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Systematic Review

Oil Sector and Sentiment Analysis—A Review

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Abstract: Oil markets reveal considerably volatile behaviour due to a range of factors. Exogenous factors, such as the COVID-19 pandemic and ongoing wars and conflicts, impose even more difficulties for prediction purposes. As a tool to better understand and improve forecasting models, many researchers are using sentiment analysis techniques to identify the sentiments being emanated in the news and on social media. Following the PRISMA standards, this work systematically reviewed 34 studies out of 320 from the Scopus and Web of Science databases. The results indicate that one can use several different sources to construct a text dataset and develop a sentiment analysis. For instance, Reuters, *Oilprice.com*, and Twitter are among the more popular ones. Among the approaches used for extracting public sentiment, it became apparent that machine learning-based methods have been increasing in prevalence in recent years, both when applied alone and in conjunction with lexicon-based methods. Finally, regarding the purpose of employing sentiment analysis, the most favourable goal for collecting sentiments concerning the oil market is to forecast oil prices. There is a consensus among the authors that sentiment analysis improves the quality of predictive models, making them more accurate. This work aims to assist academics, researchers, and investors interested in the oil sector.

Keywords: sentiment analysis; opinion mining; oil sector; oil prices forecast; literature review

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1. Introduction

Crude oil plays a crucial role in the global economy, impacting various macroeconomic variables such as inflation, GDP, stock market returns, interest rates, and exchange rates (e.g., [1–4]). It is not only a widely traded commodity but also a significant factor in portfolio selection, risk management, and option pricing for investors [5]. For instance, Chatziantoniou et al. [6] propose that the tail risk connectedness between crude oil and refined petroleum products rises with major crisis episodes such as the COVID-19 pandemic, which in turn, can lead to greater exposure to losses in other markets. Accounting for the interconnectedness of the oil market with several different sectors, the fluctuations in oil prices can reflect the state of the global business cycle and financial market sentiment [7].

As a result, accurately forecasting crude oil prices has garnered significant attention from both investors and academics, leading to the exploration of various methods, including econometric models and machine learning approaches (e.g., [8–11]) (For instance, Shobana et al. [12] and Nosratabadi et al. [13] presented reviews about how econometrics and ML models have been applied to economic data). However, among the difficulties in forecasting crude oil prices, nonlinearity and the errors in price prediction due to its complex market structure and unpredictable factors that disrupt the market equilibrium [14] are some of the principal challenges posed in this task.

As pointed out by Yu et al. [15] and Bildirici et al. [16], the price volatilities are affected by micro- and macroeconomic variables—e.g., competition across providers, substitution with other energy sources, technique development, domestic economy, deregulation activities—in addition to speculative activities and non-economic variables such as the COVID-19 pandemic, natural disasters, the oil price war between Russia and Saudi Arabia, and other geopolitical tensions [17]. Although the market normally tries to quantify how exogenous variables might affect oil prices, these events are difficult to predict and even more complicated to quantify [18,19].

As a proxy for this behaviour, a good option would be financial market news—or even textual signals issued by country leaders, central bank presidents, big oil companies, and other important figures in the oil market—since they can provide information for use in decision making and risk management by both investors and governments [20]. Given the increasing usage of the Internet, it has become the worldwide and most vital source of information [21]. Adding to that, online data are provided more often than statistical indicators and offer more qualitative information than official statistical data [19].

One potential approach to gain insights into market sentiment and exogenous influences is through sentiment analysis, a field that combines computer science, computational linguistics, data mining, psychology, and sociology, aiming to extract opinions and sentiments from text data [22]. Roughly speaking, Stine [23] defines sentiment analysis as the challenge of building a classifier from a text in the sense that it labels a body of text as expressing either a positive or a negative opinion.

In the literature, there are many different applications of sentiment analysis, such as predicting elections' results, tracking peoples' emotions regarding the COVID-19 pandemic, and predicting stock market returns (e.g., [24–26]). Specifically, several authors have applied some sort of sentiment analysis aiming to forecast the oil market, and there is a consensus among them that the output from sentiment analysis models improves the quality of the forecasting results (e.g., [19,27,28]).

Regarding sentiment analysis reviews, the literature already provides a solid baseline over the models and steps involved in several applications of sentiment analysis. For instance, Mäntylä et al. [29] found that, even though sentiment analysis is rooted in studies on public opinion analysis in the early years of the 20th century, it was only after 2004 that 99% of papers were published. Nanli et al. [30] demonstrated that sentiment analysis was still an immature field in 2012 but was growing with the development of text mining, natural language processing (NLP), web mining, and ML. It is worth mentioning that sentiment analysis could be characterized as a complex assignment since it requires the consideration of various NLP subtasks such as sarcasm and subjectivity identification. Furthermore, the material is not usually ordered as it is in books or newspapers, and it may have numerous orthographic errors, colloquial idioms, or abbreviations [21].

For Medhat et al. [31], sentiment analysis is the computational study of people's opinions, attitudes, and emotions toward individuals, events, or topics. Their study found that *naïve* Bayes and support vector machines (SVM) are the most-implemented ML algorithms for dealing with sentiment classification, since these models are generally the baseline for comparison.

Accordingly, Stine [23] showed that innovative and sophisticated neural network methods progressively improve classification accuracy. However, the computational time consumption can be enormous, and they can generate a considerable reduction of transparency, i.e., the layers of learning are becoming so deep that it has become difficult to understand precisely how the models work.

Comparing different types of techniques to perform sentiment analysis, Nandwani et al. [32] found that the lexicon-based technique performs well in sentiment and emotion analysis, while the corpus-based method is more accurate but lacks generalization. ML algorithms and deep learning algorithms depend on the pre-processing and size of the dataset. Recurrent neural networks, especially the long short-term memory (LSTM) model, are prevalent in sentiment and emotion analysis due to their ability to cover long-term dependencies and extract features.

Sudhir and Suresh [33] conducted a comparative study of different approaches, applications, and classifiers for sentiment analysis. They cited three distinct approaches:

rule-based, machine learning-based, and lexicon-based. All of these have advantages and limitations, but considering the accuracy of the tests performed, SVM and deep learning methods like gated recurrent unit and bidirectional encoder representations from transformers bore exceptional results, exceeding conventional classification models such as *naïve* Bayes and decision tree.

From a larger perspective, the tertiary study on sentiment analysis techniques performed on by Ligthart et al. [34] indicates that sentiment analysis has been used in a variety of contexts, with social media being the most widely used. Since deep learning algorithms can recognize more intricate textual patterns and excel when applied to bigger datasets, there appears to be a trend toward utilizing more sophisticated deep learning methods. The study demonstrated that domain and language dependencies are challenging to address in sentiment analysis.

Different from previous reviews, this work aims to fill a gap by focusing solely on the analysis of sentiment towards the oil market. Currently, to the best of the authors' knowledge, there are no papers that examine the relationship between sentiment analysis and oil markets. Our paper aims to fill this void by evaluating the contributions made to the field and the directions in which research is moving. For instance, besides the works that comprehensively reviewed or surveyed sentiment analysis methods, there are reviews interested specifically in the oil sector. These are mainly focused on forecasting models' structured data used for oil prices. However, they do not focus on auxiliary methods, like sentiment analysis (e.g., [35,36]). In this sense, the advantages of having a specific application for sentiment analysis allowed this review to answer three main questions:

- What are the main sources available for researchers and/or enthusiasts in the field of oil markets willing to perform sentiment analysis?
- What are the most-used techniques and the differences between them?
- What are the most common applications of sentiment analyses and the outcomes from their use?

Secondary issues are also discussed, such as the challenges and recommendations in this specific field.

To accomplish the task, a systematic literature review based on the PRISMA (Preferred reporting items for systematic reviews and meta-analyses—PRISMA is an evidence-based set of items for reporting in systematic reviews and meta-analyses. For more information, access www.prisma-statement.org (accessed on 15 April 2023)) standards was performed, since it is an already well-established methodology to perform systematic review (e.g., [37–39]) and allow for the replication of the results. Out of 320 search results, 34 studies relating to the analysis of sentiment towards the oil market were extracted from the Scopus and Web of Science databases, both of which encompass a large number of different publishers.

Systematic review of the articles indicates that there are several different sources that one could use to construct a text dataset and develop a sentiment analysis. For instance, Reuters, *Oilprice.com*, and Twitter are among the most popular ones. Among the approaches for extracting sentiments, it was possible to see that machine learning-based methods have been increasing in recent years, both when applied alone and in conjunction with lexicon-based methods. Finally, regarding the purpose of employing sentiment analysis, the most desired goal for collecting sentiments about the oil market is to forecast oil prices. There is a consensus among the authors that sentiment analysis improves the quality of the predictive models, making them more accurate.

The remainder of the paper is divided as follows: Section 2 discusses how the PRISMA methodology was defined; Section 3 details the leading techniques and processes of sentiment analysis in the oil market literature followed by a discussion in Section 4; next, challenges and recommendations are provided in Section 5; and last, in Section 6, some final remarks are presented.

2. Systematic Review Approach

The review approach employed is based on the PRISMA (preferred reporting items for systematic reviews and meta-analyses) standards, a widely used method for systematic reviews and meta-analyses. Many works used this approach for reviews in other domains, such as computer sciences and medical research [38–40]. The PRISMA approach has various advantages. It fosters transparent and complete reporting by providing a systematic framework that includes all areas of the review process. The defined rules promote uniformity and methodological rigor, increasing the dependability of the outcomes. PRISMA promotes extensive literature searches and explicit research selection criteria, avoiding biases and enhancing the search technique. It also permits critical analysis of included studies, allowing for the assessment of their quality and danger of bias [41]. As noted by Kar et al. [42], PRISMA proves itself useful by replicating the review methodology, structure, and format so as to offer a reference point for other reviewers. However, the PRISMA methodology has limitations. Publication bias may still exist despite PRISMA's efforts, and it is primarily designed for quantitative data, making it less suitable for qualitative research or other evidence synthesis approaches. Nonetheless, according to Page et al. [43], the main steps are:

- to specify the inclusion and exclusion criteria;
- sources information;
- to define the search strategy;
- to use methods to decide whether a study meets the inclusion criteria of the review;
- to implement automation tools used in the process;
- data items;
- study selection;
- to review the results of individual studies.

Following this structure, an article must relate sentiment analysis, opinion mining, or text mining with the oil market to be eligible. Figure 1 summarizes all the filtering steps applied in the analysis.

