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THE INFLUENCE OF AI ON PRICE FORECASTING. THE VIEW OF THE ACADEMIC COMMUNITY

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Abstract. In the context of the impressive development of Big Data, AI algorithms have proven their efficiency in processing and analyzing large volumes of data. Price prediction was no exception. In the modern economic fields, the need for advanced prediction models, with increased efficiency, has become more and more important. Thus, the interest in the potential of AI solutions in terms of price prediction for all industries has also grown progressively. The present study aims to capture, by using several Natural Language Processing techniques, the feeling that the academic community has in relation to the subject of price prediction and the way in which opinions have evolved over the years. For this purpose, the abstracts of the works indexed in the Clarivate WoS that addressed this topic are included in the current analysis. The scores obtained after the analysis reveal a slightly positive attitude towards the subject, but nevertheless quite reserved. The main topics existing in these articles are also extracted by means of Latent Dirichlet Allocation. Our analysis makes contributions to the formulation of the position that specialists in the scientific community have in relation to price prediction and AI evolution. Further, it provides new research directions for future studies.

Keywords: AI, price prediction, research publication, LDA, sentiment analysis, volatility.

JEL Classification: O16, O33, O14.

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1. Introduction

In the business environment, price prediction occupies an important place, companies tending to a higher level of predictability of potential changes, especially in the case of markets with increased volatility and with a multitude of factors that can significantly influence the price trend. Estimation of price movements is essential for good planning of the economic activity of a company, implicitly for the most correct strategic decisions (Moon & Kim, 2023). Among the established methods used for price prediction, the regression analysis forecasting method, the grey model prediction method, the time series forecasting method and others, each of them having both strengths and limitations (Sun et al., 2023). However, the intense technological evolution of recent years has expanded the range of useful methods to make forecasts on the evolution of prices. Thus, traditional methods have been joined by intelligent forecasting methods.

The last few years have been marked by a pronounced evolution in the field of technology. With significant improvements in hardware resources and the development of Big Data, one of the branches that has seen impressive development is that of artificial intelligence. AI solutions have been adopted in many economic sectors and are now an integral part of important processes. Machine learning algorithms, part of the AI sphere, have proven their effectiveness when it comes to analyzing large volumes of data and improving the decision-making system, at the same time (Choy & Ho, 2023).

Compared to traditional price estimation methods, AI solutions reduce data processing and analysis time, can be continuously trained, and have the ability to efficiently manage unstructured data, which can lead to more accurate predictions and increased accuracy. Although there are several methods and tools dedicated to price prediction for multiple fields today, this remains a thorny problem for companies all over the world. The efficiency of predictive analyses and the increase in the accuracy of results on the stock market has become a critical point, in the context of competition in the capital market and the impressive increase in data volumes (Li & Ming, 2023). In a constantly moving market, characterized by rapid changes and influenced by a multitude of factors that are easier or harder to analyze, investors are constantly looking for the best possible methods of making predictions with a high level of accuracy and identifying the most suitable moments for making important transactions. Solutions based on AI in continuous evolution have a high level of applicability in this case, being valid for the efficiency of the price prediction from a wide variety of fields such as the financial market, the real estate market, or for the prices of consumer goods. Among the existing variants, there is the analysis of historical data, the use of neural networks, supervised and unsupervised learning algorithms, sentiment analysis methods or even deep learning methods. Several key advantages qualify AI solutions as effective price prediction methods, such as the ability to analyze large volumes of data, the ability to identify complex patterns, the increased level of adaptability in the face of continuous changes and the ability to efficiently manage unstructured data.

AI solutions identify correlations between various variables by training on historical data sets and have the potential to outline patterns and trends determined by various factors such as geopolitical events, news, seasonal activities, etc. Sentiment analysis also has the advantage of having the potential to extract significant characteristics from data sets extracted from the social media sphere or from the press in order to observe the degree of influence they have on prices. Each available AI method has particular advantages and disadvantages. Their efficiency for price prediction may vary depending on the accuracy of available data, the complexity of the market and the adaptive capacity of the models in the face of imminent changes in the economy. In addition, numerous studies have shown that combining several methods can often lead to more precise results than those obtained by applying a single method (Yang et al., 2022).

Price prediction plays an important role in business environments, particularly in markets characterized by high volatility and a multitude of influencing factors. The recent advancements in AI and Big Data have made it possible to improve prediction accuracy, maintaining a competitive edge in rapidly changing markets like financial, real estate and consumer goods sectors. While traditional methods for price prediction exist, they come with limitations in handling large and unstructured data, adapting to continuous changes and accurately identifying complex patterns. The efficiency and potential of AI methods for price forecasting have been demonstrated, but there remains a research gap in understanding the academic community's collective sentiment and perspectives on the integration of AI in price prediction over time. Additionally, there is a need to explore how these opinions have evolved and what main topics have emerged in the literature.

Our research aims to analyze the sentiment of the academic community towards the use of AI in price prediction, particularly focusing on how these sentiments have evolved over the years. This is achieved by applying Natural Language Processing (NLP) techniques to the abstracts of academic works indexed in the Clarivate Web of Science (WoS) and published between 1990 and April 2024. Additionally, the study seeks to identify the main topics discussed in these academic works using Latent Dirichlet Allocation (LDA). Understanding the academic community's sentiment towards AI in price prediction provides insights into the acceptance and perceived effectiveness of AI methods in this field, highlights the evolving attitudes over time, and sheds light on the main areas of focus within the literature. It is valuable for guiding future research, identifying emerging trends and clarifying the broader impact of AI on economic forecasting.

As mentioned, our research employs NLP techniques to analyze the sentiment expressed in academic abstracts related to AI and price prediction. Additionally, LDA, a topic modeling technique, is used to extract and categorize the main topics discussed in the selected academic works. The analysis reveals a generally positive but somewhat reserved attitude of the academic community towards AI in price prediction. The study also identifies several key topics that dominate the discussion in the literature, providing a structured overview of the main areas of focus. The results suggest that while AI is recognized for its potential, there is still caution in fully embracing it as a definitive solution for price forecasting. Concerns about bias and trust in AI-driven price prediction solutions are prominent within the academic community.

Our research contributes to the literature by providing a comprehensive analysis of the academic community's sentiment towards AI in price prediction and identifying the key topics within this field. It offers a unique perspective by tracking the evolution of opinions over time and highlighting emerging trends. The findings may help shape future research directions, offering a foundation for further exploration of AI's role in economic forecasting.

The originality of our research consists of its comprehensive analysis of the academic community's evolving sentiment towards AI in price prediction, using advanced NLP techniques. By focusing on the abstracts of works indexed in the Clarivate Web of Science, our research provides a unique insight into how experts' opinions have shifted over time, reflecting the broader technological advancements in AI and Big Data. Furthermore, it employs LDA to extract and categorize the main topics discussed in these academic works, offering a structured overview of the field's key areas of focus. This dual approach, analyzing both sentiment and thematic content, allows for a deeper understanding of the academic discourse surrounding AI and price prediction.

The current research is organized to first present the background and importance of the topic (current section), followed by the literature review (next section), methodology (Section 3), results (Section 4), and finally, the implications and potential research paths that arise from the findings (discussions – Section 5 and conclusions – last section).

2. Literature review

This section synthesizes the prevailing views within the academic community, providing an overview of how sentiment towards AI in price prediction has developed and its perceived role in shaping future market predictions. The rationale for selecting references in this review is multifaceted. Foremost, the motivation is fundamentally linked to evaluating the effectiveness of predictive models across several sectors. Each sector poses distinct challenges due to their inherent volatility, influenced by factors such as economic fluctuations, environmental transformations and geopolitical developments. Moreover, the factors affecting prices have evolved over time to encompass the perceptions and sentiments expressed by individuals in the online sphere, which can considerably influence price variations. Consequently, we have also incorporated previously published studies that examined the progression of sentiments articulated by social media users and the role of psychological factors in price dynamics. The literature review thus explores how public sentiment impacts prices and also foreshadows the significance of understanding the perspectives and sentiments of the academic community itself, as these can also influence market predictions and model developments.

Numerous scientific works investigating the effectiveness of price prediction methods in the case of different fields have been published over time. Among the fields characterized by high price volatility for which prediction methods are of great importance are the financial markets, the real estate market, the energy sector, the agricultural field, but also that of cryptocurrencies. In the case of financial markets, the price of shares, bonds or goods can experience large variations in a short period of time. To anticipate substantial increases or decreases in prices and to estimate risks as accurately as possible, investors and traders generally rely on predictive models. In articles published in recent years on this topic, models based on Long Short-Term Memory (LSTM) have been proposed for short-term predictions (Shen & Shafiq, 2020), Artificial Neural Networks (ANN) (Selvamuthu et al., 2019), sentiment analysis through NLP techniques (Bâra & Oprea, 2024; Fazlija & Harder, 2022). A study published in 2022 compares the prediction performance of RBFNN models, RNN, and LSTM on the Sukuk index tracking the performance of Islamic fixed income securities globally (Metlek, 2022).

