/10.48550/arxiv.2311.07513

Henrietta, H. M. (2024). Artificial intelligence in agriculture: A review of current applications and future trends. https://doi.org/10.58532/v3bcag11p1ch1

Jarrah, M. (2024). Time series prediction analysis of long short term memory models. *ICCI 2024*. https://doi.org/10.1109/icci61671.2024.10485015

Johari, N. (2024). Artificial intelligence in time series prediction, classification, and sequence-to-sequence problems. *Internet of Things*. https://doi.org/10.1007/978-981-97-1432-2_7

Liauw, T. T. (2022). Content analysis and its application with dynamic online content. *Jurnal Teknik Industri: Jurnal Keilmuan dan Aplikasi Teknik Industri*. https://doi.org/10.9744/jti.24.2.105-116

Massahi, M., & Mahootchi, M. (2023). A deep Q-learning based algorithmic trading system for commodity futures markets. *Expert Systems with Applications*. https://doi.org/10.1016/j.eswa.2023.121711

Mishra, S. (2023). Forecasting the geopolitical impact among Russia and Ukraine on commodity export prices: An AI-based analysis. *ICTACS 2023*. https://doi.org/10.1109/ictacs59847.2023.10390383

Mohammad, T., & Amani, Y. O. (2024). Efficient commodity price forecasting using long short-term memory model. *IAES International Journal of Artificial Intelligence*. https://doi.org/10.11591/ijai.v13.i1.pp994-1004

Murugesan, R., Mishra, E., & Krishnan, A. H. (2021). Deep learning based models: Basic LSTM, Bi LSTM, stacked LSTM, CNN LSTM and Conv LSTM to forecast agricultural commodities prices.

Mustakim, R., Mamat, M., Wong, F., Mohamad, S. N. A. S., & Dasuki, M. (2024). Інноваційний підхід у прогнозуванні часових рядів: Від традиційних методів до новаторської моделі timesfm. *Інформаційні технології в металургії та машинобудуванні*. https://doi.org/10.34185/1991-7848.itmm.2024.01.084

Nees, J. V., & Waltman, L. (2009). VOSviewer: A computer program for bibliometric mapping. *Research Papers in Economics*.

Nwagwu, W. E. (2024). Bibliographic coupling networks of global research on data literacy by documents, sources and authors. *Journal of Librarianship and Information Science*. https://doi.org/10.1177/09610006241252655

Passas, I. (2024). Bibliometric analysis: The main steps. *Encyclopedia*. https://doi.org/10.3390/encyclopedia4020065

Pertsev, Y., & Korotka, L. (2024). ІННОВАЦІЙНИЙ ПІДХІД У ПРОГНОЗУВАННІ ЧАСОВИХ РЯДІВ: ВІД ТРАДИЦІЙНИХ МЕТОДІВ ДО НОВАТОРСЬКОЇ МОДЕЛІ TIMESFM. *International Scientific and Technical Conference Information Technologies in Metallurgy and Machine Building*.

Phan, H. V., Lai, C. P., Li, H., Le, H. T. M., & Nguyen, T. K. (2024). Mapping the investment efficiency: A co-citation analysis. *International Journal of Industrial Management*. https://doi.org/10.15282/ijim.18.1.2024.10426

Reinartz, W., & Ulaga, W. (2008). How to sell services more profitably. *Harvard Business Review*, *86*(5), 90-96.

Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Applied Soft Computing*, *90*, 106181. https://doi.org/10.1016/j.asoc.2020.106181

Shen, D., Ruvini, J., & Sarwar, B. M. (2012). Large-scale item categorization for e-commerce. *Proceedings of the 21st ACM International Conference on Information and Knowledge Management*.

Sun, L. (2017). Research on product attribute extraction and classification method for online review. *Proceedings of the International Conference on Industrial Informatics - Computing Technology, Intelligent Technology, Industrial Information Integration (ICIICII)*, 117–121.

Tami, M., & Owda, A. Y. (2024). Efficient commodity price forecasting using long short-term memory model. *IAES International Journal of Artificial Intelligence (IJ-AI)*.

Taneja, A., Nair, G., Joshi, M., Sharma, S., Sharma, S., Jambrak, A. R., Roselló-Soto, E., Barba, F. J., Castagnini, J. M., Leksawasdi, N., & Phimolsiripol, Y. (2023). Artificial intelligence: Implications for the agri-food sector. *Agronomy*.

Tian, B. (2023). A review of time series prediction methods based on deep learning. *Proceedings of the International Conference on Artificial Intelligence and Communication Technologies (AICIT)*. https://doi.org/10.1109/aicit59054.2023.10277969

Tiwari, A. K., Sharma, G. D., Rao, A., & Dev, D. (2024). Unraveling the crystal ball: Machine learning models for crude oil and natural gas volatility forecasting. *Energy Economics*. https://doi.org/10.1016/j.eneco.2024.107608

Tunison, S. (2023). Content analysis. In *Springer Texts in Education*. https://doi.org/10.1007/978-3-031-04394-9_14

Usha, B. A., Manjunath, T. N., & Mudunuri, T. (2019). Commodity and forex trade automation using deep reinforcement learning. *Proceedings of the International Conference on Advanced Technologies in Intelligent Control, Environment, Computing & Communication Engineering (ICATIECE)*, 27–31.

Utilization of artificial intelligence in the food industry. (2022). *Studies in Computational Intelligence*. https://doi.org/10.1007/978-3-031-13702-0_6

Vancsura, L., Tatay, T., & Bareith, T. (2023). Evaluating the effectiveness of modern forecasting models in predicting commodity futures prices in volatile economic times. *Risks*.

Vardar, G., Coskun, Y., & Yelkenci, T. (2018). Shock transmission and volatility spillover in stock and commodity markets: Evidence from advanced and emerging markets. *Social Science Research Network*.

Vuppalapati, C. (2021). Commodity markets: Machine learning techniques. *International Series in Operations Research & Management Science*.

Wang, S., & Zhang, T. (2023). Predictability of commodity futures returns with machine learning models. *Journal of Futures Markets*. https://doi.org/10.1002/fut.22471

Wei, Z., & Zhang, X. (2021). A filtering algorithm of main word frequency for online commodity subject classification in e-commerce.

Weng, B., Ahmed, M. A., & Megahed, F. M. (2017). Stock market one-day ahead movement prediction using disparate data sources. *Expert Systems with Applications*, *79*, 153-163. https://doi.org/10.1016/j.eswa.2017.02.028

Williams, E. N. (2024). Bibliographic coupling networks of global research on data literacy by documents, sources and authors. *Journal of Librarianship and Information Science*. https://doi.org/10.1177/09610006241252655
Xiong, T., Li, C., & Bao, Y. (2018). Seasonal forecasting of agricultural commodity price using a hybrid STL and ELM method: Evidence from the vegetable market in China. *Neurocomputing*, *275*, 2831-2844. https://doi.org/10.1016/j.neucom.2017.09.028
Yun, J. (2022). Generalization of bibliographic coupling and co-citation using the node split network. *Journal of Informetrics*. https://doi.org/10.1016/j.joi.2022.101291
Zhang, W., Liu, F., Zhang, Z., Liu, S., & Huang, Q. (2020). Commodity text classification based on e-commerce category and attribute mining. *Proceedings of the IEEE International Conference on Multimedia Information Processing and Retrieval (MIPR)*. https://doi.org/10.1109/MIPR49039.2020.00028