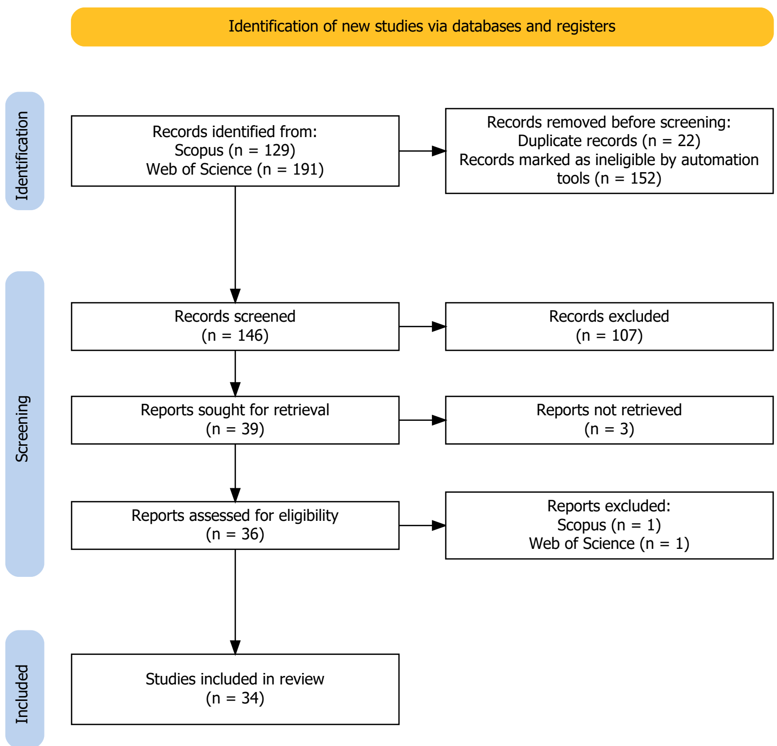

Figure 1. PRISMA flow diagram applied in the study.

As for the sources, Scopus maintains an extensive database with more than 7000 publishers including Springer, Elsevier, Science Direct, Taylor & Francis, Wiley, Emerald Group Publishing, Cambridge University Press, IEEE Xplore, and many others (A complete list of all publishers and journals indexed in Scopus is available in https://www.elsevier.com/__data/assets/excel_doc/0015/91122/extlistMarch2023.xlsx (accessed on 16 April 2023)). Also among them is the Thomson Reuters Web of Science (WoS), which was also included as a source of research papers. In both databases, the search queries can be defined with the use of Boolean operators such as *AND*, *OR*, and, in the case of Scopus, proximity operators such as *W/n* that are utilized to find words within a certain distance from each other (For a complete guide on Boolean and proximity operators functionalities in Scopus, access https://service.elsevier.com/app/answers/detail/a_id/11365/ (accessed on 16 April 2023)). The string query applied in Scopus was *("sentiment analysis" OR "opinion mining" OR (text W/5 mining) OR (Twitter W/5 sentiment) OR (web W/5 scraping) OR (text W/5 information)) W/5 oil*, meaning that interest relies upon the terms in quotes being within five words of proximity of the string *oil*. In this way, the search becomes wide enough to include the vast majority of terms related to sentiment analysis for the oil market while removing results that use the term oil sporadically and not as the main point. The search returned 121 documents plus 8 secondary documents, summing up to 129 articles. For the WoS database, the string queries applied were *("sentiment analysis" OR "opinion mining" OR "text mining" OR "Twitter sentiment" OR "web scraping" OR "text information") AND oil*, a slightly more embracing string query, since it does not require a defined word distance between the terms in quotes and *oil*. Using these settings, the WoS database returned 191 documents.

Several other Boolean operators were tested, specifically less-restrictive operators; however, the results were polluted with topics non-related to the oil market. In conducting the systematic review, it is important to acknowledge the specific nature of the research topic, which focuses on sentiment analysis specifically applied to the oil market. Due to this specialized focus, the available body of literature is relatively limited compared to broader sentiment analysis studies. However, this presents an exciting opportunity to explore a relatively uncharted area within sentiment analysis and extract valuable insights for the oil market.

With this in mind, both databases returned 320 documents overall that were subjected to an algorithm that applied 3 different filters: i. First, all words from the title, the abstract, and the journal were set to lowercase in order to reduce disparities between possible duplicate entries. In this step, 22 duplicate documents were removed. ii. The second filter removed the articles that contained the terms "review", "survey", and "biomedical" from the titles and also removed the ones with the strings "medic", "genome", "neuro", and "biology" from the name of the journals where the articles were published, removing in total 45 documents. iii. In the third step, only documents that included the string "oil" in their abstract were kept. This procedure removed 152 documents from the dataset, leaving 146 documents to be screened manually through the analysis of the title and/or abstract of the articles.

Specifically, the interest of this review relies on topics to help one to understand the oil market structure, such as its price, supply or demand factors, exogenous impacts, and so on. However, during the screening process, papers that related sentiment analysis with the drilling process or environmental disasters like oil spills were excluded because, although these events can cause changes in the oil structure, they are more related to oil exploration, risk management, or climate issues than to the oil market itself. This step removed 107 entries leaving 39 documents to be included in the next screening stage, which encompasses a full-text reading of the documents. However, 3 of them were not found, leaving 36 of the reports sought for retrieval. After a full-text reading, from the 36 documents filtered thus far, 2 were excluded as they did not concern themselves with the entire oil sector but only with a few specific companies (A complete list of the articles analyzed, and the ones excluded from the study can be requested with the authors).

3. Results

The articles included in the review range from 2007 until 2022, most of which are from 2022, clearly depicting the growing interest in this kind of application in recent years. A first attempt to identify the trends in the selected documents is to analyze the cloud of words from all the abstracts present in the articles, which can be seen in Figure 2. As one can notice, besides "oil", the terms "news", "crude", "price", and "forecasting" are the ones depicted most frequently. Not surprisingly, from all the selected documents, the majority utilize some sort of sentiment analysis approach in order to predict the price changes in the oil market, whether it is crude oil, crude oil futures, Brent, West Texas Intermediate (WTI), or Dubai-Oman.

To understand the state-of-the-art of sentiment analysis toward the oil market, the studies can be divided into three segments: the text source; the main technique used to extract the "sentiments" from the texts; and their applicability and main result. Moreover, in Table 1, it is possible to view all the selected studies chronologically and in detail, such as the objective for applying sentiment analysis, the text source, the tool used to extract the sentiment, and whether the tool is classified as lexicon-based, machine learning-based, or hybrid.

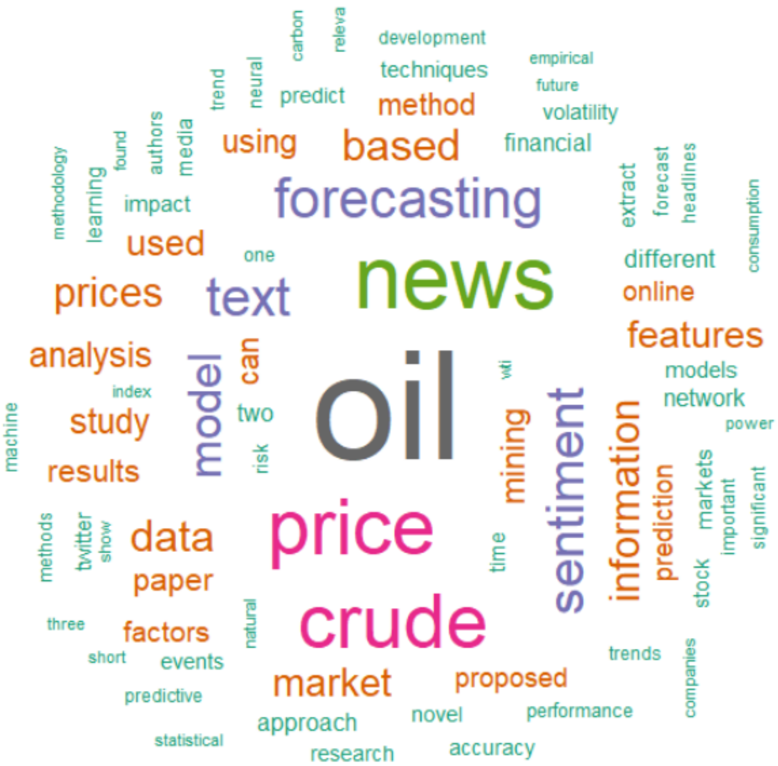

Figure 2. Cloud of the most frequent words in the documents' abstract.

Table 1. Review summary.

Study	Application	Text Source	SA Tool	SA Approach
Xu et al. [44]	Oil price factors	Reuters (full text-English)	RSWNN (topic modeling)	Hybrid
Abdullah and Zeng [45]	Oil price forecasting	Google News (full text-English)	Manually	Lexicon
Wex et al. [46]	Oil price forecasting	Reuters (full text-English)	Manually	Lexicon
Wex et al. [47]	Oil price forecasting	Reuters (full text-English)	LM and manually	Lexicon
Feuerriegel et al. [48]	Bubbles in the oil market	Reuters (full text-English)	HFSD and Net-Optimism	Lexicon
Ratku et al. [49]	Oil price forecasting	Reuters (full text-English)	HFSD and Net-Optimism	Lexicon
Li et al. [50]	Oil price forecasting	Reuters (full text-English)	HFSD and Net-Optimism	Lexicon
Chuaykoblap et al. [51]	Oil price forecasting	Reuters (headlines-English)	EDTM	Lexicon
Elshendy et al. [52]	Oil price forecasting	Twitter, Wikipedia and GDELT project (English)	Condor and IDF	Machine learning