On the real estate market, property prices are mainly influenced by economic, social and demographic factors. Price prediction helps decision makers adopt appropriate real estate policies and also provides valuable information to owners and real estate agents so that they can make the right choices when it comes to selling/renting a property or purchasing a new property (Pai & Wang, 2020). The academic community proposed, following the studies carried out, multiple methods that could be used in this sense, such as: Least Squares Support Vector Regression (LSSVR), classification and regression tree , general regression neural networks and backpropagation neural networks (Pai & Wang, 2020), Random Forest (RF) (Levantesi & Piscopo, 2020), Principal Component Analysis (PCA), Deep Neural Networks (DNN) (Mostofi et al., 2022).

In the energy industry, price fluctuations are influenced by factors such as weather conditions, geopolitical factors and the level of demand and supply. In the entire energy sector, the exploration and exploitation of modern price prediction models has become essential (Hu et al., 2012). In the case of the fossil fuel market, the variations in the price of crude oil are closely monitored, especially since we are in a period of increasing interest in the effects of the climate crisis and alternative solutions to obtain energy, more friendly to the environment (Chen, 2022; Gupta & Nigam, 2020). In an article published in 2020, Nalini Gupta and Shobhit Nigam proposed a method based on ANN for price prediction. The study concluded that the ANN-based model is a powerful and efficient one, leading to good results, with high accuracy, in the case of short-term crude oil price prediction. A study carried out in 2020 (Shen & Shafiq, 2020) proposed the use of a hybrid model to predict crude oil prices based on complex network analysis and LSTM of deep learning algorithms. The results obtained by applying the chosen techniques to the crude oil price data in Nigeria were satisfactory, confirming the robustness and efficiency of the model. The results of another study (Bristone et al., 2020) confirmed a high level of efficiency of the proposed models VMD-LSTM-SSA-DO (Variational mode decomposition-LSTM-Sparrow Search Algorithm-Disputation operator) and LSTM-SSA-DO, by comparison with LSTM. It was also specified that decision makers in this field could take into account the results obtained by applying these methods in the adjustment process of monetary and fiscal policies, so that the effects of the increase in the price of crude oil on inflation were reduced. Regarding the prediction of electricity prices, fewer studies have been published over time. However, preparing such a forecast with a high level of accuracy remains difficult due to the nonlinearity and volatility of electricity, which are more complicated to manage. A big impact in this sense is also the general trend of migration toward alternative energy sources, which also increases the competitiveness between the existing energy suppliers on the market. Gradually, electric cars are also gaining ground in front of internal combustion cars. And this is where multiple price prediction methods come into play: deep belief network, LSTM and Convolutional Neural Network (CNN) from the recurrent neural networks (RNN) (Putra et al., 2023; Zhang et al., 2020).

Furthermore, in the case of the agricultural sector, climatic factors can have a major impact on prices, but there can also be significant price fluctuations caused by changes in agricultural policies. The use of appropriate predictive models can support both farmers and traders and processors in making informed decisions and planning specific activities appropriately in relation to market changes (Sun et al., 2023).

The field of cryptocurrencies is known to have pronounced volatility; eloquent examples of this are Bitcoin and Ethereum. The cryptocurrency market has undergone impressive growth over the years. In 2022, it was evaluated at two billion dollars, its value becoming comparable to the value of the largest companies in the world. With an impressive number of daily transactions, the cryptocurrency market is unpredictable and, as with other financial systems, making forecasts regarding price fluctuations is not an easy task. Also in this case, AI shows a high level of applicability. Among the methods proposed by specialists are multivariate regression, Support Vector Machine (SVM), LSTM, ANN, RF, but also sentiment analysis is included as input feature (Amirzadeh et al., 2022; Jay et al., 2020; Pour et al., 2022; Seabe et al., 2023). In addition to the specific factors of each domain, among the most well-known factors that have a strong influence on the changes in prices are the demand and supply, the variation of the production costs, the inflationary phenomenon, the political instability, the macroeconomic factors, the changes in the government regulations, the psychological factors, politics and other factors. However, without denying the contribution that solutions make to price prediction, it is important to specify that there are a multitude of nonspecific factors that increase the dose of unpredictability. Therefore, the results should be subjected to a responsible subsequent evaluation.

As mentioned above, psychological factors have an important place among factors that influence prices. The perceptions and feelings that consumers and investors have, such as the optimistic or pessimistic attitude toward the economy as a whole or certain economic sectors, can have a major impact on purchasing behavior and investments, a fact that can later translate into price fluctuations. In the modern landscape, the feelings expressed by society in relation to a company have a crucial influence on the value of the respective company's shares. Those that can provide an impressive amount of data that can outline the general state of mind of the population in relation to the products or services offered by a company are social networks (Bharathi & Geetha, 2017).

As Nguyen et al. (2015) points out, the use of social media data alongside historical data can have a positive impact on the results of predictive analyses. However, although the opinions expressed by people on-line through posts on social networks are an important factor in predicting the prices of a company's shares, data from social networks are difficult to analyze because most of the posts contain few words, often abbreviated, and the results of the analysis can be inconclusive. Previously conducted studies such as (Li & Ming, 2023; Nguyen et al., 2015), use data sets extracted from the Twitter and Yahoo Finance platforms and apply methods based on ML algorithms (LDA, method based on JST neural networks, decision tree, KNN, boost algorithm, SVM, etc.), analyze the connection between the evolution of prices and the evolution of human feelings expressed in the online environment. Another study used data exported from the Twitter social network with the Nasdaq website to emphasize the efficiency of KNN, RF, SVM and Naive Bayes in making price forecasts, (Mehta et al., 2021).

LDA is also used by another study to identify the topics most analyzed regarding prosumers (Oprea & Bâra, 2024). More recent studies that employ bibliometric analysis, particularly focusing on topics such as price prediction, AI and others, are highlighted (Chopra et al., 2024; Sandu, Ioanăș, Delcea, Florescu, et al., 2024; Sandu, Ioanăș, Delcea, Geantă, et al., 2024; Vuong et al., 2024). Moreover, consumer behavior can be influenced by news articles. Information transmitted through televised news bulletins or through press articles added to the online environment brings to people's attention political, economic or even social events that can have a non-negligible impact on people's opinions and implicitly on their decisions. This aspect is highlighted by several previously conducted studies, such as (Agarwal et al., 2023) that took into account news articles published in various countries, over more than 15 years.

3. Research methodology

The present study aims to describe the attitude of the academic community in relation to the subject of price prediction. The evolution of feelings expressed through scientific articles published by specialists is followed over time.

To build the dataset for subsequent analysis, the Clarivate Web of Science database was selected. The keywords "price prediction" and "price forecasting" were chosen to filter scientific papers within the Clarivate database. These keywords facilitated the extraction of a dataset containing articles that addressed the topic of price prediction, intersecting with various other fields, as evidenced by the diversity of Web of Science categories associated with the extracted works. The period covered by this extraction includes publications from 1990 up to the date of data extraction, April 2024.

The research questions to which the authors aim to answer are:

(RQ1) What is the general trend regarding researcher sentiments about price prediction?

(RQ2) How have the feelings of the academic community about price prediction evolved in recent years marked by the progress of AI?

(RQ3) What are the most relevant key topics addressed by the academic community in relation to price prediction?

This study aims to analyze the general trend of the opinion of the academic community on price prediction. In this purpose, there have been included in the analysis indexed Web of Science, published over the last 34 years. The articles analyzed in this study were published from 1990 until April 2024, the month in which data was extracted from the Clarivate database for further analysis. The motivation of carrying out the study is also given by the changes in the area of price forecasting methods, against the background of impressive development of the field of AI and increasing interest in the potential benefits that automatic learning algorithms can bring. In this section, the methods used in the current study are described. Figure 1 shows the proposed flow of the methodology.