Table 1. *Cont.*

Study	Application	Text Source	SA Tool	SA Approach
Kelly and Ahmad [53]	Oil price forecasting	WSJ and FT (full text), Oildrum blog (English)	GI dictionary, Platts and Oil & Gas UK glossaries	Lexicon
Keshwani et al. [54]	Oil price forecasting	SP500, GE, STW and NYSE (full text-English)	SentiWordNet	Lexicon
Oussalah and Zaidi [55]	Oil price forecasting	Twitter (English)	SS and SNLPS	Hybrid
Li et al. [27]	Oil price forecasting	Investing.com (headlines-English)	CNN, Textblob and LDA	Machine learning
Loughran et al. [56]	Oil price forecasting	DJES (full text-English)	Net-Optimism	Lexicon
Prusa et al. [57]	Oil price forecasting	IEA oil reports (English)	TF-IDF	Lexicon
Zhao and rong Zeng [58]	Oil price forecasting	Reuters (full text-English)	SVM	Machine learning
Zhao et al. [59]	Oil market risk factors	Reuters (full text-English)	LDA (topic modeling)	Machine learning
Zhao et al. [60]	Oil VaR measurement	Reuters and UPI (full text-English)	Two-layer NMF (topic modeling)	Machine learning
Zhao et al. [61]	Oil price forecasting	Reuters and UPI (full text-English)	VADER	Lexicon
Chen et al. [62]	Oil price forecasting	Sina Weibo and Twitter (Chinese, English)	CEWO and RNN	Hybrid
Jain et al. [20]	Oil price forecasting	YFMB (English)	MCSSD	Lexicon
Liu and Huang [63]	Oil price forecasting	The Guardian and TNYT (full text -English)	VADER	Lexicon
Lucey and Ren [64]	Oil price forecasting	Financial Times (full text-English)	HFSD and LM	Lexicon
Wu et al. [14]	Oil price forecasting	Oilprice.com (headlines-English)	CNN-VMD	Machine learning
Wu et al. [65]	Oil price, production, consumption, and inventory forecast	Oilprice.com (headlines-English)	CNN	Machine learning
Bai et al. [18]	Oil price forecasting	Investing.com (headlines-English)	TextBlob	Lexicon
Gong et al. [19]	Oil price forecasting	Oilprice.com (full text)	CNN, LDA, TextBlob, and FinBERT	Hybrid
Jiang et al. [66]	Oil price forecasting	Oilprice.com (headlines-English)	Sentimentr	Lexicon
Jiang et al. [28]	Oil price forecasting	Eastmoney forum (Chinese)	BAT APIs	Hybrid
Jiao et al. [67]	Oil price forecasting	Investing.com and oil.in-en.com/ (headlines-English)	SnowNLP	Lexicon
Lakatos et al. [68]	Oil price forecasting	Twitter (English)	VADER, SRLE and TRBS	Hybrid
Li et al. [69]	Oil and investor sentiment correlation	Baidu (Chinese)	Own dictionary	Lexicon
Wu et al. [70]	Oil consumption prediction	Oilprice.com (headlines-English)	CNN	Machine learning
Yilmaz et al. [71]	Social media and energy sector stock prices correlation	Twitter (English)	Textblob	Lexicon

Note: To accommodate the entire table, acronyms were used, and their explanations can be found in the Abbreviations Section below.

3.1. Text Sources

Unlike social media sources, online news is selected as a source of analysis for the majority of the research gathered for systematic review. Yet, understanding the major distinctions between the two source types is of relevance. On the one hand, Li et al. [27] indicated that online news is superior to the general discussions often found in social media. Accordingly, Wu et al. [65] highlighted that online news is more persuasive and quieter than other social media, such as Twitter and blogs. Specifically dealing with the oil sector, online news sources enhance the accuracy of oil market forecasting. On the other hand, some authors explore social media (e.g., [28,52,62,68]) since it can reflect investors' opinions.

For instance, Elshendy et al. [52] searched for signals of economic awareness on online social media and tested their significance in economic predictions. The study analyzed the relationship between the West Texas Intermediate daily crude oil price and the multiple predictors extracted from Twitter; Google Trends; Wikipedia; and the Global Data on Events, Location, and Tone (GDELT) database. Their results demonstrated that the combined analysis of the four media platforms carries valuable information in financial forecasting. Twitter language complexity, GDELT number of articles, and Wikipedia page reads have the highest predictive power.

Among the studies that utilize online news as their source, another topic for discussion is whether to use only news headlines or the entire text body. Some authors choose the headline over the full article because the headline is the essence of the content [18,70]. Additionally, Li et al. [27] indicated that headlines are easier to retrieve and are mostly summaries of the full text. Nonetheless, the numbers of articles that use the full text or headlines are similar. Birjali et al. [21] explored this issue, stating that the sentiment analysis applied to headlines is considered a sentence-level sentiment analysis, while the analysis performed on the full article is a document-level sentiment analysis. On the one hand, at a sentence-level, the sentence needs to be classified as objective, expressing factual information, or subjective, expressing views and opinions. On the other hand, at a document-level, each document is categorised based on the opinion holder's overall mood toward a specific entity. The document-level categorization works best when the document is created by a single individual and is ineffective when evaluating or comparing different entities.

With respect to the sources of online news, Thomson Reuters leads the ranking of sources most used. Ratku et al. [49] claimed that Reuters transmits independent, third-party announcements with a shorter delay than printed media and can thus be used to evaluate stock market reactions. Similarly, Feuerriegel et al. [48] highlight that Reuters conveys news about commodity markets, a critical issue when analyzing the oil sector; and as opposed to newspapers, news agencies feature a shorter time lag and lack the perturbations caused by edits.

In second place comes *Oilprice.com*, which is one of the world's largest websites concerning energy news [19,66]. Moreover, it also collaborates with the most renowned names in financial news and provides news and analysis to other sites, such as Yahoo Finance, CNBC, CNN Money, Fortune, TIME Magazine, USA Today, and Business Insider [14].

Other sources are less prominent in the oil and energy sector but are still worth mentioning. *Investing.com* is a financial website that provides real-time information and news about thousands of financial investment products, including global stocks, foreign exchange, futures, bonds, funds, and digital currency, as well as a variety of investment tools [18]; The Wall Street Journal, which discusses news about Dow Jones Industrial Average companies, and the Lex column from the Financial Times, which is considered to have a long-term view of business and finance events [53] are worth noting, as is the Dow Jones Energy Service, which provides real-time news on the oil market [56].

3.2. Sentiment Analysis Techniques

The task of sentiment analysis can be divided into four stages: extraction, pre-processing, analysis, and knowledge discovery [72]. The extraction and pre-processing steps are performed with the aid of NLP techniques. Although text mining tools are not in the scope of this review, Table A1 in the Appendix depicts the first steps in the data construction process. The most common pre-processing steps generally involve tokenization, negations and stop word removal, synonym merging, and stemming. The process of tokenization involves splitting each announcement into individual words and sentences, referred to as tokens. Negations are handled by inverting the meaning of subsequent words and sentences when encountering negating terms like "no", "rather", "could not", "was not", etc. Stop words are those that lack significant meaning. Synonym merging is the grouping of synonyms with similar meanings through pseudoword generation. Finally, stemming reduces inflected words to their stems [48]. Table A1 also shows the web search terms used in the selected studies and the document representation to perform the sentiment analysis.

It is also customary to implement effective weighting for information retrieval before sentiment analysis. To a large extent, the term frequency-inverse document frequency (TF-

IDF) is one of the most well-established [66]. TF-IDF reflects the importance of a specific word in a document with respect to a collection of documents [27]. In other words, the key idea of TF-IDF is that if a word or phrase appears in one article with high frequency and with low frequency in other articles, it may indicate that the word has good differentiation ability and is, therefore, suitable for text classification tasks [67]. According to Li et al. [27], the metric can be denoted as:

$$TF\text{-}IDF(t, d, D) = f_{t,d} \cdot \log \frac{N}{n_t}, \qquad (1)$$

where $f_{t,d}$ is the raw frequency of term t in document d, N is the total number of documents in the corpus, and n_t is the total number of documents containing at least one occurrence of term t. In this way, the TF-IDF value increases proportionally with the occurrence of a word within a document and decreases with the number of documents containing this word across the entire corpus [27].

Beyond the initial steps required to perform the sentiment analysis, the chief interest relies on the analysis and knowledge discovery from the treated documents. Following the authors of References [31,73], three basic approaches are available in the literature for sentiment analysis: lexicon-driven, machine learning-based, and hybrid (a mix of lexicon and machine learning).

Although lexicon-based methods are the most frequent in works regarding the oil market, machine learning-based and hybrid approaches are becoming more popular in recent years, as is shown in Figure 3. In brief, lexicon-based methods rely on a pre-defined set of words, called a lexicon, which is associated with a specific sentiment (e.g., positive, negative, or neutral). The sentiment of a piece of text is determined by counting the number of positive, negative, and neutral words it contains.

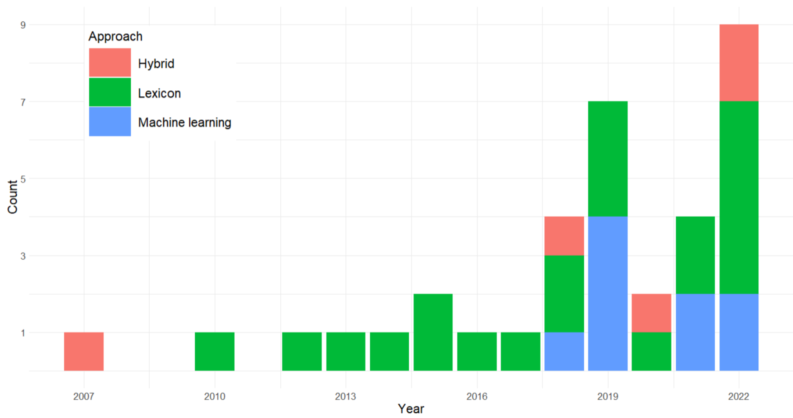

Figure 3. Frequency of documents by year and approach.

In contrast, machine learning-based methods rely on training a model on a labeled dataset of text, where the sentiment of each piece of text is already known. The model can then be used to predict the sentiment of the new text. Examples of machine learning-based sentiment analysis tools include convolutional neural networks (CNN), recursive neural networks (RNN), and BERT models. Some packages provide assistance in this regard, such as NLTK and Stanford NLP.

The chief difference between the two approaches is that lexicon-based methods are relatively simple and easy to use but may not perform as well as machine learning-based methods on more complex or nuanced text. Machine learning-based methods, on the other hand, can be more accurate, but they require a labeled training dataset and may be more complex to implement and maintain.

A hybrid sentiment analysis combines the strengths of lexicon-based and machine learning-based methods to improve the model's performance. This can be achieved by using a lexicon-based approach to pre-process text and to provide input to a machine learning model or by combining the results of both approaches. The hybrid approach may also include a combination of the lexicon, rule-based, and machine learning techniques. These methods can be more robust and accurate than a single approach alone.

One way to implement a hybrid method is to use a lexicon-based approach to pre-process the text and identify words or phrases associated with specific sentiments. The resulting feature set can then be used as input for a machine learning-based model, such as a neural network, to make the final sentiment prediction. This approach can be useful in cases where the lexicon-based approach cannot fully capture the sentiment of the text but can provide valuable information to guide the machine learning-based model.

The simplest way to analyze sentiments within a text document is by manually analyzing it, i.e., reading and inferring an emotion over a term, sentence, or another set of words. This approach was implemented totally or in part by some authors (e.g., [45–47,51]), where the sentiments were filtered by experts.

Among lexicon-based methods, a common way to analyze sentiments in text documents is by previously defining positive and negative words and then comparing them with a specific text of interest. This is the case for specialized dictionaries. One of the most popular in finance literature is Henry's Financial-Specific Dictionary [74], which contains 105 positive and 85 negative words. Another dictionary is the Loughran–McDonald Oil-Specific Dictionary [56]. This oil-specific dictionary contains 130 oil-related words and 827 modifiers, of which 291 are positive (e.g., *add*, *growing*, and *upgraded*) and 536 are negative (e.g., *deteriorates*, *fading*, and *slowed*). Specifically, there are 59 positive keywords associated with an expectation of oil price to increase, 19 negative, and 52 keywords that need to be combined with a modifier to indicate their expectations on price [56] (More than just comparing the positive and negative words from the dictionaries, these analyses usually apply a net-optimism metric, which measures the difference between the count of positive and negative words normalized by the number of total words [48]. Following the methodology of Li et al. [50], the metric can be denoted as:

$$S_t = \frac{w_p(A_t) - w_n(A_t)}{w_p(A_t) + w_n(A_t)} \tag{2}$$

In Equation (2), subscript t indicates the time, A_t is the available news or social media posts, $w_p(A_t)$ is the total number of positive words in A_t, $w_n(A_t)$ is the total number of negative words, and $S_t \in [-1, 1]$ is the corresponding sentiment, i.e., -1 being a more negative sentiment and +1 a more positive sentiment. In summary, the result is the difference between the counts of positive and negative words divided by the sum of positive and negative word counts in the available news articles or social media posts [50]).

Similar approaches can be utilized in specific packages in different programming languages, such as Java, Python, and R. From the selected articles, at least four are present: Sentimentr, SentiWordNet, TextBlob, and VADER. In Sentimentr, the words in each sentence are searched and compared to a dictionary of polarized words (e.g., a combined and augmented version of Jokers [75] [originally exported by the Syuzhet package] and Rinker's augmented Hu and Liu [76] dictionaries in the Lexicon package). Positive and negative words are tagged with a +1 and -1, respectively. Polarized words will form a polar cluster, which is a subset of a sentence (Information retrieved from the Sentimentr GitHub repository available in https://github.com/trinker/sentimentr (accessed on 16 April 2023)). Then, the sentiment polarity score of each treated news headline returns a value within the range of $[-1, 1]$ for each headline.

In Keshwani et al. [54], the sentiment analysis is performed with SentiWordNet. As shown by the authors, SentiWordNet is a free software package that classifies the polarity of a sentence with positive, negative, and objective scores. It contains a collection of words matched with the text-data input given. As a word can have several meanings, SentiWordNet divided the words into groups of their synonyms. Each group is known as a Wordnet. Then, it searches in all Wordnets and undertakes a maximum matching on the sentence, where the Wordnets selected are given the respective scores.

Textblob was used by Li et al. [27] to construct their sentiment score, i.e., polarity and subjectivity scores. It is a Python (Natural Language Processing) library that provides a simple application programming interface (API) for common NLP tasks such as part-of-speech tagging, noun phrase extraction, and sentiment analysis. TextBlob uses a pre-trained model and a lexicon-based approach for sentiment analysis, during which it calculates the sentiment polarity by traversing all the words in the sentence and averaging them through the labels of its dictionary [18].

Another type of method based on a dictionary is the Valence Aware Dictionary for sEntiment Reasoning (VADER). This technique was used by the authors in references [61,63,68]. The algorithm behind VADER is similar to other lexical-based methods, i.e., it relies on a dictionary to evaluate the intensity of each term and then produces a sentiment score. Among its advantages, Zhao et al. [61] highlights that, as it contains a public dictionary, it is simpler to explain, thereby making the calculated text tendency more realistic. Additionally, it is both self-contained and heuristic, with strong portability, and without supervision, it can avoid the high costs of tagging data.

SentiStrength and the Stanford NLP Sentiment analyzer are also free tools used to perform sentiment analysis. Both are Java libraries and were utilized in the research by Oussalah et al. [55]. SentiStrength is lexicon-based, while Stanford NLP Sentiment is a machine learning-based analyzer. For each input (e.g., a phrase), the SentiStrength sentiment outputs are two integers ranging from 1 (no sentiment) to 5 (high sentiment). The Stanford NLP is responsible for the pre-processing tasks, including lowercase, stop-word removal, HTML tags, and non-English removal, as described by the authors.

Other methods rely on ontologies, as in the case of Chen et al. [62], the Chinese emotion word ontology (CEWO) is constructed based on Ekman's theory of six basic emotions. Each emotion word in the ontology has its emotion category tag, an intensity value, and a polarity value.

Besides lexicon-based methods, it is becoming more common to see machine learning-based models applied to sentiment analysis. Zhao et al. [58] developed a method based on SVMs to explore the timeliness of news regarding the oil price. This kind of model belongs to the supervised category of machine learning algorithms [73]. SVM is based on the structural minimization risk principle from computational learning theory. Satisfactory performance in textual classification relies on the possibility of managing large spaces of features and high generalization ability [77]. The optimization algorithm locates the best boundary separating positive and negative sentiments. This boundary is called the maximum margin hyperplane, and it defines the decision surface that the SVM uses to make sentiment predictions. In the work of Zhao et al. [58], SVM is used to classify the relationship between information in the news and oil prices. The SVM analyzes the sentiment expressed in news articles related to the oil market and predicts how the sentiment is likely to impact oil prices.

Deep learning models are also prominent. Chen et al. [62] utilized a recursive neural network (RNN) to predict the subjectivity of sentences. This approach considers the position of each word in a sentence in order to predict the successive words of the sentence. RNN is a type of supervised learning neural network model where neurons are connected with one or more feedback loops. The aim is to optimize the neural network weights by minimizing the training error, given by the difference between the predicted outputs and the corresponding labeled target values [78]. In other words, the model can be trained on a labeled dataset of text, where the sentiment of each piece of text is already known. During the training process, the model learns to associate specific words and phrases with positive or negative sentiments.

Li et al. [27] utilized a CNN model to learn hidden patterns embedded in crude oil news and to predict the price movements of the crude oil market. According to the researchers, the advantage of the CNN classifier is based on multi-layer networks and convolution architecture. This allows for the composition of different semantic fragments of sentences and for learning the interactions between composed fragments, thereby fully exploiting the inter-modal semantic relations of crude oil news. In CNNs, a filter is applied over the input words and is moved across the input to identify relevant features. These filters can be trained to identify specific word patterns associated with positive or negative sentiment.

Several aspects of ML models require attention, including dataset distribution, parameter tuning, and evaluation metrics. Nevertheless, only studies that use CNN models provide more information on their parameters. One explanation for this is that the filter used to determine study eligibility limits the sentiment analysis of the oil market. This implies that sentiment analysis is employed as a supplement to the core goal of the work, rather than as the major point. This is why Tables A2–A4 refer only to CNNs.

In this regard, in the Appendix, a summary is shown of the works that apply CNN models. Table A2 depicts the distribution of training and test sets where the mean values for the training and test sets are 43.6% and 56.4%, respectively. The proportion between the training and test datasets in CNN models is important because it affects the model's ability to generalize to new content. If the dataset is not representative of the population it aims to model, or if the model is overfitted—i.e., when it is too complex or has too many parameters relative to the amount of training data available—it could lead the model to perform well on the training data, but poorly on the test data. To avoid overfitting, the dataset can be split into a training set, a validation set, and a test set, and cross-validation techniques can be used to tune the model's hyperparameters and evaluate its performance.

Regarding the parameter settings, Table A3 displays the configuration defined in the studies that utilize CNN models. Hyperparameters help optimize the model's performance and are set before the training process begins and cannot be learned by the model during training. Some examples include the batch size, embedding dimension, optimizer, weight initialization, dropout rate, and activation functions. The hyperparameters can be adjusted using various techniques such as grid search, random search, and Bayesian optimization to find the optimal combination of hyperparameters that results in the greatest performance of the CNN model.

In Table A4, the evaluation metrics achieved by the CNN models are highlighted. They measure how well the model performs in terms of accuracy, precision, recall, and F-measure (The accuracy, precision, recall, and F-measure are defined as follows:
$Accuracy = (TP + TN)/(TP + FP + TN + FN)$
$Precision = TP/(TP + FP)$
$Recall = TP/(TP + FN)$
$F\text{-}measure = 2 \cdot TP/(2 \cdot TP + FP + FN)$
TP is the number of positive observations which are classified as positive; FP is the number of positive observations which are classified as negative; TN is the number of negative observations which are classified as negative; and FN is the number of positive observations which are classified as negative [70]). These metrics aid in determining whether the model is suitable for the problem at hand and whether it can help in identifying areas where the model may need improvement. Additionally, they allowed for comparison between different models in order to determine which one performs better.

The methods Roberta large English (SRLE); Twitter Roberta base sentiment (TRBS) [68]; and FinBERT [19] are all BERT-based architectures, where BERT stands for bidirectional encoder representations from transformers. It provides pre-trained transformer models for natural language processing, which can be fine-tuned for sentiment analysis on financial market data. FinBERT is a BERT model pre-trained on financial communication text. According to its maintainer Hugging Face (Available in https://huggingface.co/blog/bert-101 (accessed on 16 April 2023)), BERT was specifically trained on Wikipedia and Google's BooksCorpus, both with around 2.5 billion words and 800 million words, respectively. Its developers claim that FinBERT substantially outperforms the Loughran and McDonald dictionary and other ML algorithms, including *naïve* Bayes, SVM, Random Forest, CNN, and LSTM, in sentiment classification [79].