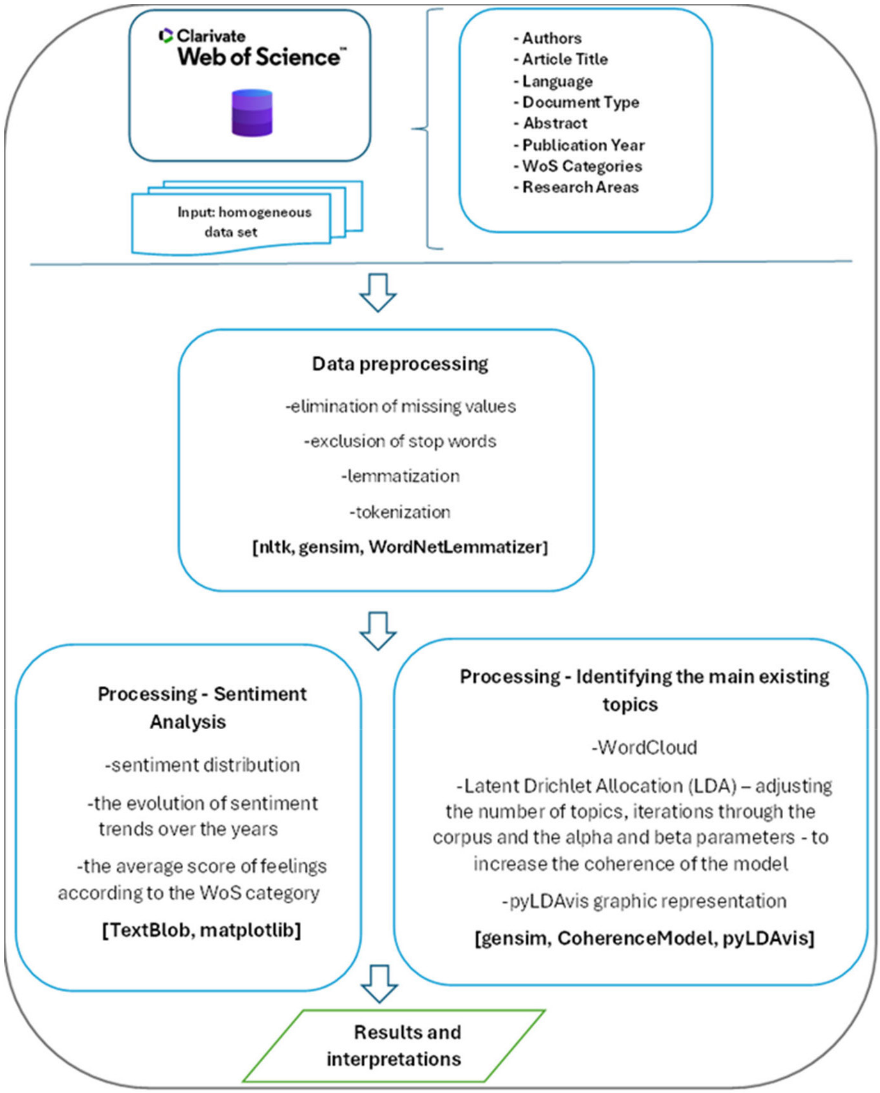

Figure 1. Methodology flow

The dataset subjected to subsequent analysis includes scientific works indexed on the Web of Science and was extracted in April 2024 from the Clarivate platform by adding the keywords: "price forecasting" and "price prediction" to the search. The result was a data set made up of 5,488 records and 72 columns. Among the data found in the columns are the following: type of publication, name of the authors, title of the publication, language in which the work was written, abstract, WoS category, year of publication, publisher, publisher's address, cited reference count, ISSN, eISSN, DOI, DOI link, number of pages, Web of Science Index, IDS Number. In the data preparation stage for processing and analysis, articles that did not have an associated Abstract section were excluded from the set (145 records were excluded from the data set, resulting in 5343 records that were subjected to analysis). Noise was also eliminated by excluding punctuation marks and common words (also known as stopwords). Text tokenization and word lemmatization methods were applied to reduce lexical variation. A graphic representation was generated, through the wordcloud library, designed to highlight the most meaningful words, with the highest frequency of appearance in the analyzed articles, for immediate visualization of key concepts.

TextBlob was used to calculate the polarity scores related to the sentiments expressed by the authors in each of the abstracts of the Web of Science indexed works. The scores were aggregated according to the year of publication of the scientific articles, in order to highlight the evolution of the feelings expressed by the academic community over time regarding price prediction. Also, using TextBlob, the average scores related to each category were calculated (depending on the WoS classification) and the first 5 WoS categories with the highest scores, as well as the last 5, with the lowest scores, were extracted. Thus, we can estimate which are the fields of activity in which price prediction methods are viewed with more optimism and which are those fields whose specialists are more reserved in relation to them. In the following section, the results of the scientific community sentiments related to the field of price forecasting will be presented.

Through the use of the Latent Dirichlet Allocation (LDA) model, the trend and topics with respect to the opinions of the academic community on the subject are analyzed. This type of analysis can provide valuable information to the academic community and outline research directions by evaluating trends and determining the attitudes and opinions expressed by specialists. In order to find the combination between the number of topics, the number of iterations through the corpus and the value of the parameters that leads to a higher coherence score, numerous possible combinations were tested. After the tests, it was chosen to extract 8 topics, composed of 5 keywords, with 10 iterations through the corpus, obtaining a coherence score equal to 0.4368. In addition, with the aim of identifying the predominant topics, the distance between the extracted topics and the list of the 30 most relevant terms for each topic, it was chosen to generate a graphic representation with pyLDAvis. The description of the topics, the relationships between them and the potential interpretations are added in the next section of this work.

A synthesis of the methodological steps and parameters is provided in Table 1.

Table 1. Methodology flow using parameters

No.	Step	Description	Details
1	Setting Objective and Scope	Objective: Analyze the evolving opinions within the academic community on price prediction methods.	Time Frame: Past 34 years (1990 – April 2024). Data Source: Web of Science.
2	Data Collection	Collection Date: April 2024. Search Keywords: "price forecasting" and "price prediction". Total Records: 5,488.	Attributes: 72 columns (type of publication, authors, title, language, abstract, WoS category, year, publisher, address, cited reference count, ISSN, eISSN, DOI, DOI link, number of pages, Web of Science Index, IDS Number).

End of Table 1

No.	Step	Description	Details
3	Data Preparation	Exclusion Criteria: Articles without an abstract. Excluded Records (ER): 145 Final Dataset Size (FDS): FDS = Total Records – ER = 5488 – 145 = 5343	Noise Reduction Techniques: Removal of punctuation and stopwords. Text Processing Techniques: Tokenization: Splitting text into tokens (words). Lemmatization: Converting words to their base form.
4	Sentiment Analysis	Tool: TextBlob. Sentiment Polarity Calculation (SPC)	- Aggregation Method - Yearly Aggregation (YA) - Category Analysis - Average Scores per Category (ASC)
5	Topic Analysis	Tool: Latent Dirichlet Allocation (LDA). Parameter Optimization. Testing Combinations: Various combinations of the number of topics T, iterations I, and keywords per topic K.	Final Parameters Coherence Score (CS): Evaluated to choose the best model.
6	Visualization	Tools Used: wordcloud library and pyLDAvis.	Visual Outputs: Word Cloud: Highlighting most frequent and meaningful words. pyLDAvis: Interactive visualization of topic models.
7	Interpre-tation and Conclusion	Findings: Trends, attitudes, and prevalent opinions on price prediction methods across different academic disciplines.	Contribution: Informing future research directions and enhancing understanding within the academic community.

This structured approach outlines the methodology flow, incorporating specific parameters to detail each step of the analysis.

4. Results

Regarding the WoS category associated with the works included in the analysis, most scientific works that have met the established conditions are part of the Engineering Electrical Electronic category (24.2% of the publications, as can be seen in Figure 2), a fact that high-

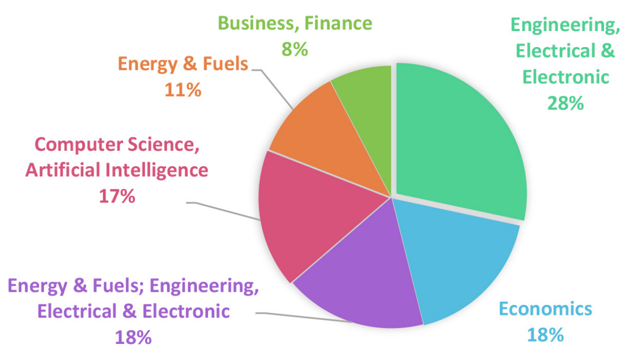

Figure 2. The main 6 WoS categories for the field of price prediction

lights the increased interest in increasing predictability in this vast field, characterized by high price volatility. The first category is closely followed by that of Computer Science Artificial Intelligence (20.6%), justified by the fact that modern price prediction methods are based on advanced automatic learning algorithms. Other fields worth mentioning in this regard are the field of Energy Fuels, Computer Science Information Systems and that of the Economy.

Looking at the evolution of the number of works published annually (Figure 3) from 2000 to 2024, it can be confirmed that interest in this subject has progressively increased in the academic community. The last years, marked by important progress in the field of AI, have associated a significantly higher number of publications that discuss issues related to price prediction.