When dealing with sentiment analysis, it is not unusual to see works that apply some kind of topic modelling. The models employed for topic modelling often belong to the category of unsupervised learning models. For instance, the authors of References [19,27,58] employ a latent Dirichlet allocation (LDA) modelling approach. Specifically, in Li et al. [27], the LDA model aims to identify latent topics embedded within the news headlines. The main assumption of the LDA model is that each document is a mixture of various topics, and each topic has a corresponding probability distribution for different words. Furthermore, the authors also incorporate the dynamic topic model (DTM) in order to consider possible time-varying effects of online news.

According to Zhao et al. [60], on the one hand, a downside of LDA models is that they are static topic models with the premise that topics do not change with time, a premise which does not match reality. On the other hand, the DTM models solve this problem, but the number of topics in DTM under each time window cannot change with time, which also differs from reality. In consideration of these problems, the authors employed a two-layer NMF topic model that identified the dynamic processes of topics based on topic modelling.

Xu et al. [44] utilized text mining techniques that involved TF-IDF metrics and a K-mixture model to select attributes from a document collection. Therefore, in order to reduce the number of attributes selected, the authors applied the rough sets theory, whose main assumption is that every object in the universe of discourse is associated with some information. If the object is crude oil listed on a commodity market, the information about the crude oil is composed of price behaviour and its variability characteristics [80]. Finally, they applied a wavelet neural network model to find the vital degree of the reduced attributes. This technique combines wavelet theory and feed-forward neural networks. The wavelet function is a local function and influences the networks' output only in some local ranges.

In summary, there has been an increasing trend towards machine learning-based and hybrid models for sentiment analysis of the oil market in recent years. An example could be using a lexicon-based approach to identify sentiment-bearing words and phrases, a rule-based approach to identify negations and intensifiers, and a machine learning-based approach to analyze the sentiment of text by processing the sequence of words in the text. This hybrid approach can lead to a more effective and accurate analysis. Nonetheless, it is up to the researcher to define the methodology that best fits their needs according to the dataset and objectives.

3.3. Sentiment Analysis Application and Results

In Table 1, it is possible to see all of the selected studies in detail. Nonetheless, Figure 4 shows the number of documents by year and the type of application. As can be seen, sentiment analysis is mainly employed to help forecast oil prices. A few documents explore different topics, like supply and demand, bubbles, and risk identification. Following these differences, a synthesis of the article's results was explored.

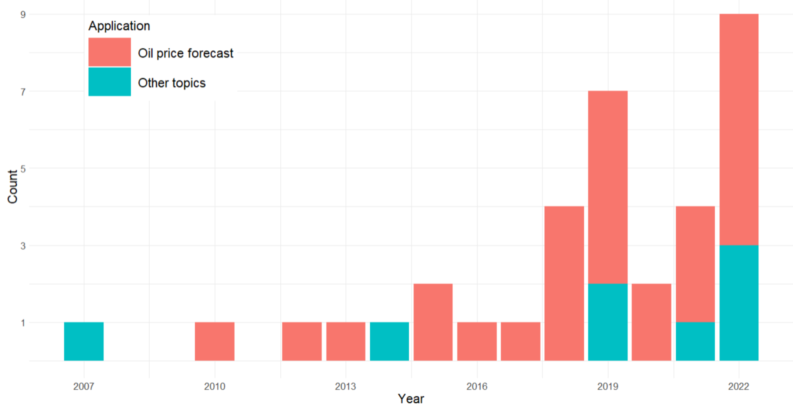

Figure 4. Frequency of documents by year and application.

Concerning oil price forecasting, all of the studies agreed that the sentiment extracted from financial news or social media helps to improve the forecast accuracy of whatever model they are inputted on. They differ in specific topics such as the type of oil price employed (e.g., crude oil, futures, WTI, or Brent), the source of the textual data, and in the different insights generated by the methodology employed. For instance, Abdullah and Zeng [45] were interested in predicting the monthly WTI crude oil price. They extracted key features from the news that cause the crude oil price market to be volatile. Data represented in the one-step returns function were successfully proven to be cleansed of errors and noise and to be made uniform, resulting in a more accurate prediction.

A similar approach was taken by the authors in References [46,47] through the study of some 45 million news messages over a period of 8 years. They showed that hidden information in online news stories can, to some extent, affect oil prices in terms of predictive value. Chuaykoblap et al. [51] investigated the performance of the expert-based Delphi text mining (EDTM) technique in effectively predicting the future trend of crude oil prices by analyzing news articles. They observed that the performance derived from an EDTM methodology can outperform traditional text mining and be even better than popular econometric models like the three-day simple moving average, and, when combining both models together, the performance of the forecasting system was substantially improved.

Li et al. [27] made use of qualitative information from financial news to improve oil price forecasting models by extracting text features and incorporating them with financial features using ML and linear regression models. The results demonstrated that the text features extracted from online news had significant cross-correlations with the oil price and contributed to its variance. Combining text and financial features in random forest and support vector regression models increases forecast accuracy.

Jain et al. [20] constructed a model to predict stock value movement using opinion mining and the clustering method on National Stock Exchange data. Their study used a domain-specific approach and selected stocks with maximum capitalization. The results indicated that sentiment values on smaller time frames can be noisy, but using a hybrid approach, i.e., sentiment analysis and clustering techniques, can improve stock market forecasting when compared to other individual sentimental or classification methods.

The study of Liu and Huang [63] proposed a new framework, AGESL, for crude oil price forecasting that integrated multi-channel information, such as historical prices, event types, event arguments, and sentimental factors extracted from news events. AGESL uses an event extraction algorithm and sentiment analysis to extract information from the news, and a deep neural network integrating this information, historical prices, and sentimental factors to predict future crude oil prices. With the advantage of integrating the strength of linear and nonlinear modules, the framework outperforms other benchmark models in the study, including single-channel and multi-channel input models like ARIMA, SVM, LSTM, LSTM-Sent, ARIMA-GARCHSent, and LSTM-Event.

Bai et al. [18] proposed a framework for forecasting crude oil prices using news headlines by utilizing advanced text mining techniques to construct high-quality features from sparse and short news headlines. The framework constructs a novel topic indicator using SeaNMF and a dynamic sentiment indicator that considers the cumulative and diminishing effect of the market and incorporates them with AdaBoost.RT. Empirical experiments showed that the proposed framework with AdaBoost.RT and these text indicators outperform benchmarks and have good forecasting performance when applied to other futures commodities.

The work of Jiang et al. [28] examined the relationship between investor sentiment and crude oil prices in China. It aimed to determine whether including sentiment improves prediction accuracy and which sentiment proxy variable is the most accurate. Additionally, it aimed to find the best model for predicting the Shanghai International Energy Exchange's crude oil futures prices with the inclusion of an investor sentiment index. The results revealed that the LSTM model combined with the composite sentiment index had the best performance, with lower prediction errors and greater accuracy in forecasting time series of one-day-ahead prices.

Jiao et al. [67] developed a method for forecasting crude oil market volatility using text mining and deep learning. Their study found that the LSTM model optimized by the particle swarm optimization (PSO) algorithm is significantly more accurate than traditional econometric models and machine learning models. Additionally, the deep learning and machine learning models have better robustness in multiple-step sizes. Using text features in the PSO-LSTM model improves forecasting accuracy, resulting in a 6.77% reduction of the mean absolute error and a 5.12% reduction of the mean square error.

Gong et al. [19] proposed an innovative approach to capturing the trend of oil futures prices using text-based news and natural language processing techniques. The text features obtained from the online oil news improve the forecasting accuracy of oil futures prices. They found that textual features are complementary in improving forecasting performance for LightGBM and benchmark models. Additionally, they demonstrated that positive and negative emotional shocks impact oil futures prices asymmetrically. The text-based news features generated robustly reduce forecasting errors, and the reduction is maximized by incorporating all the features.

Dictionaries are common in NLP techniques. An oil-specific dictionary was created by Loughran et al. [56], who presented a new list of 130 oil-related keywords and modifiers to measure the information content of oil news stories. They discovered significant short-term overreaction to the text of Dow Jones oil-related news articles. Phrases such as *output cut*, *production cut*, *shortage*, and *demand up* in lagged news articles were linked to lower oil prices the next trading day. This supports the idea that oil traders overreact to widely-read news articles.

Lucey and Ren [64] investigated the relationship between the news tone and crude oil prices and evaluated the ability of the news tone to forecast oil prices. The study made use of the oil-specific dictionary from Loughran et al. [56] and a financial dictionary [74] to measure sentiment in 3579 oil news articles from the Financial Times. The results indicated that the oil dictionary helps forecast monthly oil prices in the short term, while the news tone constructed by the financial dictionary does not have forecasting power.

Regarding time-dependency, Ratku et al. [49] examined whether news reception in the oil market varies according to the time the news was released using a rolling window regression. Their results suggested that there are times when investors pay more attention to news announcements, whereas sometimes, news reception is barely significant. In the same direction, Li et al. [50] aimed to understand the relevant information of online news articles and formulate an oil price trend prediction method. They highlighted three conclusions: i. the extracted sentiment revealed a similar trend as in the oil price data with directional changes; ii. there is evidence that when the sentiment series is strictly Granger, it causes (The Granger causality methodology aims to evaluate the causal relationship between two time series. Specifically, when dealing with the stock market, a good explanation can be found in Hiemstra and Jones [81].) a price series with a predictive lag order of 3 weeks; and iii. the predictive power of sentiment for oil price trends was statistically significant.

Zhao and Zeng's [58] work made use of SVM and text mining methods to investigate the timeliness of news and its relationship with oil prices. The authors proposed a multi-scale trend discovery method to identify oil price trends using TF-IDF for text representation and employing an asynchronous approach to label news. The text information is then extracted using SVM, and the accuracy and recall rates are used to measure the amount of information in the text that corresponds to the oil price trend. The results indicated that the information in the news is more likely to reflect future oil price changes, and that news is more accurate in predicting oil price trends 5–8 days after release, with the impact diminishing afterward. The information in the news also tends to reflect long-term trend information.

In the work of Jiang et al. [66], it was proposed that a novel decomposition–ensemble approach combined with sentiment analysis could be used for forecasting crude oil futures prices. The approach was tested and validated using daily WTI crude oil future and news headlines data and was shown to significantly outperform other comparable models in terms of forecasting accuracy and hypothesis tests across different forecasting horizons.