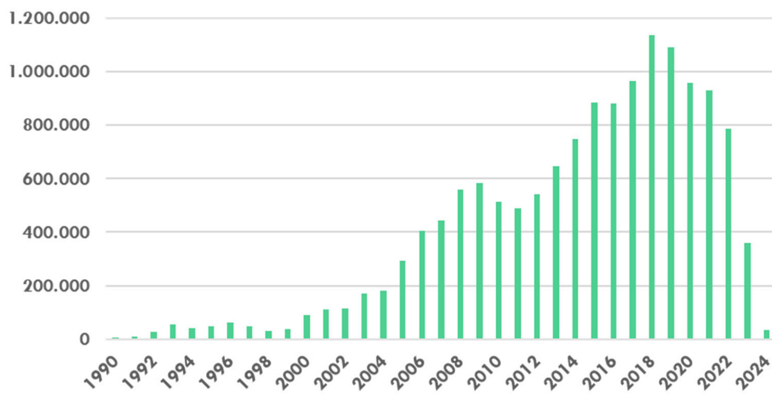

Figure 3. The evolution of the annual number of published and indexed WoS works related to price prediction

Most of the works belong to Chinese authors (30.4%), followed by the ones from United States (14%) and India (8%) (as in Figure 4).

This large number of scientific works in the field of price prediction in the China could be explained by multiple phenomena that appeared in the economic area but also in the area of technology. Notable in this regard are rapid economic growth and massive investments in technology aimed at optimizing techniques for managing economic complexity. Taking into account the volatility and uncertainties in the energy sector, which, as previously mentioned, are not neglected by the academic community, this major concern can also be justified by the fact that the China is one of the largest consumers and producers of energy in the world.

To visualize the most frequent keywords in the data set abstracts, the Python library WordCloud (Figure 4) was used. The generated WordCloud provides an immediate visualization of the key terms and concepts that dominate the debated aspects in the papers whose abstracts are analyzed.

As can be seen in Figure 5, terms such as “data”, “model”, “method” and “results” are prominent, suggesting a strong focus on analytical studies.

Not to be neglected are the key words that refer to domains marked by which price prediction occupies an important place: “stock price”, “crude oil” and “electricity price”. These may suggest that a significant number of works focus on topics such as the stock market, investments, financial market behavior, the oil industry and the supply of electricity.

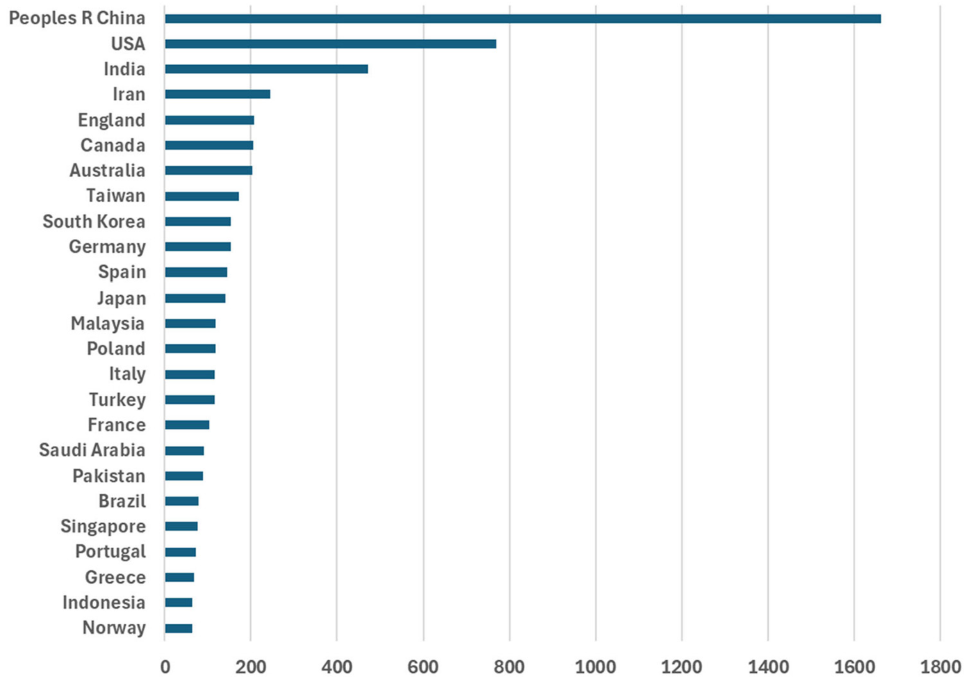

Figure 4. Number of Web of Science Indexed Articles by Country (1990 – April 2024)

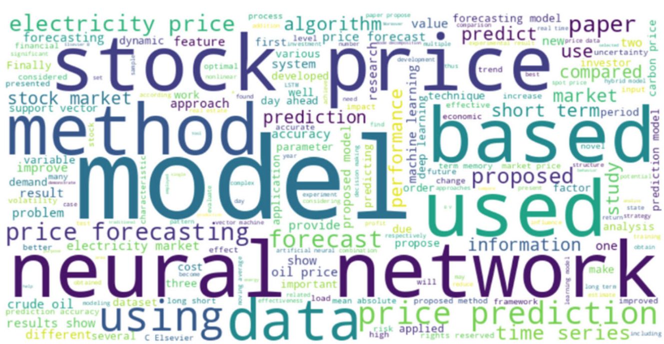

Figure 5. Word Cloud graphic representation of the main keywords

Therefore, the topics of major interest discussed by specialists are identified. At the same time, directions can be identified to formulate new questions in research activity and address less discussed topics in relation to the subject of price forecasting, such as the particularities of other volatile sectors.

To better capture and understand the general opinion of the academic community about price prediction, it is chosen to apply sentiment analysis to the abstracts of the data set extracted from the Clarivate database. For this purpose, 145 records that did not have an abstract are excluded from the initial data set, leaving 5,343 records in the data set subject to analysis.

In the sentiment analysis, the Python TextBlob library is used to determine the predominant sentiment in each abstract (positive, negative, neutral) according to the calculated polarity score.

After applying this method to the 5,343 abstracts, it is found that the general tone of scientific writing can be considered as slightly positive, given the average sentiment of 0.094. This average score can be translated into a reserved attitude, as it is a value that does not deviate much from 0. The sentiment range varies considerably, from –0.5 to 1.0, with an average (median) sentiment of 0.092, reaffirming the overall slightly positive tone.

The minimum calculated score is –0.5, reflecting the existence of at least one abstract with a clear negative tone. The maximum value is equal to 1.0, a sign that there are abstracts with a positive tone. The standard deviation value is equal to 0.099, suggesting a moderate variation in the sentiments of the abstracts. Most scores fall within the range of 0.036 (the value of the first quartile – 25%) and 0.153 (the value of the third quartile –75%).

Abstracts in the analyzed dataset tend to have a slightly positive tone, which may reflect a tendency in the literature to emphasize the benefits brought by the advancement of AI-based technologies on the performance of price forecasting methods. However, it is worth mentioning that there is a significant variability of feelings, indicating that the authors address both achievements and challenges in the field in their work. The evolution over the years of the feelings expressed by the scientific community in the written works is analyzed; the graphic representation of the results is presented in Figure 6.

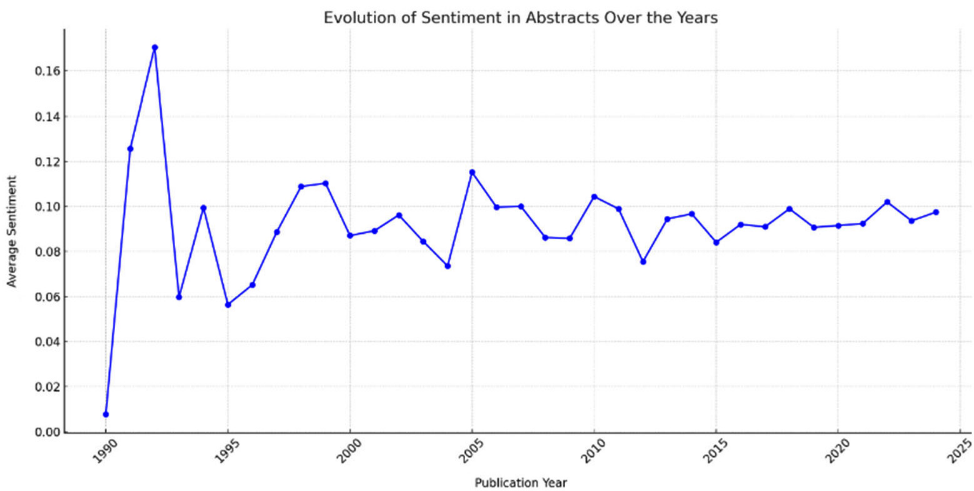

Figure 6. The evolution of the feelings of the scientific community in relation to price prediction

It is notable that the years 1991, 1992 and 2005 had relatively more positive average sentiments (approximately 0.125, 0.170 and 0.115 respectively), suggesting that in these years published research is perceived as having a more optimistic tone. It is known that the 90's were marked by an important technological advance in the field of computers that led to the improvement of data processing and analysis capabilities. In these first years, the score of the polarity of the feelings varied quite a lot, reflecting the divided opinions of the specialists in relation to the subject of price prediction, a fact that can be normal in the conditions in which the field is at the beginning. The years in which the effects of the financial crisis that began in 2008 were felt, had lower scores compared to previous years, a sign that this event did not remain without an echo in the scientific community (Aydin & Cavdar, 2015). In recent years, which are related to a development of solutions based on artificial intelligence, blockchain and cryptocurrencies, a stabilization of sentiment is observed around the average of 0.09 – 0.1. Average sentiment by year indicates relative stability in the positive tone of the abstracts, with minor year-to-year fluctuations. This visualization helps us better understand the dynamics of sentiment in the literature and may indicate periods when research in certain areas is perceived as more optimistic or promising. Understanding how the sentiment toward publication varies over time helps anticipate trends in research. Sentiment analysis was also performed for abstracts depending on the WoS category to which they belong (as in Figure 7). The minimum threshold of 50 abstracts per WoS category is selected to ensure robust analysis.

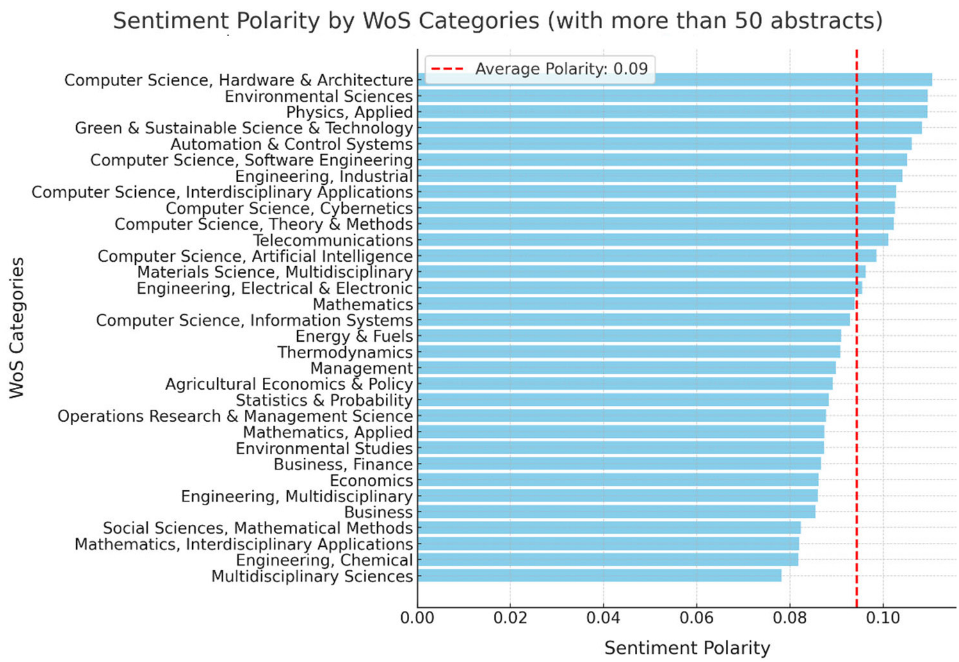

Figure 7. The average of feelings according to the Web of Science category

The main categories with predominantly positive feelings, as well as those with negative scores, can be found together with the average score in the table below (Table 2).

The first five categories in Table 1 are the categories that have higher scores, indicating a more optimistic perspective on the respective research, possibly due to technological advances, ecological innovations or recent scientific successes. However, the following five categories are associated with lower scores, reflecting a slightly positive but reserved attitude. This could be related to the challenges, limitations, or critical issues frequently discussed in articles in these categories.

Following the calculation of the polarity related to each WOS category, subsequently, it is sought to extract the main topics present in the WOS indexed scientific works. To extract the main topics from the analyzed abstracts, the probabilistic method LDA is used. Thus, groups

Table 2. The average of feelings according to the field (Web of Science category)

No.	WoS Category	Score
1	Computer Science, Hardware & Architecture	0.111
2	Environmental Sciences	0.110
3	Physics, Applied	0.109
4	Green & Sustainable Science & Technology	0.108
5	Automation & Control Systems	0.106
6	Business	0.085
7	Social Sciences, Mathematical Methods	0.082
8	Mathematics, Inter-disciplinary Applications	0.082
9	Engineering, Chemical	0.082
10	Multidisciplinary Sciences	0.078

of words that frequently appear together have been identified. In the pre-processing stage, stop words, punctuation and stemming or lemmatization application are removed to ensure noise reduction and improve the quality of the extracted topics. Empirically, LDA was applied for various combinations of the number of topics and the number of iterations through the corpus during training. The highest coherence (value equal to 0.39), simultaneously with a reduced overlap of topics, is obtained in the case of the model with five topics. Then, we adjust the values of the "alpha" and "beta" parameters (also known as "eta" in the gensim package). Changing alpha affects the distribution of the extracted topics, while beta has an impact on the distribution of words related to each topic. To identify the optimal number of topics to be extracted, the level of coherence has been measured that can be obtained for a multitude of combinations of the values of the alpha and beta parameters with a certain

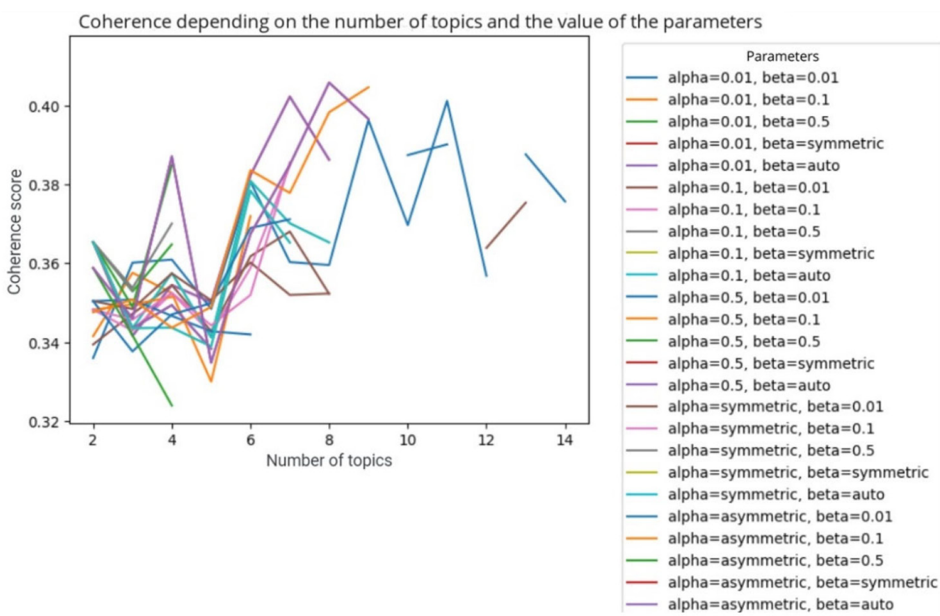

Figure 8. Coherence according to the number of topics and the value of the parameters

number of topics. The results obtained can be observed in the graphic representation (Figure 8), generated by the Matplotlib package. Following this verification, the application of the LDA model was chosen for the extraction of eight main topics, associating the value "asymmetric" for the "alpha" parameter and "auto" for the "beta" parameter.

Thus, the application of the LDA model with 10 iterations was chosen to extract 8 topics, with 5 words for each topic. The coherence score obtained for this model is 0.4368. The words of the extracted topics can be found in Table 3, accompanied by the score for each.