With respect to the text source, Kelly and Ahmad [53] showed that news specific to a domain, such as opinion columns on market-level news or industry news, has a more consistent and significant impact on returns than general news. Moreover, the high readership of these sources also affects the significance of sentiment on returns. These findings were developed with a method that uses multiple dictionaries to analyze the content of news in specific domains and evaluate its impact on financial benchmarks in the equity and oil markets. Finally, among the authors' results, they found that incorporating news sentiment into a trading strategy can increase annual returns when compared to a simple buy-and-hold strategy.

Besides financial news, Oussalah and Zaidi [55] created a new model that predicts the weekly direction of WTI crude oil prices using sentiment analysis of US foreign policy and oil companies using their tweets as the textual data source. Their statistical analysis revealed a strong correlation between the novel inputs and WTI prices. A predictive model was developed using these findings, with the best performance being achieved using an SVM algorithm. The model's accuracy exceeded that of existing models found in the literature when using these novel features.

In the research of Chen et al. [62], the authors compared user behaviour and public mood on Sina Weibo and Twitter regarding commodities markets, with the goal of finding similarities and differences in the topics discussed and public mood, and whether these can be used to predict crude oil prices. The study found significant differences in user behaviour on the two websites and showed that public mood on Sina Weibo and Twitter is correlated with crude oil prices in the Shanghai and New York exchanges.

Another approach utilized reports as text sources. Prusa et al. [57] focused on the study of WTI crude oil, proposing nine different machine learning algorithms and utilizing features extracted from monthly IEA reports to predict undervalued, overvalued, and accurate valuations of the oil futures between 2003 and 2015. The results indicated that four of the algorithms—SVM, multi-layer perceptron (MLP), logistic regression (LR), and the radial basis function (RBF) network—achieve a statistically superior classification performance when compared to Random or ZeroR, thereby challenging the efficient market hypothesis (EMH) (EMH, first proposed by Eugene Fama in 1970 in the Journal of Finance, is a theory that posits that financial markets are efficient in that the prices of securities reflect all available information at any given time, making it difficult for investors to consistently achieve returns above the market average using publicly available information. There are three forms of EMH: weak, semi-strong, and strong. The weak form states that all historical prices and data are reflected in current stock prices, the semi-strong form states that all publicly available information is reflected in stock prices, and the strong form states that all information, both public and private, is reflected in stock prices). Decision tree-based models and 5NN perform poorly, possibly due to their widespread utilization in the market. MLP was found to be the top-performing algorithm, and this difference is statistically significant when measured with GMeasure. Additionally, the inclusion of text-based features significantly improves performance, suggesting that the use of publicly available information can yield better market predictions than without it.

A broader approach was taken by Elshendy et al. [52], who examined the usefulness of selected online data sources in forecasting financial events by analyzing daily traffic activity on four different social media platforms, including Twitter, Wikipedia, Google Trends, and GDELT, in order to predict the WTI crude oil price. The results indicated that combining the analysis of these four platforms provides valuable information for financial forecasting and that the language complexity of Twitter, the number of articles from GDELT, and the Wikipedia page reads have the highest predictive power.

Wu et al. [14] studied the relationship between Google Trends and crude oil price volatility and examined the use of artificial neural networks and decomposition techniques to extract oil news information in order to improve the accuracy of crude oil price forecasting. They also investigated how using online media and Google Trends together can improve forecasting accuracy and compared the performance of different prediction techniques. Results indicated that the proposed text-based and online, big-data-based forecasting methods outperform other techniques, with a mean absolute percentage error of 0.0571 and 0.0459 for the two cases, respectively, showing that combining news headlines and Google Trends is beneficial for accurate crude oil price forecasting.

The relationship between the news and oil can also be extended to other commodities. This was the case for Keshwani et al. [54], who used sentiment analysis and machine learning to predict stock market trends for gold, silver, and crude oil. They found a strong correlation between public sentiment and stock market fluctuations.

Zhao et al. [61] proposed a new hybrid oil price prediction model that uses text mining to incorporate the text sentiment obtained from web information into oil price forecasting. It explores the relationship between web information and oil prices, tests the performance improvement effect of introducing text sentiment, investigates the differences between types of text sentiment in their impact on oil price forecasting, and examines how big-data information improves oil price forecasting performance. The results showed that the model can reduce the root mean squared error and error variance, improve accuracy and stability, and reveal that text with strong intensity can better support oil price forecasting.

Lakatos et al. [68] presented a natural text processing model for predicting the price of exchange-traded products using machine learning and general statistics. Their model forecasts the trend of oil prices on a daily basis using tweets. The sentiment of tweets from different news sources captures the trend of price movements, but human factors such as the correlation quality of news posts varying from period to period must be taken into account. The authors developed a statistical-based NLP method to generate a better-quality dataset from the tweets for machine learning models. Sentiment analysis was found to support the forecast and increase accuracy along with other indicators, but the method is greatly influenced by the quality of each news source and the ability to remove noisy items.

Besides oil price forecasting, other topics were also explored. [65] aimed to determine which type of news was most relevant to oil prices, production, consumption, and inventory during the COVID-19 pandemic. The authors also examined how social media information can improve forecasting performance. Their results revealed that social media information contributes to the forecasting of oil price, production, and consumption, with mean absolute percentage errors of 0.0717, 0.0144, and 0.0168, respectively, during the pandemic. The study of Wu et al. [70] proposed a novel news-based oil consumption prediction methodology that uses CNN to automatically collect news and a new approach, attention-based JADE-IndRNN, which combines adaptive differential evolution (JADE) with attention-based independent recurrent neural network (IndRNN) to forecast oil consumption monthly. The results indicated that this news-based approach is more accurate than traditional methods, as the news might contain some explanations of the relevant confinement or reopen policies during the COVID-19 pandemic.

Xu et al. [44] employed text mining techniques to evaluate the related factors affecting oil prices and found that the world's total demand and supply are the most crucial factors, while demand is dominant. Furthermore, they also found that world economic growth and exchange rates affect crude oil prices as well and increase their volatility. In line with the author, Zhao et al. [59] introduced a news recognition model for the oil market that extracts the main oil market risk factors from internet news using text mining technology by applying clustering methods based on text topics. The results expressed that various risk factors are centered around geopolitical events, war conflicts, environmental protection, OPEC policies, and market supply and demand, with political conflicts, economic sanctions, and warfare involving oil-producing regions being the most prominent factors. This method is more comprehensive, detailed, and easy to operate when compared to traditional expert consultation and brainstorming methods. The relationships between the factors were analyzed in order to assess the structure of the oil market risk factors and analyze a specific part of the supply chain.

Zhao et al. [60] employed a two-layer non-negative matrix factorization model and natural language processing to extract dynamic risk factors from online news and improve the accuracy of the crude oil VaR measurement. They also proposed a method called giant information history simulation (GIHS) to forecast crude oil VaR, and their results indicated that considering dynamic risk factors from online news improves the accuracy of the crude oil VaR measurement, providing a useful tool for analyzing crude oil price risks and supporting risk management for investors, as well as promoting sustainable and green transformation.

In contrast to other authors, Feuerriegel et al. [48] were interested in identifying bubbles in the oil market with the aid of news sentiment. They developed a method that categorizes any market period into bullish (explosive) and bearish (stationary) phases depending on price movements. Accordingly, they discovered that news processing is fundamentally different in bullish and bearish markets, with news sentiment presenting a greater impact on stock market prices when the economy is facing a bust phase. Moreover, they found that extreme messages pulled out from outlier news announcements are more common in bullish markets.

The work of Li et al. [69] examined the dynamic relationship between crude oil prices and investor sentiment. It used a web crawler to construct a Chinese investor sentiment index and employed a VAR model to decompose crude oil price shocks into three categories: crude oil supply shocks, aggregate demand shocks, and oil-specific demand shocks. Then, it used wavelet coherence analysis to study the dynamic correlation between the oil price (shocks) and investor sentiment in the time and frequency domains and explored the asymmetric dynamic correlation between them under different oil price trends. The results suggest heterogeneous dynamic correlations and lead–lag relationships between the crude oil price (shocks) and investor sentiment over different time and frequency domains, and asymmetric dynamic correlations and lead–lag relationships under different trends of the crude oil price.

Yilmaz et al. [71] studied the relationship between social media activity and stock prices in the energy sector. Their sample covered the monthly period from June 2015 to May 2020 and used energy stocks, the S&P 500 index, the stock market volatility index, the trade-weighted USD index, and Brent oil prices as independent variables. Three different models were created using augmented mean group to analyze the link between returns, volatility, trading volume, and Twitter sentiments of 20 energy companies traded in the S&P 500. The results indicated that Twitter sentiment does not affect firms' returns and volatility, but does, however, affect trade volume. Positive tweets do not affect trade volume, and thus only negative tweets have an impact on the investment decisions of individuals. However, this effect is not impactful on volatility and returns.

There is a consensus among studies that sentiment analysis of textual databases, whether news, social media, or corporate and government reports, provides relevant information that results in more accurate models. Although several studies focus on forecasting oil prices, other areas have still barely been explored, opening up ample space for future research. For instance, changing the energy base to a clean source has been on the agenda in the most diverse spheres in favour of alleviating climate impacts on the planet. How this trend is observed by society can be an indicator of future oil prices, as well as dictating new supply and consumption environments.

4. Discussion

This systematic mapping focuses on uncovering the key components and processes involved in sentiment analysis as it relates to the oil market. Through examination, four crucial questions can be answered: i. What are the potential text sources, their relative relevance and the reasoning behind their significance? ii. What are the current trends in sentiment analysis techniques? iii. What is the primary utilization of sentiment analysis in the oil market? iv. What is the importance of grasping the inherent sentiments within the oil market?

To address the first question, in Table 1, it is possible to see several different sources that can be used to perform sentiment analysis regarding the oil market, such as news articles and websites, social media, analyst reports, governments and industry reports, and online forums and discussion boards. They all reflect facts or opinions about the market. For instance, news articles provide a variety of valuable insights into the sentiments of market participants and experts. Social media platforms such as Twitter, Sina Weibo, and the Eastmoney forum can be useful sources of real-time sentiment data from a broad range of individuals and organizations.

A growing field in economics, nowcasting, is interested in predicting real-time macroeconomic indicators, economic activity, stock volatility, and commodities prices. As news and social media posts are generally released daily, they facilitate understanding market behaviour in real-time. However, news portals and social media have their differences.