Table 3. Main Topics – Extracted using LDA

No.	Score * the first keyword	Score * the second keyword	Score * the third keyword	Score * the fourth keyword	Score * the fifth keyword
1	0.034*"system"	0.020*"fuzzy"	0.019*"problem"	0.011*"function"	0.011*"pricing"
2	0.054*"price"	0.025*"forecast"	0.019*"model"	0.012*"market"	0.008*"future"
3	0.033*"network"	0.033*"price"	0.030*"prediction"	0.029*"model"	0.025*"neural"
4	0.042*"oil"	0.038*"forecasting"	0.036*"model"	0.026*"price"	0.018*"proposed"
5	0.070*"stock"	0.024*"market"	0.019*"earnings"	0.018*"financial"	0.015*"trading"
6	0.037*"cost"	0.035*"energy"	0.017*"gas"	0.016*"unit"	0.016*"auction"
7	0.077*"model"	0.048*"error"	0.033*"mean"	0.024*"arima"	0.024*"forecasting"
8	0.068*"electricity"	0.057*"market"	0.049*"price"	0.044*"forecasting"	0.023*"power"

PyLDAvis was used to generate an interactive graphic representation of the topics resulting from the application of LDA. This type of graphic representation also contributes to a clearer observation of the existing distance between topics or their overlap. It can be interpreted that each identified topic refers to a specific area of interest, be it advanced technological applications (such as neural networks), financial analysis or resource modelling and management in the energy sector. In what follows, the interpretation of each of the topics will be briefly described. Furthermore, the PyLDAvis graphic representations for each topic (Figures 9–16) is shown, so that the first 30 terms with the highest frequency within the topic can also be observed.

The first of the topics whose keywords extracted by LDA are "system", "fuzzy", "problem", "function", "pricing" refer to the use of fuzzy systems in solving complex problems, possibly in the field of optimization or decisions based on multiple factors. "Pricing" suggests applying these techniques to pricing modelling or game theory. This first topic is represented by a circle with a large area, indicating its increased importance and relevance, a fact already anticipated. It is noticeable in the graph a partial overlap of this first topic with topics 2, 3, 4 and 7, which will be described in the following.

Topic number 2 is focusing on the modelling and prediction of prices in financial markets. The terms "forecast" and "futures" indicate an orientation towards anticipating market trends, using statistical or economic models. The second topic is also associated with a large symbol in the PyLDAvis representation, which also indicates a high degree of its importance. Its overlap with the first topic is justified; considering that the series of methods suitable for predicting prices for the financial market is a wide one, the first of the topics refers to such methods.

Topic number 3 focuses on the use of neural networks for price prediction, possibly in the context of capital markets or other commercial markets. The "neural" and "network" suggest the application of AI and automatic learning. So, in this case, too, the overlap with the first topic, visible in the graphic representation above, is justified.

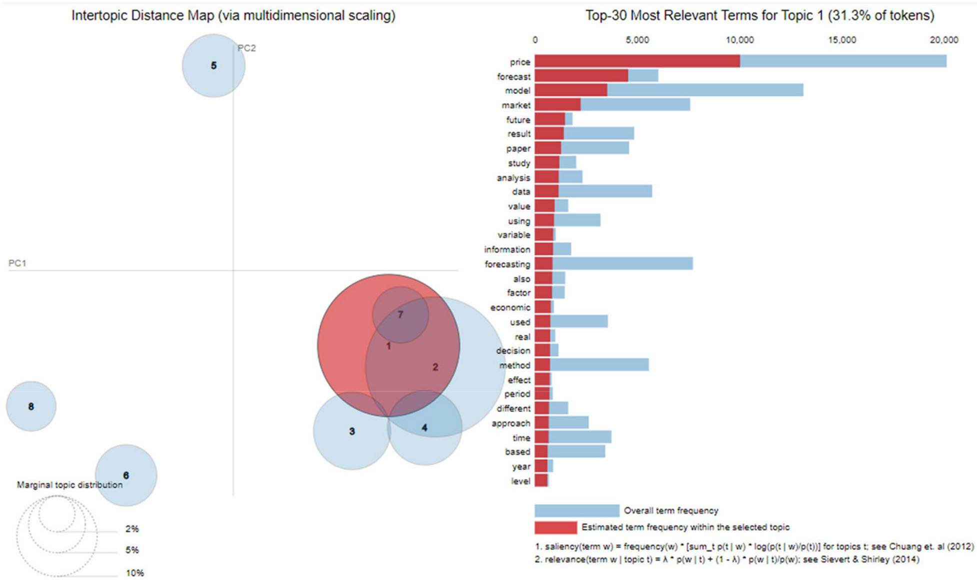

Figure 9. PyLDAvis: The first topic

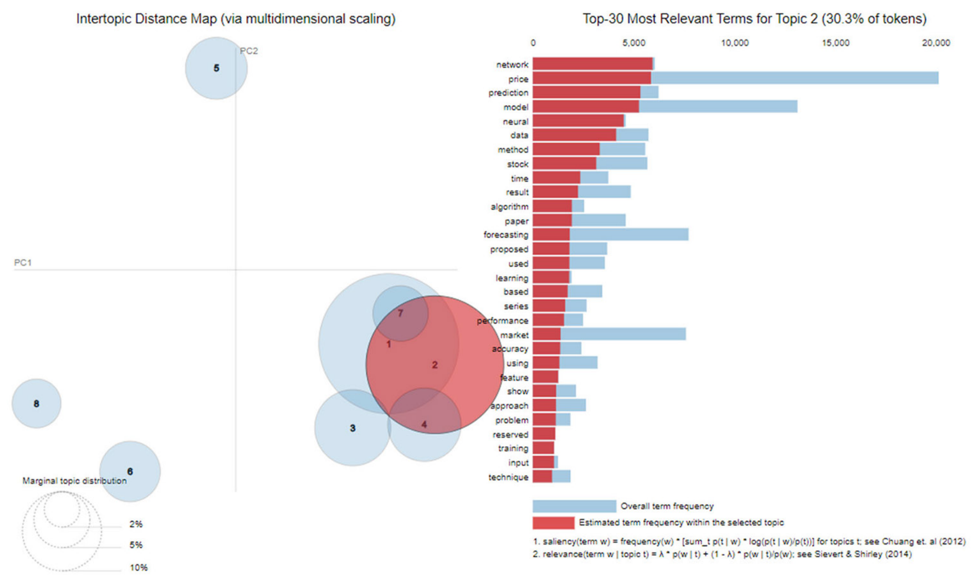

Figure 10. PyLDAvis: The second topic

The topic discusses modelling and prediction of oil prices. The terms "forecasting" and "proposed" refer to new or improved price forecasting methodologies in the petroleum industry. As mentioned in this paper, this topic of price prediction in the oil industry is hot, with fluctuations in crude oil prices having a great impact on multiple industries.

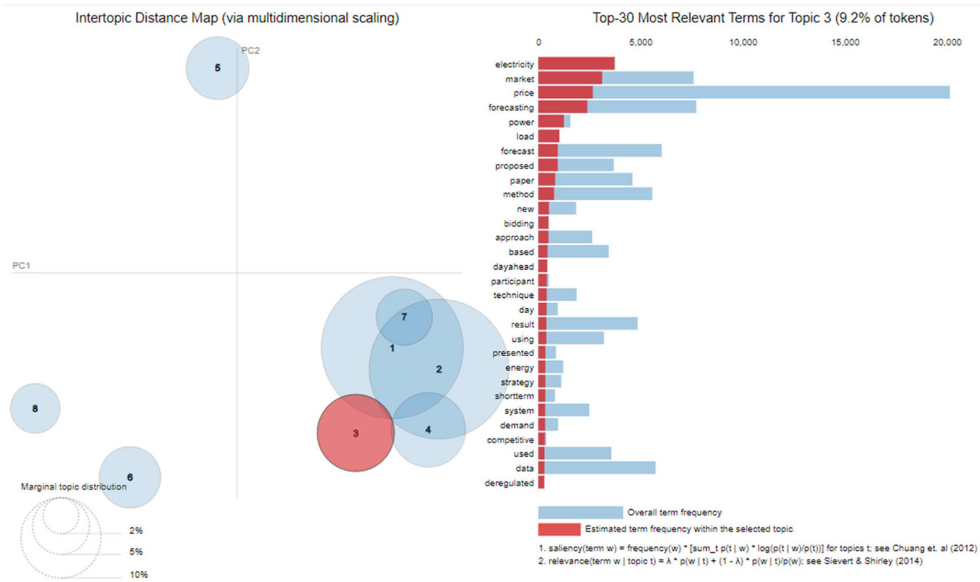

Figure 11. PyLDAvis: The third topic

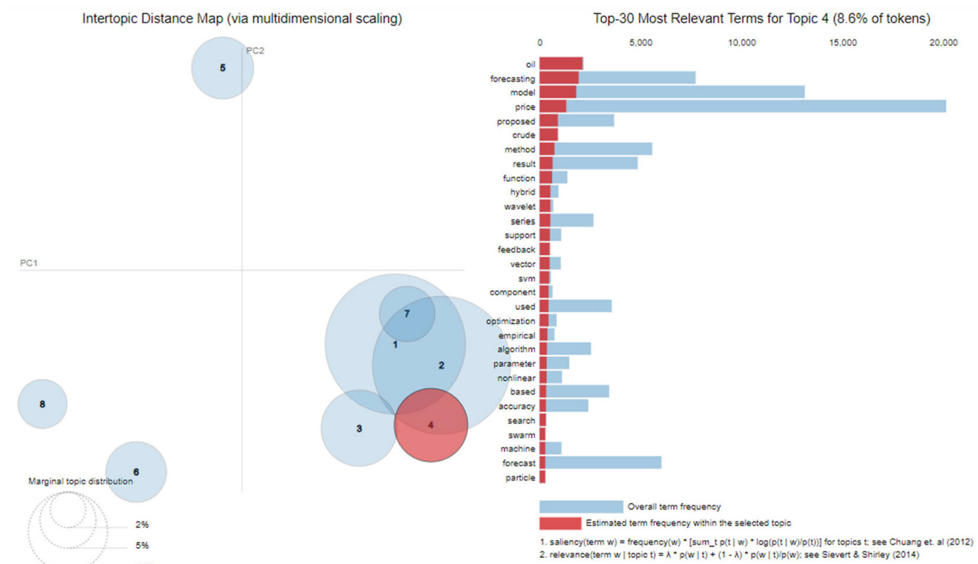

Figure 12. PyLDAvis: The fourth topic

This fifth topic is focused on the capital market, exploring the relationships between market performance, earnings and trading strategies. Reflects interest in financial and economic analysis. This topic overlaps with both the first and the second topic. A significant distance is observed between this topic and the other extracts by applying the LDA model.

The sixth topic addresses the cost estimation and price variations in the energy sector, with a possible focus on natural gas and market mechanisms such as auctions.

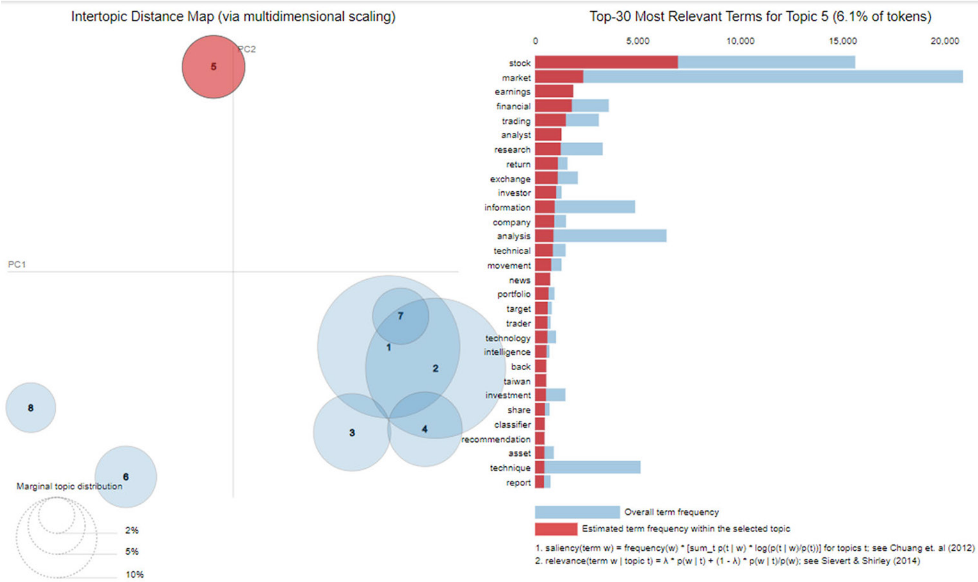

Figure 13. PyLDAvis: The fifth topic

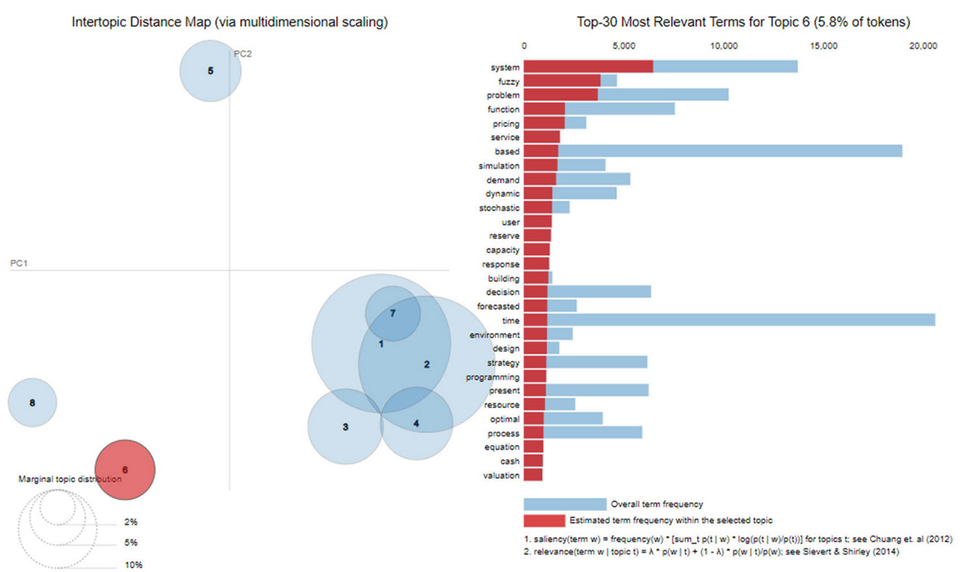

Figure 14. PyLDAvis: The sixth topic

Topic number 7 is focused on statistical forecasting methods such as ARIMA models, and this topic explores techniques to minimize errors and improve the accuracy of predictions.

The last topic, whose keywords are "electricity", "market", "price", "forecasting", and "power", focusses on the electricity market, discussing price dynamics, predictions and strategies for managing supply and demand. energy.

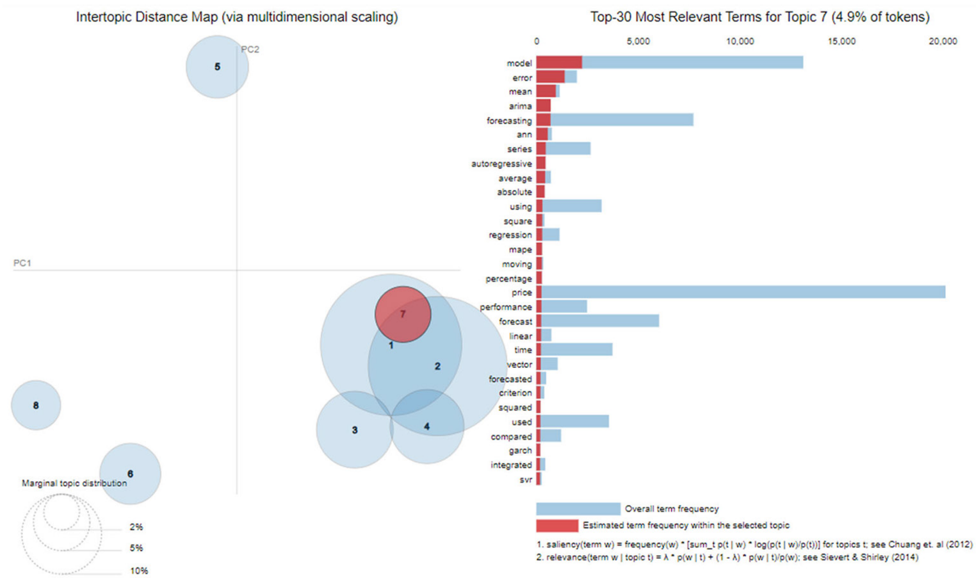

Figure 15. PyLDAvis: The seventh topic

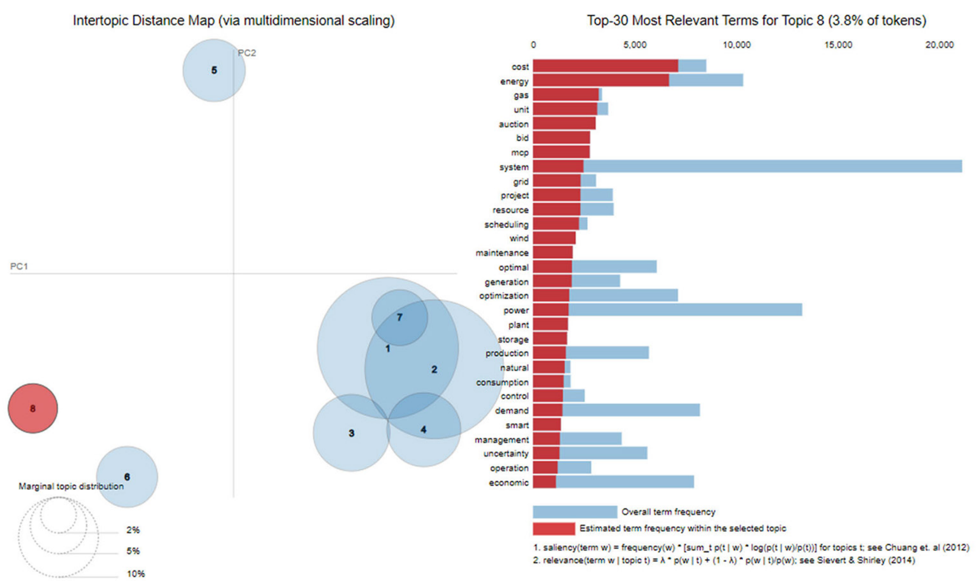

Figure 16. PyLDAvis: The eighth topic

5. Discussions

Returning to the research questions formulated at the beginning of this paper, following the application of the described methods, the following answers can be formulated.