- Reliability: News portals such as Reuters and *Oilprice.com* are known for their rigorous reporting standards, whereas social media platforms may contain a mixture of credible and unreliable information;
- Timeliness: News portals typically publish articles in real-time, while social media posts can be delayed and may not reflect current market conditions precisely;
- Objectivity: News portals aim to provide objective, unbiased reporting, while social media can reflect the personal opinions and biases of individual users;
- Volume of information: Social media generates a massive volume of data, generally containing noisy and irrelevant information, while news portals typically provide more in-depth and comprehensive articles on a particular topic;
- Type of information: News portals typically provide official news, analysis, and expert opinions, while social media focuses on user-generated content and personal experiences.

To fully grasp the sentiment towards the oil market, it is wise to examine a diverse range of sources. News portals and social media offer unique perspectives and advantages regarding understanding market sentiment. In a way, the noisy and biased information available on social media, despite its extremely large volume, can be used as a herd behaviour for a wide range of users. On the other hand, only the expectation of the behaviour people will assume when they react to some kind of news may be a good indicator of the sentiment.

Table 1 also confirms Reuters to be the most-used news portal to assess sentiments in the oil market. Reuters is a reputable news and media organization that has been covering the oil market for decades. It is well-known for providing accurate reporting on the latest developments and trends in the oil industry. Besides its application to the oil market, Reuters is also the text source for sentiment analysis of the stock market in References [82,83].

By monitoring news and events related to the oil market, Reuters can provide insights into the sentiment and expectations of various stakeholders, such as investors, governments, and industry players. This information can prove to be valuable for individuals and organizations trying to understand the oil market sentiment and make informed decisions. Nonetheless, as mentioned previously, it is crucial to note that the perception and outlook towards the oil market, like any other market, is subject to various exterior factors, including geopolitical occurrences, supply chain interruptions, and market dynamics shifts. It is, therefore, essential to consider a range of sources and cross-check the data in order to gain an all-encompassing perspective of the market sentiment.

The text source is the first step to inferring a sentiment from the market. The second question aims to identify the trends within this analysis. From this perspective, sentiment analysis is a growing and evolving field, and no singular approach has emerged as the clear leader. Instead, there are a multitude of options available in terms of software packages, technical frameworks, libraries, and tools that are used across a variety of industries.

There is, though, increasing usage of machine learning methods in sentiment analysis, mainly because of their good performance. These results are in line with those of other authors, such as Birjali et al. [21]. Machine learning algorithms have become more sophisticated and better equipped to handle complex text data. The combination of large amounts of data, powerful computing resources, advances in deep learning, and the development of transfer learning methods has led to a significant improvement in the accuracy of sentiment analysis, making it a useful tool for various applications such as market analysis, customer feedback, and opinion mining.

Models such as CNNs and RNNs have demonstrated excellent performance on various sentiment analysis tasks, such as sentiment classification and sentiment regression. Other approaches, such as Transfer Learning and Pre-trained Language Models, like the popular BERT model, have demonstrated remarkable potential. These techniques tap into vast amounts of pre-existing text data to enhance the accuracy of sentiment analysis results. Several studies have employed BERT to forecast stock returns [84,85]. Specifically, Sousa et al. [86] claimed that, comparing the accuracy rates, BERT outperforms CNN and word embeddings to an order of 8.6%. Furthermore, hybrid models seamlessly blend the advantages of lexicon-based and machine learning-based techniques in sentiment analysis. This combined approach offers the potential to augment the strengths of each method, leading to a more comprehensive sentiment analysis system.

Regarding the oil market, the subject that most authors are interested in is oil price forecasting. Table 1 shows that, from all 34 studies, 28 of them utilize sentiment analysis to improve their forecasting models. This is a hot topic for several reasons. The oil industry is a major contributor to many economies worldwide, and oil prices significantly impact various sectors, such as transportation, agriculture, and energy production. Additionally, the volatility of oil prices can have far-reaching effects on financial markets and the public since it plays a considerable role in the inflation basket.

There is a consensus in the literature that the high volatility and non-linearity of crude oil markets create difficulties in predicting market movements [27]. The prices can be affected by supply and demand factors, climate policies, technological innovations—for example, the production of other commodities including natural gas, coal, and renewable energy may have a substitution effect which also leads to the volatility of oil price indirectly [87]—natural disasters, geopolitical events, economic conditions, exchange rates, and also by more subjective factors, such as speculation and investor sentiment.

Lakatos et al. [68] hypothesized that stock market news has a significant effect on price movements, so it is likely to precede price movements in time, as traders also act according to this news. In other words, investor sentiment can impact oil price forecasting by affecting the demand and supply of oil. When investors have a positive sentiment towards the oil market, they are more likely to invest in oil-related assets, which can increase the demand for oil and gravely increase its price. Conversely, when investors have negative sentiment, they are less likely to invest in oil, which can decrease demand and lower its price.

Positive sentiments can be related to news like technological breakthroughs in the drilling process or the discovery of new oil wells, which tend to decrease prices as the oil supply tends to increase. In the opposite direction, news that reflects potential threats to the oil supply chain can increase the prices since a scarcity period may occur. From the demand perspective, news related to the economic environment, such as changes in the exchange rates or the interest rates, may increase or decrease the purchasing power of a country which, in the final stage of the consumption chain, may affect the demand for oil-related products and subsequently affect oil prices.

Answering the fourth question, text streams reflect collective expressions that are valuable in any financial decision [88]. Identifying the sentiments attached to them plays an important role in forecasting oil prices, which is a topic of great interest to a wide range of stakeholders, including governments, investors, and industry players. Accurately forecasting oil prices can help individuals and organizations make informed decisions, minimize risk, and potentially capitalize on favourable market conditions.

5. Challenges and Recommendations

There has been a growing interest in sentiment analysis in recent years, which can especially be observed in the field of oil industry research. There are, however, several challenges and gaps that remain open in this literature.

The first source of worry is the quality of research applying sentiment analysis in the oil business. Table A1 illustrates the quality assessment index, which measures the amount of detail provided in each study by the existence of crucial phases in the sentiment analysis process, as emphasized in the study of Wankhade et al. [89]. It is worth noting that 21 of the 34 studies do not include one or more stages. The scarcity of high-quality studies suggests that there are still untapped research prospects. In this regard, it is suggested that future studies concentrate on the most important components of the analysis and exploit them thoroughly.

Addressing the text source, especially when dealing with social media, Habimana et al. [90] highlights some interesting challenges. First, there is a time-dependency issue wherein the vocabulary used by users can change over time and the number of users that are involved in the discussion of a specific topic can also change over time. Second, modelling and predicting the sentiment information that will follow an important social figure's tweet requires capturing the influence of the speaker. In this regard, the authors suggest combining the textual and network information by applying deep learning approaches like RNN or CNN.

In general, most sentiment analysis research focused on English texts. Among the selected studies, only a few gather text information from non-English sources (e.g., [28,62,69]). In turn, tools such as sentiment lexicons and corpora are scarce in other non-English languages [91].

Another challenge sentiment analysis faces is that natural language is often ambiguous and subjective, making it difficult to determine sentiment accurately. Social media and other sources of sentiment data may contain irrelevant or misleading information, which can negatively impact sentiment analysis results. Different sources may use different terminology or methods for expressing sentiment, making it challenging to compare results across sources. Furthermore, sentiment toward the oil market can be influenced by various external factors, such as geopolitical events, supply chain disruptions, and changing market conditions, e.g., the COVID-19 pandemic.

To accommodate these issues, models that utilize pre-trained models such as FinBERT, specifically designed for financial text analysis, usually report good performance in the face of these difficulties. The advantage of such models for sentiment analysis is that they have already been trained on a large corpus of financial-related text and so have a solid understanding of the language and terminology used in the financial domain. This allows them to produce more accurate sentiment predictions when compared to generic language models that have not been fine-tuned for financial text. There are, however, diverse options for performing sentiment analysis. This highlights the complexity of this kind of analysis and the need for tailored solutions based on specific requirements and goals [92].

6. Conclusions

Oil markets show considerably volatile behaviour when compared to other commodities since they are affected by a large and complex range of factors (e.g., oil consumption, supply, conflicts, war, economic development, and political instabilities). Recently, more uncertainties have arisen with COVID-19 and the Russia–Ukraine geopolitical conflict. It is important to assess and predict the sector's behaviour in order to make better investment decisions and policies that mitigate the chain effects that the oil market imposes.

In this sense, sentiment analysis is incorporated to help investors, governments, and people better understand the market. The "emotions" emanated in news and social media are of great value in this regard. This work proposed a systematic review of what has been researched in this field. For this purpose, 34 studies from a pool of 320 were selected and reviewed following the PRISMA standards.

Among the main results, it can be listed that several different sources can be used to construct a text dataset and develop a sentiment analysis. Among the studies gathered in the review, authors used Reuters, *Oilprice.com*, Twitter and many others, though Reuters was the most-used news portal source, probably because of its short time lag and the section dedicated to commodity markets. Furthermore, several sentiment analysis techniques were discussed. A prominent trend was seen in the use of ML models, especially the transformers class of models, which present promising results. Sentiments were mainly applied in forecasting models, where oil prices are the major interest.

It is important to recognize the special character of this review, which focuses on sentiment analysis specifically applied to the oil market. Due to this narrow emphasis, there is a smaller body of accessible research than in more general sentiment analysis investigations. In part, this also leads to works that could be considered relatively shallow with respect to the detail given to all the steps involved in the sentiment analysis process. This implies a gap that must be filled by future research.

Some limitations faced in this review must be considered. First, the search strategy was based on keywords, titles, and abstracts, which can sometimes lead to the exclusion of relevant articles. Additionally, only papers written in English were selected. Thus, any relevant papers written in other languages were omitted. Second, the papers collected for the study were sourced from digital databases, and it is possible that some relevant papers were not properly indexed and, therefore, were not included in the study. Last, the study only considered peer-reviewed journals and conference papers and excluded any non-peer-reviewed sources, such as book chapters and books, and studies that conducted a systematic literature review.

The scarcity of existing research in this specific area underscores the importance of this systematic review and the need to consolidate and synthesize the available knowledge. By critically examining and analyzing the existing studies, the authors aim to provide a comprehensive overview of the current state of sentiment analysis toward the oil market and identify avenues for further exploration and improvement.

Furthermore, the limited number of high-quality studies presents an opportunity for future research to delve deeper into this domain. This review serves as a catalyst for researchers to address this research gap, develop innovative methodologies, and contribute to a more refined understanding of sentiment analysis in the context of the oil market. It is the authors' hope that the work stimulates further interest and investigation, encouraging scholars to explore new approaches, gather more extensive datasets, and expand the scope of sentiment analysis.

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Abbreviations

The following abbreviations are used in this manuscript:

APIs	Application Program Interfaces
BAT	Baidu, Alibaba and Tencent
CEWO	Chinese Emotion Word Ontology
CNN	Convolution Neural Network
DJES	Dow Jones Energy Service
EDTM	Expert-based Delphi Text Mining
FT	Financial Times
GDELT	Global Data on Events, Location and Tone
GI	General Inquirer dictionary constructed from the Harvard IV-4 dictionary
GE	Gold Eagle
HFSD	Henry's Financial-Specific Dictionary
IEA	International Energy Agency
LDA	Latent Dirichlet Allocation
LM	Loughran-McDonald Oil-specific Dictionary
MCSSD	Manually Created Sector Specific Dictionary
ML	Machine Learning
NB	Naive Bayes
NMF	Non-negative Matrix Factorization model
NW	Negative Words
NYSE	New York Stock Exchange
PW	Positive Words
RNN	Recursive Neural Network
RSWNN	Rough Set Wavelet Neural Network
SA	Sentiment Analysis
SC	Sentiment Score
SP500	Silver Phoenix 500
SNLPS	Stanford NLP Sentiment analyser
SRLE	Sentiment Roberta Large English
SS	SentiStrength
STW	Stock Twits Website
SVM	Support Vector Machine
TF-IDF	Term Frequency-Inverse Document Frequency
TNYT	The New York Times
TRBS	Twitter Roberta Base Sentiment
UPI	United Press International
VADER	Valence Aware Dictionary for sEntiment Reasoning
VaR	Value at Risk
VMD	Variational Mode Decomposition
WSJ	Wall Street Journal
YFMB	Yahoo Finance Message Board

Appendix A. Complementary Tables

Table A1. SA data construction and quality assessment.

Study	Web Search Terms	Pre-processing Steps	Document Representation	Quality Assessment Index
Xu et al. [44]	Crude oil price, crude oil market, crude oil volatility	TF-IDF, K-mixture model	Full text division, Keywords/indexed	1.00
Abdullah and Zeng [45]	Crude oil: price	NA	NA	0.33
Wex et al. [46]	OILS, CRU, HOIL, ENR, JET, MOG, NSEA, OPEC, RFO	Keyword-list	# of oil messages per day	1.00
Wex et al. [47]	OILS, CRU, HOIL, ENR, JET, NSEA, OPEC	Keyword-list	# of oil messages per day, # of negative words	1.00
Feuerriegel et al. [48]	CRU	Tokenization, negations, stop words removal, synonym merging, stemming	Keywords/indexed	1.00
Ratku et al. [49]	Crude oil related announcements	Tokenization, negation, stop word removal, stemming	Keywords/indexed	1.00
Li et al. [50]	NA	Tokenization, negations, stop words removal	Keywords/indexed	0.66
Chuaykoblap et al. [51]	NA	Tokenization, stop word removal, stemming	Three vector representations	0.66
Elshendy et al. [52]	Crude oil price	NA	NA	0.33
Kelly and Ahmad [53]	Crude oil (FT crude oil news)	Relative frequency of negative terminology	Keywords/indexed	1.00
Keshwani et al. [54]	NA	Tokenization, stemming, speech tagging, parsing	Keywords/indexed	0.66
Oussalah and Zaidi [55]	Tweets from specific accounts	Lowercased, stop words removal, HTML tags, and non-English removal	SQL database (Date/time, Tweet, Username)	1.00
Li et al. [27]	Crude oil news section (Investing.com)	Tokenization, stop words removal, punctuation, non-alpha words removal, TF-IDF	Bag-of-words (vector)	1.00
Loughran et al. [56]	Oil, crude, OPEC, Brent, WTI	Numbers, single letters, acronyms, and proper nouns removal	Keywords/indexed	1.00
Prusa et al. [57]	NA	NA	Numeric word vector	0.66
Zhao and rong Zeng [58]	Oil, market and risk	TF-IDF	TF-IDF vector	1.00
Zhao et al. [59]	Oil, market and risk	Blank text, irrelevant symbols, stop words removal, and morphological conversion	Bag-of-words (vector)	1.00
Zhao et al. [60]	Oil, gas, gasoline, diesel, fossil, fuel, kerosene, WTI, benzine, Brent, OPEC	Duplicate news, stop words, symbols removal	Bag-of-words (vector)	1.00
Zhao et al. [61]	Oil price, oil market, petroleum, gas, gasoline, benzine, diesel, fuel, Paraffin, kerosene, coal oil, OPEC WTI Brent, fossil, Mobil, Royal Dutch, Shell Group of companies, Total, Chevron, Gazprom, Phillips	Abnormal vocabulary, stop words, root extraction removal and vocabulary normalization	NA	0.66
Chen et al. [62]	Crude oil	Word phrases generation algorithm (Chinese language), LDA, bdc, total discounted number of words, LDA, stemming	English and Chinese topic list	1.00
Jain et al. [20]	NA	Parsing, tokenization, filter, stemming, TF, TF-IDF	NA	0.33
Liu and Huang [63]	Crude oil, energy oil	NA	NA	0.33
Lucey and Ren [64]	Crude, brent, oil, OPEC, WTI	Stop words removal	News tone per article	1.00
Wu et al. [14]	Crude oil news section (Oilprice.com)	Tokenization, punctuation and stop words removal, padded sequence, TF-IDF	Bag-of-words (vector)	1.00

Table A1. *Cont.*

Study	Web Search Terms	Pre-processing Steps	Document Representation	Quality Assessment Index
Wu et al. [65]	Crude oil, American oil, American oil production	Tokenization, punctuation, stop words removal	Each word as a unique vector (word2vec)	1.00
Bai et al. [18]	Futures news column (Investing.com)	Tokenization, stop words removal, segmentation	Word vector matrix	1.00
Gong et al. [19]	News from ARCHIVE section (Oilprice.com)	Tokenization, stop words removal	Numerical vectors (GloVe)	1.00
Jiang et al. [66]	News data related to crude oil	Punctuation and stop words removal, lowercase conversion, TF-IDF	Treated news headline vector	1.00
Jiang et al. [28]	Comments on the crude oil futures market	Segmentation (nouns, verbs, and adjectives), frequency calculation	NA	0.66
Jiao et al. [67]	WTI Crude Oil Information section (Investing.com)	Segmentation, stop words removal, TF-IDF	Word vectors	1.00
Lakatos et al. [68]	Tweets containing the word *oil*	NA	NA	0.33
Li et al. [69]	NA	Word frequency	NA	0.33
Wu et al. [70]	American oil India oil	Tokenization, stop words removal, padded sequence	Word vectors	1.00
Yilmaz et al. [71]	NA	NA	NA	0.00

Note: NA stands for not available. In Wu et al. [70], the authors performed two numerical examples: U.S. oil consumption forecasting and Indian oil consumption forecasting. Each result in the table is shown respectively. The quality assessment index is a simple average of the three data construction indicators: web search terms, pre-processing steps, and quality assessment index—i.e., if the field is NA, then a value of zero is attributed to the study in that aspect, while a value of one is otherwise attributed. The index ranges from 0 to 1 and aims to give an idea about the level of detail in the sentiment analysis process.

Table A2. CNN dataset summary.

Study	CNN Ultimate Application	Dataset		
		Total	Training	Test
Li et al. [27]	Forecasting price	6756 (headlines)	60%	40%
Wu et al. [14]	Forecasting price	4837 (headlines)	52%	48%
Wu et al. [65]	Forecasting price	6793	35%	65%
	production	6793	35%	65%
	consumption	1461	43%	57%
	inventory	6793 (headlines)	35%	65%
Gong et al. [19]	Forecasting price	24,308 (news articles)	61%	39%
Wu et al. [70]	Forecasting consumption	1749	32%	68%
		1176 (headlines)	39%	61%
Mean	–	–	43.6%	56.4%
Min	–	–	32%	39%
Max	–	–	61%	68%

Note: CNN ultimate application refers to how the CNN model outcome was used.

Table A3. CNN parameter settings summary.

Study	CNN Ultimate Application	Parameter Setting									
		Batch Size	# Filters	Filter Size	Emb. Dimension	12 Regulation	Drop Out Prob.	Max Seq. Lenghts	Loss Function	Optimizer	Activation Function
Li et al. [27]	Forecasting price	NA	NA	3, 4, 5	128	0	0.5	NA	NA	NA	Softmax
Wu et al. [14]	Forecasting price	64	64	3, 4, 5	300	0	0.5	150	NA	NA	Softmax
Wu et al. [65]	Forecasting price, production, consumption, inventory	54	64	3, 4, 5	100	0	0.5	150	NA	NA	ReLU, Softmax
Gong et al. [19]	Forecasting price	4	100	2, 3	100	NA	0.3	NA	BCE With Logits Loss	Adam	Softmax
Wu et al. [70]	Forecasting consumption	50 47	128 128	2, 3, 4 2, 3, 4	100 100	0 0	0.5 0.5	150 150	NA	NA	Softmax

Note: NA stands for not available. CNN ultimate application refers to how the CNN model outcome was used. In Wu et al. [65], although the authors perform four different applications of the CNN model (forecasting of oil price, production, consumption, and inventory) the parameter settings applied were the same in all cases.

Table A4. CNN evaluation metrics summary.

Study	CNN Ultimate Application	Evaluation Metrics			
		Accuracy	**Precision**	**Recall**	**F-Measure**
Li et al. [27]	Forecasting price	0.61	0.60	0.31	0.65
Wu et al. [14]	Forecasting price	0.60	0.79	0.47	0.43
Wu et al. [65]	Forecasting price	0.66	0.70	0.58	0.63
	production	0.70	0.70	0.70	0.70
	consumption	0.64	0.66	0.56	0.61
	inventory	0.75	0.75	0.73	0.74
Gong et al. [19]	Forecasting price	0.58	0.58	0.58	0.54
Wu et al. [70]	Forecasting consumption	0.63	0.63	0.63	0.63
		0.72	0.72	0.72	0.72
Mean	–	0.65	0.68	0.58	0.62
Min	–	0.58	0.58	0.58	0.54
Max	–	0.75	0.75	0.73	0.74

Note: CNN ultimate application refers to how the CNN model outcome was used.

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