(RQ1) What is the general trend regarding researcher sentiments about price prediction?

(RQ2) How have the feelings of the academic community about price prediction evolved in recent years marked by the progress of AI?

(RQ3) What are the most relevant key topics addressed by the academic community in relation to price prediction?

Answering the first of the questions (RQ1), we can say that the general sentiment of the academic community regarding price prediction seems to be positive, although it does not deviate much from the neutrality score. Regarding (RQ2), it can be said that the interest of researchers in price prediction has grown progressively, and it is worth noting that, although the mean of the polarity score, which measures the intensity of the feelings expressed, has experienced fluctuations in years marked by important events, the value remained positive. It can be considered that this optimism was fueled by advances in price prediction methods, as modern modeling techniques and advanced algorithms have brought improvements in the accuracy of predictions. However, the tendency of the scores to remain low can be justified by the fact that circumspection is felt in the context of the debate on the challenges inherent in price modeling. In the case of markets characterized by strong volatility and unpredictability, such as capital markets and the energy sector, the limitations and uncertainties in the field are recognized. At the same time, the reserved attitude is also related to the difficulties regarding the quality and availability of data, but also to the robust resources needed to implement advanced price prediction models.

To answer the third formulated question (RQ3), the main topics debated by specialists in relation to the subject of interest were analyzed. In this case, it can be concluded that there is a special concern for the development of efficient, precise and robust methodologies that improve the accuracy of predictions in a context dominated by unpredictability. Thus, the focus falls on advanced modeling techniques and the identification of the most suitable solutions that can adapt to the complexity of various industries in order to provide the best possible results in the case of price prediction.

6. Conclusions

The analysis revealed that 24.2% of the publications analyzed fall under the Engineering Electrical Electronic category, followed closely by 20.6% in the Computer Science Artificial Intelligence category. Other notable fields include Energy Fuels, Computer Science Information Systems and Economics. Geographically, most of the works were authored by Chinese researchers, accounting for 30.4% of the publications, followed by 14% from the United States and 8% from India.

Sentiment analysis of the abstracts indicated a slightly positive tone, with an average sentiment score of 0.094. The sentiment ranged from –0.5 to 1.0, with a median score of 0.092 and a standard deviation of 0.099. The first quartile of sentiment scores was 0.036 and the third quartile was 0.153, indicating a moderate variation in sentiment. In terms of sentiment by category, the highest average scores were found in Computer Science, Hardware & Architecture (0.111), Environmental Sciences (0.110), Physics, Applied (0.109), Green & Sustainable Science & Technology (0.108), and Automation & Control Systems (0.106). Our study highlights the general trend of the attitude that the scientific community has toward price prediction. The results reflect feelings with a slightly positive trend, without large fluctuations in recent years. However, it should be mentioned that the scores are kept quite low, which shows that the attitude of the specialists is reserved in relation to this subject.

Using LDA, the main topics existing in the Web of Science indexed works included in the analysis were also extracted. Interpreting these topics, we can say that the methods used for price prediction are intensely debated, as well as the particularities of the capital market or areas known for large price variations such as fossil fuels and electricity. The topic modeling using LDA extracted 8 main topics from the dataset, with a coherence score of 0.4368, suggesting a good balance between topic distinctiveness and interpretability.

Additionally, the data shows a marked increase in publications over the years, particularly after the year 2000, indicating a growing interest in this field. Starting from negligible publication numbers in the early 1990s, a steady rise beginning in the early 2000s is indicated. This upward trend becomes more pronounced after 2010, with the number of publications peaking around 2018. The peak represents a significant focus on price prediction research, likely driven by advancements in AI and machine learning technologies during this period. After 2018, there is a noticeable decline in the number of publications, which could reflect either a shift in research focus or the saturation of the field with existing methodologies. However, the number of publications remains relatively high, showing sustained interest in the topic.

In summary, the necessity of our research lies in the growing importance of accurate price prediction in an increasingly volatile and complex global market. Traditional methods of price prediction, while still valuable, have limitations in handling large volumes of unstructured data and adapting to rapid market changes. The introduction of AI solutions offers new possibilities for more accurate and efficient predictions, yet the academic community's perspective on this shift has not been fully explored.

7. Managerial implications

The findings of this research reveal several managerial implications, particularly in sectors where price volatility plays a significant role, such as energy, technology and finance. The sentiment analysis, which identified a slightly positive average sentiment score of 0.094, reflects the generally optimistic outlook of the academic community towards the effectiveness of current price prediction methods. However, the moderate variability in sentiment across different fields – ranging from strongly positive in areas like Computer Science, Hardware & Architecture, and Environmental Sciences, to more neutral or varied tones in others – highlights the nuanced perspectives within the academic community.

For managers, positive sentiment in specific areas can indicate emerging opportunities where investment in advanced predictive models may yield substantial returns. Conversely, the more varied sentiments suggest areas where the effectiveness of these models may be more uncertain, necessitating cautious and customized application. The academic community's evolving perspective on price prediction, influenced by the rapid advancements in AI and machine learning, should be a signal for managers to continuously adapt their strategies to align with cutting-edge research and industry best practices.

Moreover, the study's findings that a large portion of the research is concentrated in Engineering Electrical Electronic (24.2%) and Computer Science Artificial Intelligence (20.6%) indicate that these fields are leading the way in developing and refining predictive models. This suggests that managers in these industries need to prioritize staying informed about the latest academic advancements to maintain a competitive advantage. Additionally, the significant contribution from Chinese researchers (30.4% of publications) points to the importance of monitoring technological developments emerging from China.

The topic modelling using LDA, which identified eight main topics with a coherence score of 0.4368, further emphasizes the complex and diverse nature of price prediction. Managers should be aware that academic discussions around these methods are intense and ongoing, reflecting the need for continuous innovation and refinement of predictive models. Finally, the upward trend in publications, particularly after 2000 and peaking around 2018, indicates a growing and sustained interest in price prediction as a strategic tool. This trend suggests that integrating AI-driven predictive models into decision-making processes is becoming increasingly significant for maintaining competitiveness. The subsequent decline in publications post-2018 might signal a shift towards the application and optimization of existing methodologies, suggesting a period of consolidation. For managers, this means the focus should now be on leveraging these established models to enhance forecasting accuracy and operational efficiency.

8. Practical/Social implications

On a social level, the findings highlight the increasing interplay between academic research and societal trends, particularly in how technological advancements are perceived and adopted by different sectors. The significant contribution of Chinese researchers, accounting for 30.4% of the publications, underscores the global nature of technological innovation and the importance of cross-cultural exchange in advancing AI and machine learning. Additionally, the upward trend in publications, particularly post-2000, signals a growing societal interest in the ethical and practical implications of AI in price prediction. This increased attention is likely driven by the broader societal debates surrounding AI, including concerns about transparency, fairness and the potential for bias in predictive models.

The positive sentiment in fields such as Green & Sustainable Science & Technology suggests a growing alignment between technological innovation and sustainable development goals, reflecting a broader societal push towards integrating environmental considerations into technological advancements.

In conclusion, the study is important for highlighting the academic community's position on AI's role in price forecasting, identifying both optimism and reservations. This analysis contributes to the existing literature by capturing a historical perspective on sentiment and also opens up new research directions by identifying less-explored areas within the field.

One of the limitations of this study is represented by the fact that only WoS-indexed works were included in the analysis and other relevant studies could be missing from the analyzed dataset. In future work, scientific works found in other important databases could be added. In addition, in future studies, the perspective could be broadened by deepening the main problems or limitations addressed by specialists regarding current price prediction methods, which maintain this reserved attitude in the scientific community.

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Author contributions

Alexandra-Cristina-Daniela Ciuverca: Conceptualization, Formal analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review and Editing, Visualization, Supervision. Simona-Vasilica Oprea: Method, Validation, Formal analysis, Investigation, Writing – Original Draft, Writing – Review and Editing, Visualization, Project administration.

Disclosure statement

The authors have no relevant financial or non-financial interests to disclose.

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